A Structured Analyse of Artificial Intelligence Techniques in IoT-Based Solar Photovoltaic Systems

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Abstract

The increasing deployment of photovoltaic (PV) systems has intensified the need for intelligent monitoring, diagnostics, and optimization solutions capable of operating under dynamic environmental and operational conditions. In this context, the integration of Artificial Intelligence (AI) techniques with Internet of Things (IoT) infrastructures has emerged as a promising paradigm for enhancing the performance, reliability, and autonomy of solar energy systems. This paper presents a structured and analytical review of AI-enabled IoT approaches applied to photovoltaic monitoring and management, with a particular focus on system architectures, data-driven intelligence, and operational functionalities.

The review systematically categorizes existing studies according to their targeted applications, including real-time performance monitoring, fault detection and diagnosis, predictive maintenance, energy forecasting, and adaptive control mechanisms. Machine learning and deep learning techniques are analyzed in relation to their data requirements, computational complexity, and deployment layers within IoT-based PV systems. In addition, the role of collaborative experimental environments, such as OASIS Colab, is discussed as a practical support tool for developing, training, and validating AI models for photovoltaic data analysis in research-oriented settings.

Beyond summarizing existing solutions, this paper identifies key technical challenges related to data quality, model generalization, scalability, and real-time implementation constraints. Finally, open research directions are outlined to guide future developments toward more robust, explainable, and scalable intelligent IoT architectures for photovoltaic energy systems.

Keywords
Artificial intelligence, Internet of Things, photovoltaic systems, intelligent monitoring, fault diagnosis, predictive maintenance, energy forecasting, OASIS Colab.

1. Introduction

The global energy sector is undergoing a profound structural transformation driven by the urgent need to reduce carbon emissions, enhance energy security, and ensure the long-term sustainability of electricity generation. Within this transition, photovoltaic (PV) technology has emerged as a cornerstone of renewable energy systems due to its modularity, declining cost, and suitability for both centralized and decentralized deployment. However, as PV penetration increases across residential, commercial, and utility-scale installations, maintaining system efficiency and reliability under real operating conditions has become increasingly challenging.

PV systems operate in environments characterized by high variability and uncertainty. Fluctuations in solar irradiance, temperature-dependent electrical behavior, dust accumulation, partial shading, and component aging directly affect energy yield and accelerate degradation processes. At large scale, these effects compound across thousands of modules and inverters, making manual inspection and static supervision strategies insufficient. Consequently, continuous monitoring, intelligent diagnostics, and adaptive operation are no longer optional enhancements but essential capabilities for sustainable PV system management [1].

Internet of Things (IoT) technologies provide a foundational layer for addressing these challenges by enabling distributed sensing, real-time data acquisition, and remote supervision across PV assets. Through networks of sensors, embedded controllers, and communication links, IoT-enabled PV systems can continuously capture electrical, environmental, and operational data, offering unprecedented visibility into system behavior [2]. Nevertheless, raw data streams alone do not translate into actionable intelligence; their effective utilization requires advanced analytical methods capable of learning complex patterns, handling uncertainty, and supporting operational decision-making.

Artificial Intelligence (AI) techniques, including machine learning and deep learning, have therefore become integral to modern PV analytics. By exploiting historical and real-time data, AI models support tasks such as fault detection and diagnosis, predictive maintenance, energy forecasting, and operational optimization [3], [4]. These capabilities enable proactive maintenance strategies, reduce downtime, and improve grid integration by supporting uncertainty-aware forecasting and energy balancing in smart grid environments [5], [8]. However, AI effectiveness in PV systems is inherently constrained by data quality, deployment latency, computational resources, and system integration.

The convergence of AI with IoT infrastructures commonly referred to as Artificial Intelligence of Things (AIoT) represents a system-level paradigm in which sensing, communication, analytics, and actuation are co-designed rather than independently deployed. In PV applications, AIoT transforms passive generation assets into adaptive cyber–physical systems capable of autonomous monitoring, learning-driven decision-making, and closed-loop control [9]. From an engineering perspective, the critical challenge is not merely algorithm selection, but determining where intelligence should reside (device, edge, fog, or cloud), how data modalities are fused, and how decisions propagate reliably to physical actuators.

In parallel, the increasing complexity of AI pipelines motivates reproducible experimentation and transparent evaluation practices. Collaborative computational environments can support the documentation and replication of preprocessing steps, model configurations, and benchmarking procedures reported in the literature. In this survey, platforms such as **OASIS Colab** are discussed strictly as research-oriented environments that may facilitate illustrative replication and methodological transparency. No assumptions are made regarding their industrial adoption, and no experimental claims are derived from their use.

Against this background, this review provides a structured and deployment-aware analysis of AI-enabled IoT approaches for photovoltaic systems. Rather than enumerating algorithms, the survey emphasizes functional objectives, architectural constraints, and evidence traceability. The goal is to support informed design choices for intelligent, reliable, and scalable AIoT-based PV systems.

1.1. Positioning Existing Surveys and the Added Value of This Work

A substantial body of review literature addresses either AI techniques in photovoltaic systems or IoT-based monitoring and automation for solar energy. AI-focused surveys typically concentrate on specific tasks such as energy forecasting, fault diagnosis, or optimization algorithms, while IoT-oriented reviews emphasize sensing architectures, communication protocols, and supervisory control frameworks. Although these works provide valuable insights, they often treat AI and IoT as loosely connected components rather than as an integrated decision pipeline.

A recent and closely related review by **Boucif *et al.* (2025)** surveys Artificial Intelligence of Things applications for solar energy monitoring and control, organizing the literature around major functional domains such as monitoring, forecasting, predictive maintenance, fault detection, and optimization mechanisms including MPPT, solar tracking, and automated cleaning [16]. While this contribution offers a comprehensive thematic overview, broader limitations persist across the review landscape:

1. **Limited deployment awareness:** Most surveys describe AI methods and applications without systematically linking them to deployment layers (edge, fog, cloud) and their associated latency and resource constraints.
2. **Weak evidence traceability:** Performance claims are often difficult to compare due to inconsistent reporting of datasets, metrics, and validation contexts.
3. **Underdeveloped system-level synthesis:** Interactions between data quality, communication reliability, model generalization, and actuation are frequently discussed qualitatively rather than analyzed as coupled system constraints.

