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IOT-DRIVEN IMPLEMENTATION OF AI PREDICTIVE MODELS FOR REAL-TIME PERFORMANCE ENHANCEMENT OF PEROVSKITE AND TANDEM PHOTOVOLTAIC SYSTEMS

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Abstract

This systematic review synthesizes how Internet of Things infrastructures and artificial intelligence predictive models enhance real-time operation of perovskite and tandem photovoltaic systems. Following a prospectively registered protocol and the PRISMA framework, we searched major scholarly databases, screened records with two independent reviewers, and extracted commensurate metrics for quantitative aggregation alongside structured narrative synthesis. In total, 115 articles met the eligibility criteria and were included in the final synthesis. Findings highlight four operational layers. For forecasting and nowcasting, multimodal pipelines that fuse plant telemetry with all sky imagery achieved error reductions relative to persistence baselines, and attention or graph based temporal models improved skill on multi hour horizons; practical latency was reported with gateway inference suitable for supervisory control. For fault and anomaly diagnostics, deep classifiers and segmentation models operating on infrared, electroluminescence, photoluminescence, and SCADA streams delivered high discriminative performance and supported explainable overlays for technician workflows. Degradation and remaining useful life estimation benefited from physics informed or Bayesian models that combine electrical and thermal or optical channels, improving early warning and calibration over purely data driven regressors. Finally, controller guidance for maximum power point tracking and thermal regulation increasingly leverages edge aware architectures while secure data fabrics align with IEC 61850 and FAIR principles. Across these layers, perovskite and tandem aware features reduce bias under heat and spectral variability and help close the gap between laboratory devices and fielded assets. The review also offers a taxonomy and decision matrix linking sensing, models, and deployment choices to operational objectives.

Keywords
Iot; Artificial Intelligence; Perovskite Photovoltaics; Tandem Solar Cells; Forecasting; Fault Detection; Remaining Useful Life;

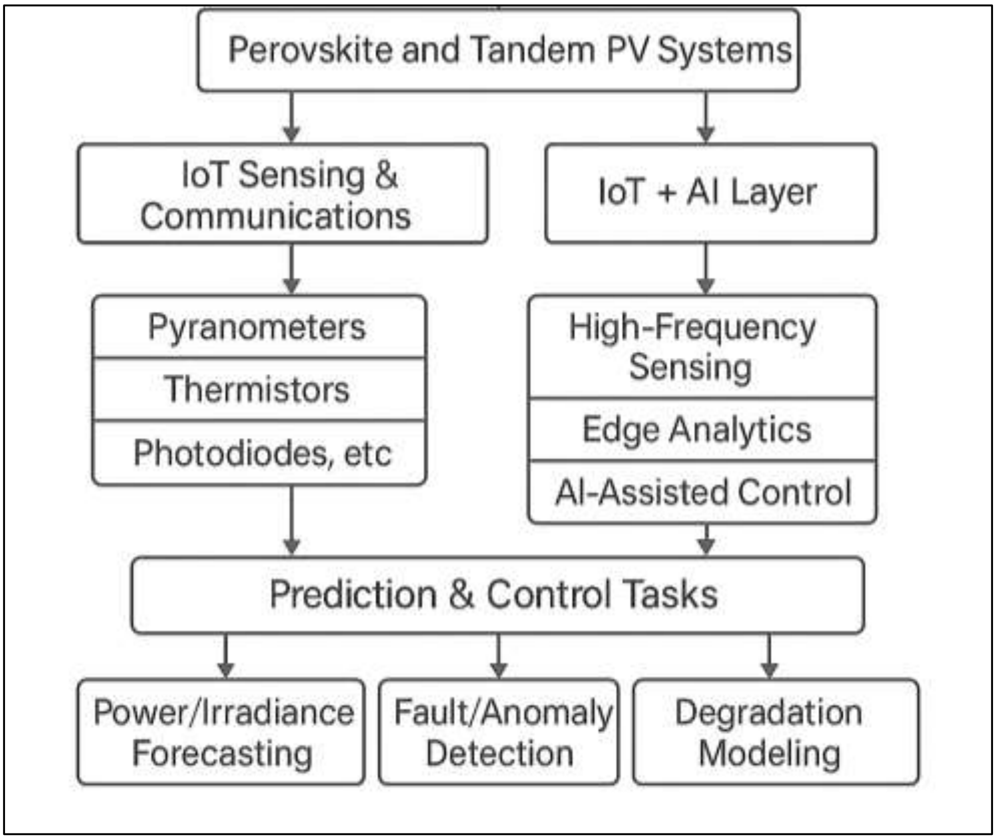
INTRODUCTION

Photovoltaic (PV) systems convert solar irradiance into electrical power through semiconductor junctions whose current–voltage characteristics reflect the material's band structure and recombination dynamics. Within the PV landscape, metal halide perovskites (ABX_3; A = MA/FA/Cs, B = Pb/Sn, X = I/Br/Cl) have emerged as a distinct materials class combining defect tolerance, long diffusion lengths, and tunable bandgaps (via A/B/X-site engineering) that enable high open-circuit voltages and current matching in stacked architectures (Isikgor et al., 2023; Saliba, 2024). Tandem PV architectures either perovskite/silicon or all-perovskite stack complementary bandgaps to exceed the Shockley–Queisser limit of single junctions, thereby improving area-normalized energy yield, which matters acutely in dense, land-limited regions and built environments (Leijtens et al., 2018; Rahman et al., 2018). In parallel, the Internet of Things (IoT) denotes networks of distributed, sensorized edge nodes, gateways, and cloud services that collect, transmit, and process time-series data from physical assets for monitoring and control (Pederiva et al., 2023). AI predictive models encompass machine-learning (ML) and deep-learning (DL) methods for forecasting power/irradiance, detecting faults and anomalies, and estimating degradation trajectories or remaining useful life (RUL), often with uncertainty quantification (UQ) (Kazem & Yousif, 2017). The coupling of IoT telemetry with AI inference in PV plants is internationally significant: it underpins grid integration under rising PV penetration, supports predictive maintenance for cost control, and offers a route to stabilize newer perovskite and tandem technologies under real-world stressors across diverse climates and regulatory regimes (Danish & Zafor, 2022). While certified device efficiencies for perovskite single-junctions and tandems now rival or surpass incumbent technologies, operational stability in the field remains the constraining challenge. Chemical and structural instabilities moisture ingress, oxygen/photoinduced reactions, ion migration, interfacial reactions with transport layers/electrodes translate into drift, hysteresis, and accelerated degradation under thermal/UV cycles, soiling, and humidity (Danish & Kamrul, 2022).

Tandem stacks add additional failure modes: current mismatch, recombination layer resistance, and thermal/mechanical stresses across sub-cells (Leijtens et al., 2018; Isikgor et al., 2023). The practical question, therefore, is not only how to fabricate high-performing devices but how to operate them as cyber-physical energy assets whose performance is continuously sensed, predicted, and adjusted under non-stationary environments. This motivates real-time or near-real-time optimization loops combining high-frequency sensing (irradiance, module/backsheet temperature, IV curves, humidity), edge analytics, and AI-assisted control to mitigate mismatch and incipient faults before energy yield loss accumulates (Alao et al., 2024; Rahman et al., 2018). Framed this way, IoT + AI becomes an operational layer that converts perovskite/tandem materials advances into stable, bankable energy services across jurisdictions with heterogeneous grid codes and climatic loads (Jahid, 2022). IoT architectures for PV commonly follow a node–gateway–cloud (or edge–cloud) topology, instrumenting arrays with pyranometers/photodiodes, thermistors/RTDs, anemometers, soiling cameras or thermal imagers, and sometimes on-board IV tracers; telemetry streams are transported over Wi-Fi, LoRaWAN, NB-IoT, 4G/5G, or wired industrial protocols to message brokers and time-series stores (Arifur & Noor, 2022). Open-source, low-cost deployments enable dense monitoring and rapid prototyping in remote or resource-constrained settings, including agricultural pumping and islanded microgrids (Al-Dahidi et al., 2019; Bekkouche et al., 2023).