Added Value of This Survey

To address these gaps, this work adopts a system-oriented perspective and contributes:

- **C1) A deployment-aware taxonomy** that jointly classifies AIoT-based PV studies by functional objective, data modality, and computational layer.
- **C2) An evidence-traceable study matrix** enabling transparent comparison of tasks, models, datasets, metrics, and validation contexts across studies.
- **C3) A constraint-driven gap analysis** that maps operational limitations (data scarcity, edge constraints, communication reliability, security) to concrete research directions.

Table 1. Positioning of Existing Surveys and Added Value of This Review

Aspect	Typical Existing Surveys	This Survey
Primary Perspective	AI **or** IoT treated separately	System-level AIoT integration
Functional Coverage	Partial (forecasting, FDD, or monitoring)	Unified coverage across PV decision loops
Deployment Awareness	Rarely addressed	Explicit (device/edge/fog/cloud)
Evidence Traceability	Narrative summaries	Structured study matrix with validation context
Real-Time Constraints	Limited discussion	Analyzed as design constraints
Reproducibility Focus	Minimal	Emphasized via methodological

		transparency
Research Gaps	High-level	Constraint-driven and deployment-aware

1.2. Review Methodology and Analytical Framework

To meet Q1 IEEE standards for rigor and reproducibility, this survey follows a structured methodology emphasizing traceable selection, deployment-aware coding, and evidence-based synthesis.

1.2.1. Sources and Search Strategy

Peer-reviewed journal articles and conference proceedings were retrieved from major scientific databases, including IEEE Xplore, Scopus, Web of Science, ScienceDirect, and ACM Digital Library. Search queries combined PV-related terms with AI and IoT concepts, for example:

- (“photovoltaic” OR “PV”) AND (“IoT” OR “edge computing”) AND (“machine learning” OR “deep learning”)
- (“PV fault” OR “anomaly”) AND (“diagnosis” OR “predictive maintenance”)
- (“PV forecasting”) AND (“LSTM” OR “deep learning” OR “probabilistic”)

The review emphasizes recent literature while retaining seminal works required to establish methodological baselines.

1.2.2. Inclusion and Exclusion Criteria

Studies were included if they:

- Utilized PV operational or inspection data for AI-based inference;
- Integrated IoT-enabled sensing or communication with PV analytics or control;
- Provided deployment or architectural considerations relevant to real systems;
- Reported evaluation metrics or validation contexts.

Studies lacking PV relevance, methodological clarity, or peer review were excluded.

1.2.3. Screening and Coding Procedure

The screening process involved deduplication, title/abstract filtering, and full-text assessment. Each included study was coded according to:

- Functional objective (monitoring, FDD, maintenance, forecasting, optimization),
- Data modality (electrical, environmental, vision/thermal),
- AI model family,
- Deployment layer,
- Evaluation metrics and validation setting.

1.2.4. Analytical Framework

The analytical framework organizes evidence along the pipeline:
Function → Data → Model → Deployment → Decision/Actuation, enabling consistent comparison across heterogeneous studies.

1.2.5. Reproducibility and Methodological Support

Collaborative environments such as **OASIS Colab** are referenced solely as illustrative tools for replicating reported preprocessing and modeling workflows, without introducing new datasets or experimental claims.

1.2.6. Methodological Outcomes

The methodology yields three artifacts used throughout the review:

1. A deployment-aware taxonomy of AIoT applications in PV systems,
2. A structured study matrix enabling evidence traceability,
3. A gap analysis linking operational constraints to future research directions.

2. AIoT in Photovoltaic Systems: Technical Background

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT), commonly referred to as Artificial Intelligence of Things (AIoT), has introduced a paradigm shift in the way photovoltaic (PV) systems are monitored, controlled, and optimized. Traditional PV systems rely on static control logic and periodic inspection, which limits their ability to adapt to dynamic environmental conditions and operational uncertainties. AIoT-enabled PV systems, by contrast, integrate intelligent data analytics with pervasive sensing and communication infrastructures, enabling real-time awareness, autonomous decision-making, and adaptive control across the entire energy conversion chain.

This section establishes the technical background required to understand AIoT-based PV systems. It introduces the core AI paradigms relevant to solar energy applications, outlines the fundamental IoT building blocks supporting data acquisition and connectivity, and discusses the computing paradigms that enable scalable and low-latency intelligence deployment.

2.1. Artificial Intelligence Paradigms for PV Systems

Artificial Intelligence encompasses a broad class of computational techniques that enable machines to perceive patterns, learn from data, and make informed decisions. In the context of PV systems, AI serves as the analytical engine that transforms raw measurements such as irradiance, temperature, voltage, and current into actionable insights for monitoring, forecasting, diagnostics, and control [5], [6].

Rather than relying on a single technique, AIoT-based PV systems typically employ a hierarchy of AI paradigms, each suited to different data characteristics, operational constraints, and decision horizons.

2.1.1. Machine Learning

Machine Learning (ML) represents a foundational AI paradigm in which models infer relationships directly from data without explicit physical modeling. ML techniques are particularly effective in PV applications where system behavior is nonlinear, partially observable, or influenced by stochastic environmental factors [8].