Recent engineering studies demonstrate sub-minute resolution acquisition of irradiance, panel temperature, backsheet temperature, DC voltage/current, and environmental variables; integrated anomaly flags support maintenance scheduling (Chaudhary, 2025). Digital-twin (DT) abstractions extend this stack by calibrating physics-based/empirical models to live data for monitoring, diagnostics, and what-if analysis of O&M interventions (Alao et al., 2024). For perovskite/tandem fields, where moisture barriers, encapsulants, and interface chemistries determine stability, the ability to measure and synchronize device-level and meteorological signals at high cadence is central to distinguishing recoverable reversible effects (e.g., ion redistribution) from irreversible degradation trajectories. AI for PV operations partitions broadly into (i) short-horizon power/irradiance forecasting (minutes–hours) to support dispatch, smoothing, and inverter scheduling; (ii) fault/anomaly detection and diagnostics (e.g., hot spots, delamination, PID, string outages); and (iii) degradation modeling/RUL estimation with uncertainty bounds. Data-driven reviews consistently find that ML/DL models (tree ensembles, SVR, CNNs, LSTMs, temporal CNNs, Transformers) outperform naïve baselines and many physics-only models for short-term forecasting, provided exogenous weather inputs and well-tuned features (Gimeno-Sales et al., 2020). Recent work integrates probabilistic layers (Gaussian processes/variational GP, quantile or distributional models) to deliver calibrated UQ for grid-facing decisions (Gour et al., 2022). For fault detection, thermal-image segmentation and classification with U-Net/DeepLab/FPN families now detect PV anomalies at scale (Kofinas, 2017) and are being extended with modern transformer backbones (e.g., Swin-T) for subtle defect patterns (Hassani et al., 2025). On degradation/RUL, physics-informed strategies and hybrid digital-twin pipelines are beginning to codify mechanistic priors ion migration, interfacial reactions, moisture diffusion into learnable surrogates suitable for online updates (Avila et al., 2020).

Figure 1: Integration of IoT Sensing and AI Control for Perovskite and Tandem PV Systems



The operational thread across these tasks is latency-aware inference with explainability for O&M crews (e.g., SHAP-style feature attributions or saliency maps), so that alerts translate into actionable maintenance tickets rather than dashboard noise (Rahaman, 2022a). Beyond prediction, IoT-instrumented PV arrays can close control loops that adapt inverter set-points, curtailment strategies, or thermal management. In the perovskite/tandem context where sub-cells exhibit different thermal coefficients and transients sophisticated MPPT (maximum power point tracking) is critical to avoid sustained mismatch losses under fast irradiance/temperature fluctuations and partial shading (Liu et al., 2023; Rahaman, 2022b). Reinforcement-learning (RL) approaches (DQN, DDPG, PPO, LSTM-augmented agents) have been demonstrated for robust MPPT, often outperforming classical P&O/INC under dynamic and partial-shading conditions and converging to global MPPs in nonconvex landscapes (Zhuang et al., 2023). Bench-scale and power-hardware-in-the-loop studies report accuracies >95% against global MPP under varied irradiance/temperature profiles, with reduced oscillation around the set-point (Rahaman & Ashraf, 2022; Rana & Kumar, 2024). Integrating these controllers with edge devices, IV tracers, and thermal sensors enables closed-loop adaptation that is sensitive to the particular electro-thermal signatures of perovskite top cells and silicon or perovskite bottom cells in tandems (Islam, 2022). The research logic of this review, therefore, centers on how model classes, instrumentation, and deployment choices (edge, cloud, or hybrid) jointly shape achievable real-time performance in perovskite and tandem PV plants. Where AI inference happens matters. Edge computing reduces latency and bandwidth, safeguards data sovereignty, and sustains operation during backhaul outages attributes favored for real-time MPPT, fast anomaly screening, and on-device feature extraction from imagery (Hasan et al., 2022; Rodríguez et al., 2023). Cloud layers remain essential for heavy training, fleet-level analysis, DT synchronization, and benchmarking across sites; hybrid patterns schedule models to the edge with over-the-air (OTA) updates and "shadow" inference for A/B evaluation. SCADA modernization for utility-scale PV increasingly exposes secure APIs for such ML services, and IoT SCADA designs tailored to PV demonstrate practical pathways for integrating AI while preserving operational reliability (Redwanul & Zafor, 2022; Singh & Pal, 2021). DT reviews in the power sector emphasize versioned data pipelines, model provenance, and quality control of sensor streams the MLOps substrate needed to keep predictive models trustworthy as environments drift (Rezaul & Mesbaul, 2022; Zhang, 2024). For perovskite/tandem deployments often pilots with evolving materials stacks this orchestration is crucial: it enables controlled rollouts of predictive models, rapid rollback on performance regressions, and lineage tracking linking device recipes to field behavior. The empirical landscape is broad but fragmented across materials science, device physics, power systems, controls, and data science. Perovskite/tandem reviews meticulously document materials, interfaces, and device architectures that raise certified efficiencies (Cen 2024; Hasan, 2022), whereas IoT/AI reviews focus on forecasting algorithms, datasets, or fault imaging often in silicon-dominant fleets (El-Hoshy & Bouzaidi, 2023; Tarek, 2022). Meanwhile, case studies show IoT platforms and low-cost nodes that actually gather the telemetry needed for real-time analytics (Cipriani, 2024; Kamrul & Omar, 2022) and recent works add high-resolution PV monitoring devices and progressive AI controllers (Fernández et al., 2021). What is missing is a structured synthesis that (a) maps IoT sensing/communications choices to the specific prediction/control tasks; (b) compares AI model classes using comparable metrics (RMSE/MAE/MAPE, F1/AUC, calibration, latency/energy overhead); (c) relates deployment location (edge/cloud) to latency and resilience constraints; and (d) compiles evidence on yield/uptime/LCOE deltas when IoT+AI is applied to perovskite and tandem assets. This review undertakes that synthesis to establish a coherent picture of what has been demonstrated across settings and how these demonstrations relate to the distinctive degradation physics and control requirements of perovskite and tandem PV systems (Hassani, 2025; Kamrul & Tarek, 2022).