ML approaches can be broadly categorized according to the availability of labeled data and the nature of system interaction:

- **Supervised learning** is commonly applied to regression and classification problems, such as power prediction, fault classification, and soiling state identification, using labeled historical measurements.
- **Unsupervised learning** is suited for anomaly detection and pattern discovery when fault labels are unavailable or incomplete, a frequent scenario in large-scale PV deployments.
- **Semi-supervised learning** bridges these two paradigms by exploiting limited labeled data alongside abundant unlabeled operational data, which is particularly relevant for rare fault conditions.
- **Reinforcement learning** enables adaptive decision-making through interaction with the environment and has been explored for control-oriented tasks such as cleaning scheduling and operational optimization [18].

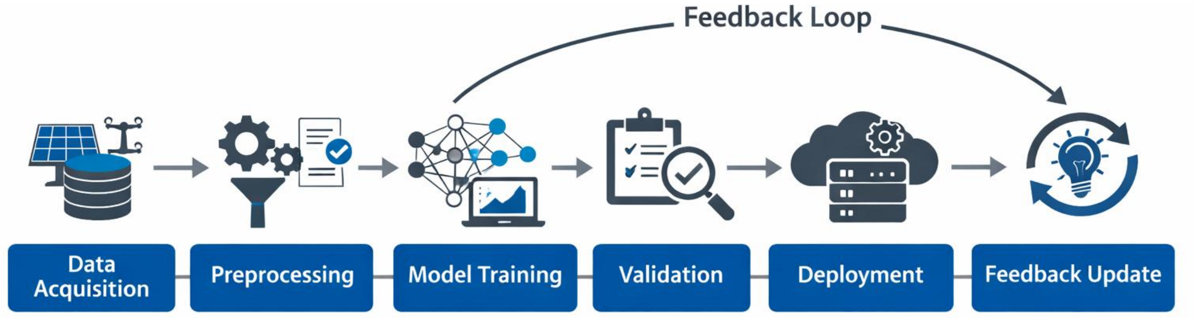

Figure 1 . *Generic Machine Learning Workflow for PV Applications*

2.1.2. Deep Learning

Deep Learning (DL) extends classical ML by employing multi-layer neural architectures capable of automatic feature extraction from raw, high-dimensional data. DL is particularly effective when PV systems generate large volumes of heterogeneous data, including time-series measurements and visual or thermal imagery [21], [27].

Different DL architectures address distinct PV-related challenges:

- **Convolutional Neural Networks (CNNs)** excel in spatial feature extraction and are widely used for image-based fault detection, soiling assessment, and module inspection.
- **Recurrent Neural Networks (RNNs)** and their variants model temporal dependencies and are therefore well suited for energy forecasting and degradation analysis.
- **Long Short-Term Memory (LSTM)** networks address long-term temporal correlations and are frequently adopted for predictive maintenance and time-series fault diagnosis [28].

While DL models often achieve superior accuracy, their deployment in PV systems must account for data availability, computational cost, and inference latency factors that directly influence the choice of deployment layer in AIoT architectures.

2.1.3. Generative AI and Data-Centric Intelligence

More recently, Generative AI (GenAI) has emerged as a complementary paradigm for PV applications where data scarcity, imbalance, or uncertainty pose significant challenges. Generative models learn latent data distributions and can synthesize realistic samples or reconstruct system behavior under nominal conditions [30], [54].

In AIoT-based PV systems, GenAI techniques support:

- **Data augmentation**, enabling more robust training of fault detection models;
- **Unsupervised anomaly detection**, by learning normal operational manifolds;
- **Scenario simulation**, assisting in stress-testing forecasting and control strategies.

Representative GenAI architectures include Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), which are increasingly explored as supporting tools rather than standalone decision engines. Despite their promise, practical deployment remains constrained by computational demands and interpretability considerations.

Where illustrative experimentation is beneficial, **OASIS Colab** may be used as a neutral cloud-based environment to prototype generative workflows and visualize learned representations, without introducing new datasets or experimental claims.

2.2. Internet of Things Foundations for PV Systems

While AI provides intelligence, IoT constitutes the physical and digital backbone that enables data flow within PV systems. IoT architectures interconnect sensors, actuators, communication networks, and computing resources to facilitate continuous observation and control of PV assets [10], [11].

2.2.1. Sensing and Actuation Layer

PV-oriented IoT systems rely on heterogeneous sensors to capture both electrical and environmental states. Typical measurements include voltage, current, irradiance, temperature, humidity, and soiling indicators. These measurements form the primary input for AI-based analytics and control logic [43].

Actuators translate AI-driven decisions into physical actions, such as panel reorientation, cleaning activation, or inverter control. The tight coupling between sensing and actuation is a defining feature of closed-loop AIoT-enabled PV systems.

2.2.2. Communication and Data Exchange

Reliable data transmission is essential for distributed PV installations, particularly in geographically dispersed or remote environments. IoT communication technologies vary in range, bandwidth, and energy efficiency, leading to different suitability profiles for PV applications [47], [48].

Rather than enumerating protocols, this survey emphasizes **functional trade-offs**:

- short-range protocols favor high data rates and local control;
- low-power wide-area technologies enable long-range monitoring with minimal energy consumption;
- wired protocols ensure deterministic performance in industrial-scale PV plants.

Table 2. Communication Technologies and Functional Trade-offs in PV IoT Systems

Communicatio	Functional	Energy	Latency	Deployment	Key Trade-

n Category	Coverage	Efficiency	Characteristics	Context in PV Systems	offs
Short-Range Wireless Communication	Local device-to-device and device-to-gateway communication	Low to moderate	Very low latency	Residential PV systems, smart buildings, local monitoring and control	High data rate but limited coverage; scalability constrained by range
Low-Power Wireless Mesh Networks	Distributed node connectivity with multi-hop routing	Very high	Low to moderate latency	PV monitoring within microgrids and smart energy communities	Robust and fault-tolerant but increased routing overhead
Low-Power Wide Area Networks (LPWAN)	Long-distance, low-throughput data transmission	Very high	Moderate latency	Utility-scale and geographically dispersed PV plants	Excellent coverage with limited bandwidth and payload size
Cellular-Based Communication	Wide-area connectivity with operator-managed infrastructure	Moderate to high	Moderate latency	Grid-connected PV plants requiring remote supervision	Reliable connectivity but higher energy and operational costs
Satellite Communication	Global connectivity independent of terrestrial infrastructure	Low	High latency	Remote and off-grid PV installations	Extreme coverage at the expense of latency and cost
Industrial Wired Communication	Deterministic, high-reliability data exchange	High (externally powered)	Very low and predictable latency	Industrial PV plants, SCADA-integrated systems	High reliability and security but limited flexibility and higher installation cost
Lightweight Messaging Protocols	Efficient application-layer data	Very high	Low latency	Cloud–edge–device data synchronization in	Minimal overhead but requires secure