This review sets out to deliver a precise, decision-oriented synthesis of how IoT-enabled AI predictive models can enhance real-time performance of perovskite and tandem photovoltaic systems. First, it will establish a unified taxonomy that links sensing modalities, connectivity options, and compute placement with specific operational tasks, including short-horizon forecasting, fault and anomaly screening, degradation and remaining-life estimation, and controller guidance for maximum power point tracking and thermal regulation. Second, it will apply a transparent and replicable screening protocol to identify and extract study-level details on device architecture, measurement cadence, data volume, modeling approach, deployment topology, and runtime characteristics, enabling like-for-like comparisons across heterogeneous studies. Third, it will benchmark model classes against common accuracy and calibration metrics alongside latency, computational footprint, and energy overhead, so that performance is interpreted jointly with the constraints of real-time operation. Fourth, it will evaluate edge, cloud, and hybrid deployment patterns by examining the relationships among network conditions, update strategies, online learning, and operational resilience, drawing explicit connections between where inference occurs and the feasibility of closed-loop control. Fifth, it will quantify reported operational outcomes such as energy yield uplifts, downtime reductions, and levelized cost effects, translating predictive gains into plant-level performance indicators and identifying the data and telemetry prerequisites that enable those gains. Sixth, it will synthesize evidence on digital-twin workflows, data engineering practices, and model lifecycle management, emphasizing traceability, versioning, and quality control as foundations for trustworthy analytics. Seventh, it will assess data security and privacy practices within IoT stacks and summarize standards and interoperability mechanisms that enable multi-vendor integration. Eighth, it will produce an evidence map that highlights well-supported method–deployment–task combinations and systematically exposes underexplored intersections relevant to perovskite and tandem technologies. Finally, it will deliver a reusable extraction schema and a practical decision matrix that practitioners and researchers can apply to match instrumentation and modeling choices to site conditions, reliability needs, and operational objectives, ensuring that findings are immediately applicable to the design and evaluation of real-time, IoT-driven AI pipelines in this domain.

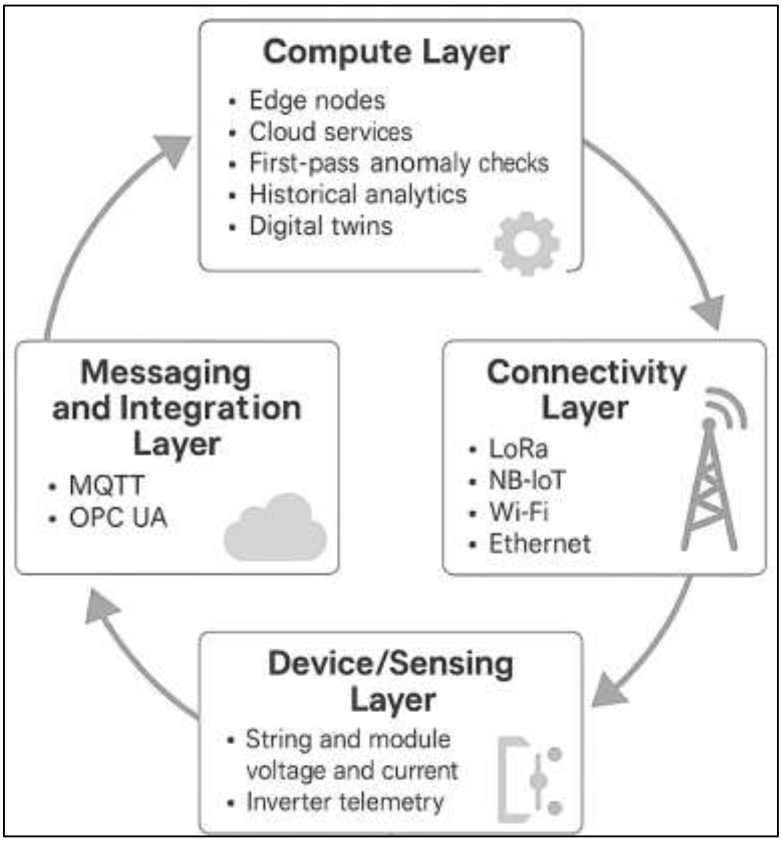
LITERATURE REVIEW

The literature on IoT-enabled AI for photovoltaics spans several partially overlapping streams that rarely speak the same language, making an integrative entry point essential before drilling into specific subtopics. Research rooted in materials and device physics focuses on the electro-optical behavior and stability of perovskite and tandem architectures, documenting how moisture ingress, thermal loads, interfacial chemistry, and current-matching constraints shape field performance; parallel work in power systems and controls treats PV plants as cyber-physical assets governed by sensing, actuation, and supervisory logic; and a third stream in data science emphasizes predictive modeling, uncertainty quantification, and deployment mechanics for streaming time-series and images. The introductory sweep of this review links these traditions by tracing the flow of information and decisions through an operational stack: sensors and IV tracers at the module and string level; connectivity layers that determine bandwidth, latency, and resilience; compute placement across edge, cloud, or hybrid topologies; and applications that transform data into forecasts, anomaly scores, degradation and remaining-life estimates, and controller guidance for maximum power point tracking or thermal regulation. Because perovskite and tandem systems exhibit distinct transient behaviors and degradation signatures, the review foregrounds how sensing choices and sampling cadence condition the learnability of relevant targets, and how model classes ranging from tree ensembles and kernel methods to recurrent and transformer architectures, physics-informed surrogates, and reinforcement-learning controllers trade off accuracy, interpretability, stability under drift, and computational footprint. Equally central is evaluation: beyond error metrics, the review treats latency budgets, on-device resource consumption, and the translation of predictive gains into plant-level indicators such as energy yield, uptime, and cost. The survey also establishes common terminology for digital-twin workflows, online learning, and model lifecycle management, since real-time performance depends as much on data engineering and MLOps practices as on algorithms. Finally, the review highlights cross-cutting constraints that shape feasibility in practice data quality and labeling, domain shift between lab and field, cybersecurity for distributed nodes and gateways, and interoperability across vendors and systems so subsequent subsections can compare methods on a like-for-like basis and identify where evidence is strong, where it is promising but nascent, and where critical gaps remain for perovskite and tandem deployments operating under real-world conditions.

IoT Architectures for Photovoltaic (PV) Monitoring

IoT architectures for PV monitoring are layered systems that translate physical sensing into actionable, time-synchronized data streams, enabling continuous observability from module to plant scale. At the device/sensing layer, instrumented nodes acquire electrical and environmental variables string and module DC voltage and current, inverter telemetry, backsheet and ambient temperatures, irradiance, wind, humidity, and sometimes IV curves or thermal imagery at cadences ranging from sub-minute to multi-minute intervals. These nodes typically combine low-cost microcontrollers (e.g., ESP32) with local storage and real-time clocks to ensure timestamp integrity and graceful degradation during backhaul loss (Melo et al., 2021). The connectivity layer links dispersed sensors to gateways and services while balancing range, power, latency, and cost. For wide-area, battery-operated deployments, LPWAN options such as LoRa/LoRaWAN are widely used to backhaul compact PV metrics over kilometers with milliwatt-level budgets, supporting campus and utility layouts. Where licensed coverage and quality of service are needed, NB-IoT offers carrier-grade connectivity for distributed PV monitoring and limited control, albeit with differing uplink duty cycles and latency envelopes . On rooftop or dense sites, Wi-Fi or Ethernet remains practical for high-rate streams and dashboard interactivity (Al-Naib et al., 2024). The messaging and integration layer generally adopts MQTT brokers for pub/sub telemetry and lightweight control topics, sometimes alongside OPC UA where industrial interoperability, strong typing, and method calls are required. Finally, the compute layer splits responsibilities between edge nodes which perform filtering, feature extraction, thresholding, and first-pass anomaly checks and cloud services which aggregate fleet data, retrain models, and serve historical analytics and digital twins. Across these layers, architectural choices are constrained by energy autonomy of field nodes, desired monitoring resolution, and the need for secure, resilient, and maintainable data paths in harsh outdoor conditions.