	exchange			PV systems	configuration

2.2.3. Computing Paradigms: Edge, Fog, and Cloud

The volume and velocity of PV data necessitate distributed computing strategies. AIoT-based PV systems commonly adopt a layered computing paradigm spanning edge, fog, and cloud resources [18], [36].

- **Edge computing** enables low-latency inference and immediate control near the data source.
- **Cloud computing** provides scalable storage and high-performance analytics for long-term optimization and fleet-level insights.
- **Fog computing** bridges these layers by supporting localized aggregation and intermediate decision-making.

2.3. From AI and IoT to AIoT-Enabled PV Systems

AIoT emerges when AI analytics and IoT infrastructures are co-designed rather than independently deployed. In PV systems, this co-design enables continuous perception, learning-driven decision-making, and autonomous actuation across multiple temporal and spatial scales [49], [55].

This integration transforms PV installations from passive energy generators into **adaptive cyber–physical systems**, capable of self-monitoring, self-optimization, and proactive maintenance. The technical background established in this section provides the foundation for the subsequent analysis of AIoT architectures and application domains.

3. AIoT Functional Applications in PV Systems

3.1 Fault Detection and Diagnosis (FDD): Vision, Sensors, and Hybridization

Vision-driven FDD targets spatially localized defects (e.g., surface damage, hotspots, soiling patterns) using deep vision models. Deep ensemble learning has demonstrated robust defect recognition in PV imagery under variability [21], while lightweight YOLO variants enable faster inference suitable for constrained deployments [22], [23]. The technical trade-off is fundamental: visual pipelines provide **high spatial observability** but are often **event-driven/periodic** (inspection windows, weather dependence), which weakens continuous protection coverage.

Sensor-driven FDD uses electrical and contextual telemetry to continuously detect anomalies. Hybrid analytical–ANN formulations compare expected and measured behavior for automated diagnosis [24], while kNN monitoring schemes improve robustness to noise and process drift in PV monitoring streams [25]. For PV arrays, intelligent diagnosis based on array voltage and string currents via Random Forest has shown strong discrimination among fault classes without relying on complex physics models at runtime [29]. However, sensor-only FDD often suffers from **fault signature ambiguity** (different faults producing similar electrical traces) and **limited fault localization granularity**.

Hybrid FDD fuses time-series electrical behavior with learned representations (e.g., CNN on structured electrical graphs, residual learning on I–V curves) to improve separability of fault modes. CNN with Electrical Time Series Graphs (ETSG) enhances feature learning directly from sequential electrical data [30], while deep residual networks operating on I–V curves and ambient conditions reduce manual feature engineering burden and can improve generalization within tested regimes [32]. Yet hybridization introduces new system burdens: **synchronization, calibration, and multi-modal alignment**, which directly increases integration complexity and maintenance overhead.

Field-oriented IoT FDD implementations reinforce an important practical point: model quality is secondary if the telemetry pipeline is fragile. Low-cost IoT monitoring and fault detection prototypes demonstrate feasibility under constrained budgets [50], and online IoT monitoring architectures for PV arrays illustrate real-time telemetry acquisition and remote visibility [51]. Communication-layer choices (e.g., ZigBee + cellular backhaul) impact end-to-end reliability and latency; ZigBee/4G real-time monitoring architectures specifically highlight how network design becomes part of the diagnostic performance envelope [52].

3.2 Predictive Maintenance (PM): From Deviation Detection to Fleet-Scale Robustness

Predictive maintenance aims to detect degradation early and plan interventions before yield losses accumulate. ANN-based PV prognostics frameworks formalize health monitoring through learned performance baselines [34], while anomaly detection approaches provide deviation alerts that can be scheduled into maintenance windows [35]. For large-scale plants, hybrid pipelines combining clustering and temporal models (e.g., K-Means + LSTM) target scalability across many strings/components [36], and trend-based analytics demonstrate that maintenance value is strongly tied to temporal drift modeling rather than point forecasts alone [37].

A critical gap remains: **transferability**. Many PM models exhibit strong site performance but degrade under new climates, sensor configurations, or PV technologies. Unsupervised anomaly detection approaches partially mitigate labeling scarcity and can detect rare patterns, but may raise false positives depending on seasonal regimes and sensor noise [33]. For soiling, IoT + ANN solutions estimate soiling ratio remotely, but accuracy depends on sensor calibration and stable data transmission [53]. Practically, PM at fleet scale demands **cross-site benchmarking and reproducibility**, motivating collaborative experimentation and reproducible pipelines (e.g., OASIS CoLab) rather than isolated model claims.

3.3 Forecasting and Operational Optimization: Closing the Loop Without Destabilization

Forecasting is operationally valuable when it is “control-relevant”: it should reduce uncertainty at the decision horizon where actuators and dispatch operate. Neural networks on preprocessed radiation time series remain widely used for day-ahead settings [38], while short-term irradiance forecastability analyses emphasize that micro-climate variability bounds achievable accuracy [39]. Hybrid PV energy forecasting methods illustrate how combining complementary learners improves robustness across varying meteorological drivers [40]. Data augmentation and weather-classification pipelines based on GANs + CNNs address data sparsity and regime imbalance in day-ahead PV forecasting [41]. Hybrid day-ahead PV forecasting approaches also show that regularization and structured preprocessing can stabilize prediction error under variability [42]. Probabilistic deep schemes (e.g., VAE-based dimensionality reduction + Bayesian learning) explicitly target uncertainty-aware forecasting for operational decisions [43].