Figure 2: Cycle Diagram of Layered IoT Architecture for Photovoltaic Monitoring



For resource-constrained sensing nodes, power budgeting drives both hardware and protocol design. Energy-autonomous IoT platforms increasingly integrate miniature PV harvesters and supercapacitors to sustain periodic telemetry without manual battery service, a property essential for distributed per-module monitoring and remote balance-of-system (BoS) assets; in such designs, opportunistic data-rate selection and duty-cycling reconcile coverage with lifetime . LoRaWAN links commonly achieve hundreds of milliseconds to seconds of latency adequate for monitoring and slow supervisory actions while edge nodes cache measurements during outages for eventual consistency . NB-IoT gateways can offload lightweight machine learning to compress or prioritize payloads, reducing radio transmissions and energy draw useful when sites push images or dense diagnostics in addition to scalar time series (Mubashir & Abdul, 2022) . At the plant level, open-source SCADA architectures that stitch together MQTT, Node-RED/flow engines, and time-series databases have demonstrated modular, auditable pipelines supporting real-time dashboards, alarm routing, and HMI controls; because components are loosely coupled, the same stack can host AI microservices for forecasting and anomaly scoring without vendor lock-in. Where PV assets must interoperate with existing industrial systems, OPC UA servers/gateways bridge legacy MODBUS devices with modern analytics and provide typed address spaces and role-based security, features that simplify integration at utility scale (Carballo et al., 2024). Taken together, these building blocks enable hierarchical

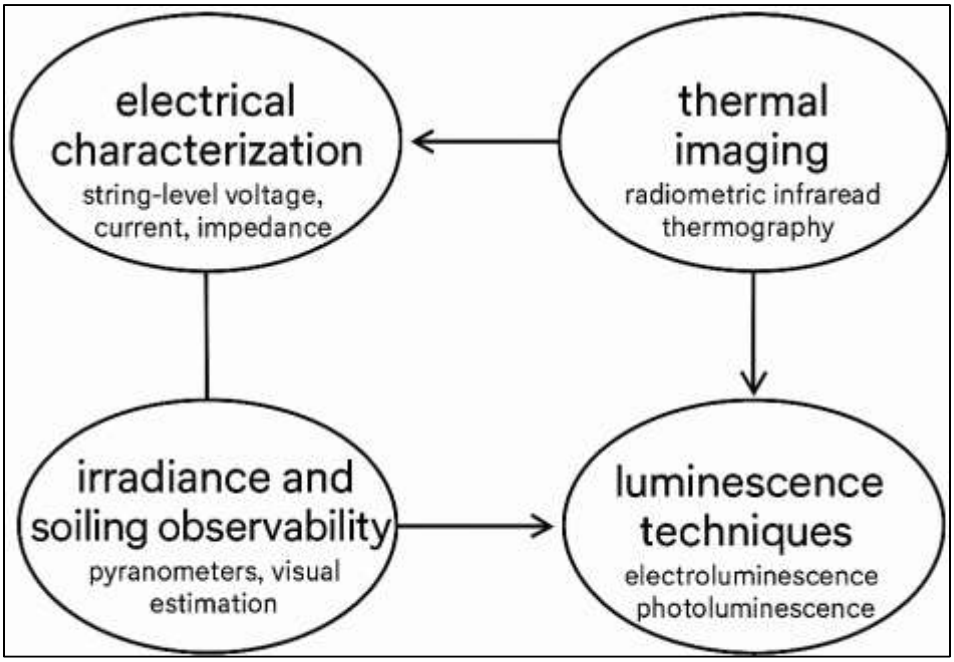
observability: per-module telemetry feeds string and inverter views, which in turn feed site- and fleet-level analytics, with policy-driven retention and down-sampling to control storage costs. Architectural rigor at this level is a prerequisite for real-time AI deployment because feature freshness, data lineage, and backpressure handling directly condition model reliability and the stability of downstream control loops (Muhammad & Kamrul, 2022).
IoT architectures also shape where analytics run and how control authority is exercised. For monitoring-centric tasks yield accounting, degradation tracking, and alarm correlation cloud aggregation suffices; but for time-sensitive functions like fast anomaly screening or wireless MPPT orchestration, inference near the source reduces latency and keeps operation resilient during backhaul loss. Recent studies demonstrate centralized or coordinated MPPT over LoRa/LoRaWAN, centralizing set-point computation while maintaining low-power, long-range links to distributed converters; such designs reduce wiring complexity and make algorithm upgrades and A/B tests tractable (Reduanul & Shoeb, 2022). For distributed PV, NB-IoT–based strategies have been proposed for real-time monitoring and voltage regulation, highlighting the need to budget for cellular attach times and coverage variability across rooftops and feeders (Kumar & Zobayer, 2022). In parallel, virtualized SCADA stacks with OPC UA cores illustrate how to modernize solar plants extending to CSP fields with secure, typed data models and mesh backhauls, thereby easing integration of analytics and hybrid human-in-the-loop control. At the gateway and data-platform tier, "bring-your-own-model" patterns expose MQTT/REST endpoints for AI microservices and schedule model updates to the edge; low-cost, open hardware makes these rollouts feasible for pilot-scale perovskite/tandem arrays where instrumentation density and failure modes differ from silicon PV (Al-Naib et al., 2024; Noor & Momena, 2022). Finally, security and reliability considerations device identity, encrypted transport, and defense-in-depth between field networks and cloud tenants must be baked into the architecture rather than layered post-hoc. Energy-autonomous nodes, typed industrial endpoints, and standards-based messaging together supply the operational substrate upon which AI forecasting, fault diagnostics, and control can act reliably in real (Istiaque et al., 2023; Melo et al., 2021).

IoT-linked Monitoring of Perovskite and Tandem PV

Reliable IoT-enabled monitoring hinges on the quality and fitness of the underlying sensors and diagnostic instruments that feed data pipelines from cell to module, string, and plant scales. In the photovoltaic domain, three complementary instrumentation families dominate: electrical characterization (e.g., I–V tracers, reference cells), thermal/infrared imaging, and luminescence-based techniques (electroluminescence/photoluminescence), each with distinct observability and latency profiles. Electrical metrology (string-level voltage, current, impedance, and I–V sweeps) provides directly actionable performance indicators, but its spatial resolution is limited unless multiplexed or paired with module-embedded sensing; recent reviews outline architectures for portable and multi-channel I–V tracers that reduce test time and allow routine field deployment in digital O&M workflows (Hasan et al., 2023; Morales-Aragonés et al., 2021). Thermal imagery especially radiometric infrared thermography (IRT) adds non-contact spatial context to electrical anomalies (e.g., hotspots from resistive defects, diode malfunction, PID), and has matured from handheld cameras to standardized aerial inspections with radiometric calibration and flight-path automation; surveys highlight how aIRT can be integrated in condition-based maintenance loops and where algorithmic generalization still lags (Gallardo-Saavedra et al., 2020; Hossain et al., 2023). For perovskite and perovskite–silicon tandem technologies whose ion migration, interfacial reactions, and moisture/thermal sensitivities may elude coarse electrical summaries in situ/operando optical probes are particularly informative. Electroluminescence (EL) and photoluminescence (PL) imaging, including emerging daylight-compatible EL with current modulation and InGaAs detection, resolve microcracks, shunts, and interconnect defects with cell-scale granularity and are increasingly being paired with explainable deep models to automate defect taxonomy and severity scoring (Santamaría et al., 2025; Rahaman & Ashraf, 2023). Together, these modalities define a sensor triad whose outputs are well-suited for edge ingestion and IoT transport, enabling cross-modal fusion (electrical-thermal-optical) that raises diagnostic confidence for both silicon-dominant and perovskite-inclusive fleets.
Designing IoT sensing stacks for perovskite and tandem PV requires attention to irradiance and soiling observability, environmental stressors, and calibration traceability. Irradiance remains the