Optimization mechanisms especially MPPT and cleaning must be evaluated by **net energy gain** versus actuation cost and risk. MPPT review literature stresses that MPPT selection is not only a tracking problem but also a stability and responsiveness problem under fast irradiance changes [54]. IoT-enabled high-efficiency MPPT charge controller implementations demonstrate near-maximum conversion efficiency under test conditions, but their value depends on robust sensing and safe control logic [55]. For cleaning, smart dust detection systems that trigger cleaning illustrate the control logic coupling between sensing and actuation (cleaning should be initiated only when energy recovery exceeds cost and water/maintenance constraints) [10].

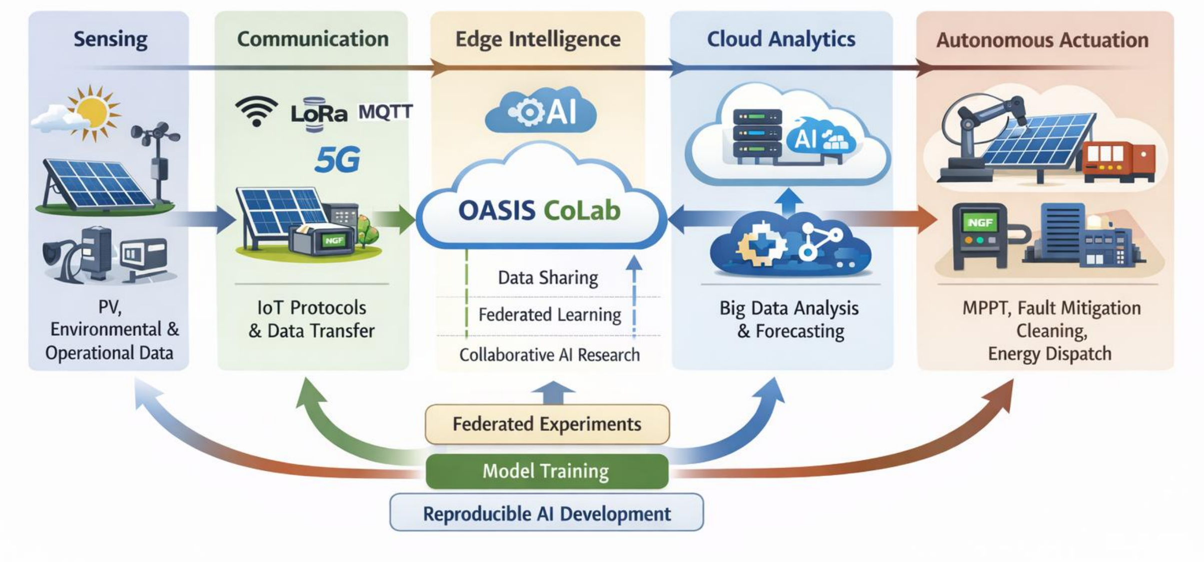

Figure 2. Functional Integration of AI and IoT in PV Energy Management

This figure illustrates the end-to-end AIoT workflow for photovoltaic (PV) energy management, starting from sensing (PV, environmental, and operational data acquisition), followed by communication through IoT protocols, edge intelligence for low-latency inference and local decision-making, and cloud analytics for large-scale learning, optimization, and long-term forecasting. The loop is closed by autonomous actuation, enabling real-time control actions such as MPPT adjustment, fault mitigation, cleaning activation, and energy dispatch. The integration of OASIS CoLab is highlighted as a collaborative layer supporting data sharing, federated experimentation, and reproducible AI model development across edge–cloud infrastructures.

Table 3. Study Matrix of Representative AIoT-Based Photovoltaic Systems

Ref.	Year	PV Task	Data Type	AI Model	Deployment Layer	Evaluation Metrics (as reported)	Validation Context
[21]	2022	FDD	Image	Deep ensemble	Edge/Cloud	(Model metrics reported in study)	Field/Benchmark imagery
[22]	2023	FDD	Image	Lightweight YOLO	Edge	(Detection metrics reported)	Field/Benchmark imagery
[23]	2023	FDD	Image	YOLOv5	Edge/Cloud	(Detection metrics reported)	Field/Benchmark imagery
[24]	2015	FDD	Electrical+Enviro	ANN +	Edge/Fo	(Detection performance	Lab/Experimenta

			nmental	analytical	g	reported)	l
[25]	2019	FDD	Electrical (monitoring residuals)	kNN monitoring	Edge/Fog	(Monitoring metrics reported)	Field PV monitoring
[29]	2018	FDD	Electrical	Random Forest	Edge/Cloud	(Accuracy/diagnosis metrics reported)	MATLAB + real PV setup
[30]	2019	FDD	Electrical time-series	CNN + ETSG	Edge/Cloud	(Diagnosis accuracy reported)	Experimental case studies
[32]	2019	FDD	I–V + Ambient	Deep ResNet	Edge/Cloud	(Accuracy reported)	Sim + real datasets
[50]	2019/ 2020*	Monitoring /FDD	Electrical+Environmental	(Rule/analytics + IoT)	Edge/Cloud	(System-level indicators)	Field prototype
[51]	2017	Monitoring	Electrical	(Monitoring + IoT)	Device/ Edge	(System-level indicators)	Field deployment
[52]	2020	Monitoring	Electrical	(Monitoring + IoT)	Edge/Cloud	(Latency/availability indicators)	Field system
[34]	2012	PM	Environmental+Electrical	ANN	Cloud	(PHM indicators)	Simulation/Experimental
[35]	2018	PM	Electrical+Environmental	ANN (anomaly)	Cloud	(Anomaly metrics reported)	Field datasets
[36]	2023	PM	Electrical+Environmental	K-Means + LSTM	Cloud/Edge	(Detection metrics reported)	Large-scale PV plant data
[37]	2024	PM	Electrical	Trend analytics	Cloud	(Sensitivity/accuracy reported)	Field PV plant
[33]	2020	PM/FDD	Electrical monitoring	Unsupervised (e.g., VAE-family)	Cloud	(Detection rate reported)	PV monitoring data
[53]	2023	Monitoring /PM	Environmental+Electrical	ANN	Cloud	MSE/R^2 (reported)	Field soiling stations
[38]	2010	Forecastin	Environmental	ANN	Cloud	Forecast errors	Historical time

		g				(reported)	series
[39]	2015	Forecasting	Environmental	kNN/ANN (analysis)	Cloud	RMSE (reported)	Multi micro-climates
[40]	2015	Forecasting	Environmental	Hybrid models	Cloud	RMSE (reported)	PV systems datasets
[41]	2019	Forecasting	Environmental	GAN + CNN	Cloud	Accuracy/RMSE (reported)	Day-ahead forecasting
[42]	2018	Forecasting	Environmental	Hybrid forecast	Cloud	MAPE/RMSPE (reported)	Day-ahead forecasting
[43]	2023	Forecasting	Environmental+PV	VAE + Bayesian DL	Cloud	Probabilistic metrics (reported)	Energy forecasting
[54]	2019	Optimization (MPPT)	Electrical	(Comparative MPPT)	Device/ Edge	Tracking performance (reported)	Review/Comparative
[55]	2020	Optimization (MPPT)	Electrical	MPPT controller	Device/ Edge	Efficiency (reported)	Hardware + testing

4. Challenges, Open Issues, and Future Research Directions (Integrated with Section 3)

The preceding evidence shows that AIoT value in PV systems is constrained less by "model choice" and more by **end-to-end system validity**: sensing integrity, communications resilience, deployment-layer suitability, and safe actuation. The following challenges are therefore framed as **system-level bottlenecks** derived directly from Section 3 findings.

4.1 Data Integrity, Drift, and Cross-Site Generalization

Field telemetry is affected by sensor drift, intermittent connectivity, and seasonal regime shifts conditions that degrade both FDD and PM reliability. Even strong learners may overfit plant-specific distributions, explaining why predictive maintenance pipelines struggle to generalize across sites [33], [35], [37]. Future work should prioritize cross-site evaluation protocols and reproducible pipelines enabling consistent benchmarking under shared assumptions.

4.2 Edge Constraints and Latency-Critical Decision Loops

Vision-based FDD and deep hybrid diagnosis can be computationally heavy, challenging edge deployment under power/latency constraints [21], [23], [30], [32]. Conversely, sensor-based schemes enable real-time operation but can be ambiguous without spatial context [24], [25], [29]. The open issue is **placement optimization**: which inference runs on-device/edge versus cloud, given bandwidth and latency envelopes.

4.3 Communications Robustness and Protocol Heterogeneity

IoT PV systems demonstrate that monitoring reliability becomes a first-order variable in diagnostic performance, especially in multi-node systems (e.g., ZigBee/4G or heterogeneous gateways) [51], [52]. Real plants require protocol interoperability with resilient backhaul and secure transport; otherwise, control loops risk being destabilized by delayed or missing data.

4.4 Control Safety: Optimization That Does Not Harm the Plant

MPPT and cleaning actuation must be controlled safely under uncertain sensing and variable irradiance. MPPT method selection is bounded by stability and transient response limits [54], and IoT-enabled MPPT controllers must be validated under realistic disturbances rather than idealized tests [55]. Cleaning triggering based on dust detection requires strict cost–benefit decision logic and environmental constraints (water, abrasion, downtime) [10], [53].

4.5 Collaborative and Reproducible AIoT as a Practical Research Direction

A practical research direction is to treat AIoT PV research as "collaborative engineering science" rather than isolated model reporting. **OASIS CoLab** can be positioned as a collaboration layer enabling shared datasets, federated experimentation, and reproducible pipelines across edge–cloud infrastructures directly addressing generalization and benchmarking gaps surfaced in FDD/PM/forecasting results.

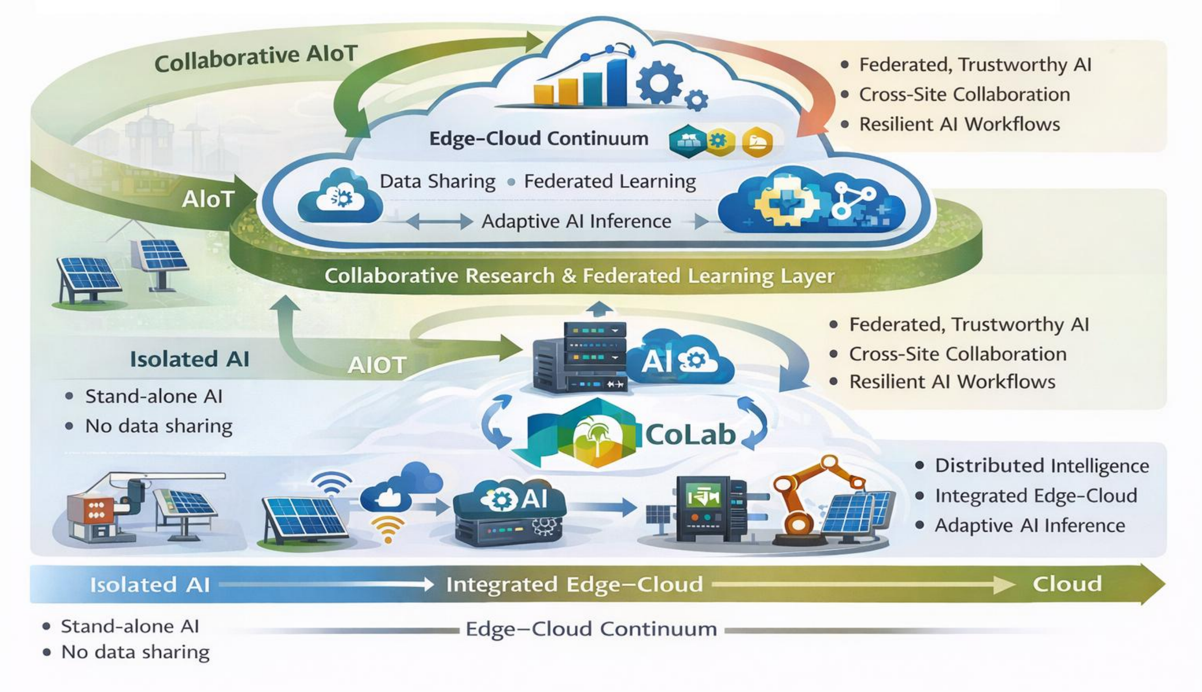

Figure 3. Future AIoT-Oriented Architecture for Scalable and Trustworthy PV Energy Systems

This vision diagram highlights the evolution from **isolated AI → AIoT → collaborative AIoT**, emphasizing the **edge–cloud continuum**, privacy-preserving **federated learning**, and **OASIS CoLab** as a collaboration and research layer that supports reproducible experimentation and cross-site validation for PV fleets.

Table 4 synthesizes the principal challenges and open research gaps in AIoT-based photovoltaic (PV) systems by mapping technical limitations to their system-level impact and corresponding research directions. The analysis reveals that data scarcity, limited model generalization, and edge-resource constraints remain the dominant barriers to scalable deployment [18], [21], [26]. Communication reliability, security, and interoperability further constrain closed-loop control and large-scale integration, particularly in grid-connected PV infrastructures [10], [43], [48].

Table 4. Key Challenges, Research Gaps, and Future Directions in AIoT-Based PV Energy Systems

Domain	Current Limitation	Observed Impact on PV Systems	Emerging Research Directions	Representative References
Data Availability & Quality	Scarcity of labeled fault and degradation data; site-specific datasets	Reduced robustness of AI models; poor generalization across PV plants	Self-supervised learning, synthetic data generation, cross-site data sharing	[18], [21], [26], [28], [29]
Model Generalization	Overfitting to specific climates, PV technologies, or layouts	Limited transferability of AI solutions between installations	Transfer learning, domain adaptation, federated learning	[21], [25], [27], [30]
Edge Intelligence	Limited computation, memory, and power at edge devices	Latency–accuracy trade-off; constrained real-time control	Lightweight models, model compression, edge–cloud co-design	[33], [34], [36], [39]
Edge–Cloud Coordination	Fragmented orchestration between edge, fog, and cloud layers	Inefficient data utilization and delayed decision-making	Hierarchical AIoT architectures, adaptive workload allocation	[36], [37], [38], [41]
Communication Reliability	Network instability and protocol heterogeneity	Control instability, data loss in large-scale PV systems	Cross-layer optimization, adaptive IoT protocols	[10], [43], [44], [46]
Fault Detection & Diagnostics	Dependence on single data modality (vision or electrical)	Missed or delayed fault identification	Multi-modal AI (vision + time-series), hybrid AI models	[22], [23], [24], [27]
Predictive Maintenance	High dependency on historical data and site-specific tuning	Limited scalability and delayed maintenance actions	Continual learning, online model updating	[30], [31], [32], [35]
Energy Forecasting & Uncertainty	Sensitivity to weather variability and data drift	Reduced forecast reliability for grid integration	Probabilistic forecasting, ensemble and hybrid AI models	[39], [40], [41], [42]
Security &	Vulnerable IoT endpoints and	Risk to grid stability	Privacy-preserving AI,	[48], [50], [51],

Privacy	centralized data storage	and data integrity	federated learning, secure edge inference	[54]
Explainability & Trust	Black-box AI models limit operator trust	Resistance to deployment in critical energy infrastructure	Explainable AI (XAI), human-in-the-loop systems	[11], [12], [13]
System Integration	Lack of unified platforms and standards	High deployment and maintenance costs	Open architectures, interoperable AIoT frameworks	[43], [44], [47]
Research Reproducibility	Fragmented experimental setups and datasets	Difficult benchmarking and comparison	Collaborative research platforms	[53], [54], [55]

5. Discussion

The synthesis presented in this review demonstrates that the value of AIoT in photovoltaic (PV) systems does not primarily arise from the choice of a specific learning algorithm, but from the **co-design of sensing, communication, computation, and actuation layers**. Across fault detection, predictive maintenance, forecasting, and optimization, the literature consistently shows that isolated improvements at the model level yield diminishing returns when system-level constraints are ignored.

5.1. From Algorithm-Centric to System-Centric Intelligence

A central observation emerging from Section 3 is that much of the reported progress in AI-based PV applications is **algorithm-centric**, while real-world deployment success is **system-centric**. Vision-based FDD models, for example, achieve high diagnostic accuracy under controlled conditions, yet their operational effectiveness is bounded by inspection periodicity, data acquisition logistics, and inference latency. Conversely, sensor-driven approaches enable continuous monitoring but suffer from limited observability and fault ambiguity.

This dichotomy reveals a fundamental insight: **accuracy metrics alone are insufficient indicators of operational intelligence**. Instead, AIoT effectiveness depends on whether inference can be executed within the temporal, energy, and reliability envelopes imposed by PV plant operation. Hybrid AIoT designs partially address this limitation, but at the cost of increased integration complexity, data synchronization overhead, and maintenance burden trade-offs that are rarely quantified in existing studies.

5.2. Predictive Maintenance as a Scalability Bottleneck

Predictive maintenance illustrates the gap between laboratory performance and fleet-level applicability. While learning-based PM models successfully capture degradation trends within individual plants, their limited transferability across sites exposes a critical scalability bottleneck. Environmental heterogeneity, sensor calibration drift, and installation-specific characteristics introduce distribution shifts that undermine generalization.

This limitation suggests that future progress in PM will not be driven solely by deeper architectures or larger datasets, but by **collaborative and reproducible learning paradigms** that explicitly account for cross-site variability. The literature implicitly converges on the need for shared benchmarking, cross-plant validation, and standardized evaluation protocols requirements that extend beyond conventional single-dataset studies.

5.3. Forecasting and Optimization: Intelligence Must Close the Loop

Energy forecasting studies consistently report improved prediction accuracy through hybrid and deep learning models; however, their operational impact depends on how forecasts are embedded within control loops. Forecasts that are decoupled from actuation risk becoming decision-irrelevant, particularly under fast-changing irradiance conditions and storage constraints.

Similarly, optimization mechanisms such as MPPT and automated cleaning demonstrate that **context awareness** is more important than continuous actuation. AIoT systems that trigger control actions only when net energy gain exceeds operational cost represent a qualitative shift from static optimization toward **cost-aware autonomy**. This shift highlights the need to evaluate AIoT solutions using system-level performance indicators such as yield stability, component stress, and maintenance overhead rather than isolated efficiency gains.

5.4. Edge–Cloud Continuum as an Enabler and a Constraint

The edge–cloud continuum emerges as both an enabler and a constraint for AIoT-based PV systems. Edge intelligence reduces latency and enhances resilience under network disruptions, but imposes strict limits on model complexity and energy consumption. Cloud analytics support large-scale learning and long-term optimization, yet introduce latency, dependency on connectivity, and data privacy concerns.

The reviewed studies collectively indicate that **optimal deployment is not binary (edge versus cloud)**, but requires adaptive partitioning of intelligence across layers. This partitioning must be guided by task criticality, response time requirements, and communication reliability dimensions that are still insufficiently formalized in current research.

5.5. Trust, Reproducibility, and the Path to Deployment-Ready AIoT

A recurring but often implicit challenge across AIoT PV studies is the lack of reproducibility and trustworthiness. Variations in datasets, evaluation metrics, and experimental assumptions make it difficult to compare results or assess readiness for deployment. This fragmentation limits cumulative scientific progress and slows industrial adoption.

Collaborative experimentation environments such as **OASIS CoLab**, positioned as a neutral research and benchmarking layer offer a practical pathway to address these gaps. By enabling shared datasets, reproducible pipelines, and cross-site experimentation without exposing raw operational data, such platforms align with emerging needs for trustworthy, scalable, and privacy-aware AIoT development.

5.6. Implications for Research and Practice

Collectively, the findings of this review suggest that the next phase of AIoT research in PV systems should prioritize:

- **System-level evaluation frameworks** that integrate sensing, learning, communication, and actuation;
- **Generalization-aware learning strategies** validated across heterogeneous PV installations;

- **Deployment-conscious AI design**, balancing accuracy, latency, energy consumption, and maintainability;
- **Standardized and collaborative research practices** that support reproducibility and cross-study comparability.

Without these shifts, further gains at the algorithmic level are unlikely to translate into meaningful improvements in large-scale PV operation.

5. Conclusion

This review has examined the role of Artificial Intelligence of Things (AIoT) in transforming photovoltaic (PV) systems from conventionally monitored assets into intelligent, adaptive, and autonomous energy systems. By critically analyzing fault detection, predictive maintenance, forecasting, and optimization applications, the study demonstrates that AIoT effectiveness depends primarily on system-level integration rather than isolated algorithmic performance. The findings highlight that sensing reliability, communication resilience, and appropriate placement of intelligence across the edge–cloud continuum are decisive factors for real-world deployment. While AI-based methods significantly enhance diagnostic accuracy and operational awareness, their scalability is constrained by data heterogeneity, model generalization limits, and resource constraints at the edge. The review further shows that optimization mechanisms deliver sustained value only when embedded within closed-loop, cost-aware control architectures. Emerging collaborative and reproducible research paradigms offer a promising pathway to address these challenges and accelerate translation from experimental studies to field-ready solutions. Overall, AIoT represents a necessary but not sufficient condition for next-generation PV systems; its full potential will be realized only through holistic co-design of data, intelligence, and control layers.

List of Abbreviations

Abbreviation	**Full Term**
AI	Artificial Intelligence
AIoT	Artificial Intelligence of Things
ANN	Artificial Neural Network
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
DL	Deep Learning
DT	Decision Tree
Edge AI	Artificial Intelligence executed at the network edge
ELM	Extreme Learning Machine
ESS	Energy Storage System
ETSG	Electrical Time-Series Graph

Abbreviation	Full Term
EV	Electric Vehicle
FDD	Fault Detection and Diagnosis
FL	Federated Learning
GAN	Generative Adversarial Network
GenAI	Generative Artificial Intelligence
GHI	Global Horizontal Irradiance
GPR	Gaussian Process Regression
GRNN	General Regression Neural Network
HE	Histogram Equalization
HIF	High Impedance Fault
HMM	Hidden Markov Model
IoT	Internet of Things
IRT	Infrared Thermography
kNN	k-Nearest Neighbors
LLM	Large Language Model
LPWAN	Low-Power Wide-Area Network
LSTM	Long Short-Term Memory
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MQTT	Message Queuing Telemetry Transport
PCA	Principal Component Analysis
PLC	Programmable Logic Controller
PNN	Probabilistic Neural Network
PV	Photovoltaic
PWM	Pulse Width Modulation
RF	Random Forest

Abbreviation	Full Term
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition
SoC	State of Charge
SOM	Self-Organizing Map
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
VAE	Variational Autoencoder
VFD	Variable Frequency Drive
Wi-Fi	Wireless Fidelity
XAI	Explainable Artificial Intelligence

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