primary exogenous driver; thus, Class A pyranometers or spectrally-matched reference cells on the plane of array are essential to normalize production metrics and to disambiguate weather-driven yield variations from degradation (Sultan et al., 2023). While electrical proxies (e.g., Isc from reference cells) can suffice for relative tracking, robust networks benefit from redundancy paired irradiance and module-backsheet temperature channels to stabilize performance-ratio estimates under transient clouds and wind. Soiling, a frequent confounder of apparent degradation in arid and agricultural regions, warrants dedicated sensing or vision-based estimation. Field studies demonstrate that machine-learning regressors trained on routine PV telemetry (Isc, module temperature, RH, pressure) can estimate soiling losses with practical accuracy, enabling economically optimal cleaning policies without costly particle counters (Hossen et al., 2023; Pérez et al., 2021). Complementarily, recent computer-vision pipelines using visible-spectrum imagery classify or quantify panel soiling and surface blemishes, performing well enough to trigger maintenance tickets and to annotate aIRT/EL inspections (Tawfiqul, 2023; Trifonov et al., 2024). On the thermal front, IRT systematization matters: reviews comparing illuminated versus dark conditions, indoor versus outdoor, and bidirectional-inverter-assisted "dark-IRT" protocols detail when each mode is most discriminative and how radiometric corrections reduce false positives due to wind, angle-of-view, and emissivity drift. Aerial radiometric IRT pipelines, coupled with deep transfer learning and post-hoc explainability, show promise for scalable, bias-aware triage under heat-wave stress conditions under which perovskite devices may exhibit accelerated ionic and interfacial changes (Borah et al., 2023; Uddin & Ashraf, 2023; Qureshi et al., 2025). For perovskite/silicon tandems specifically, PL/EL channels add sensitivity to sub-bandgap defect states and interlayer recombination that precede power loss, positioning optical sensing as an early-warning layer above electrical baselines (Borah et al., 2023; Momena & Hasan, 2023; Qureshi et al., 2025).

Figure 3: Cycle Diagram of Sensing and Instrumentation for IoT-Linked Monitoring



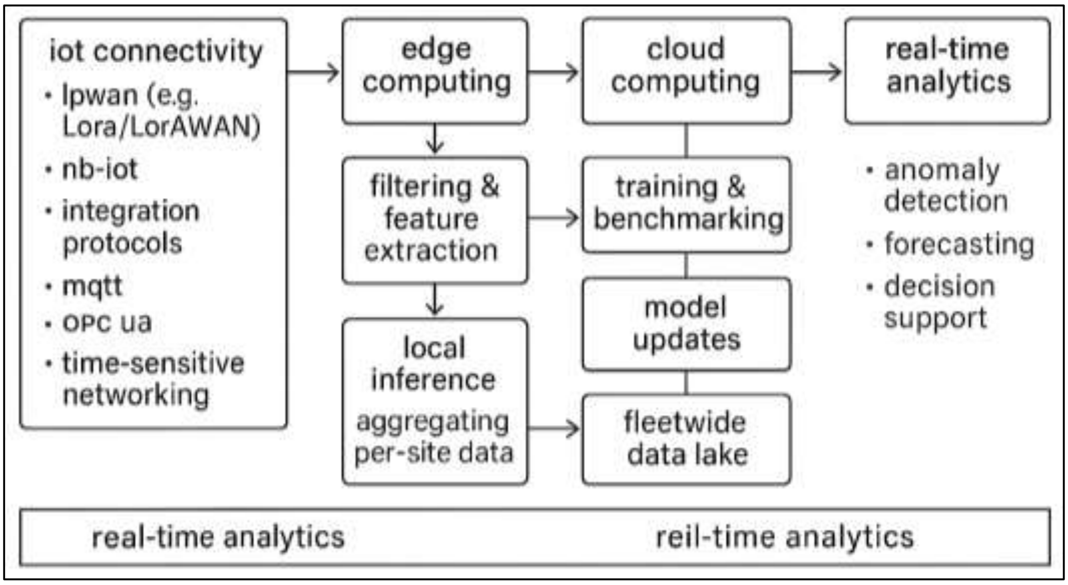
Critically, perovskite stability research motivates IoT-ready, in situ/operando instrumentation that can run unattended during realistic duty cycles and environmental excursions. Operando frameworks integrate controlled humidity/temperature/illumination with continuous tracking of PV parameters and optical observables to capture fast and reversible ionic phenomena versus slow and irreversible degradation, a distinction vital for predictive modeling (Fukuda et al., 2025). For fielded tandems, practical compromises involve embedding miniature sensors (humidity, temperature) in junction boxes or backplates, synchronizing their time series with edge-executed I–V sweeps and periodic EL snapshots. The recent literature argues for standardized metadata (illumination spectra, spectrum-mismatch, thermal boundary conditions) and for fusing optical kinetics (e.g., PL quenching/recovery) with electrical drifts to disentangle transport-layer failure from photoabsorber chemistry. In operational plants, portable and multi-channel I–V tracers with smart multiplexers shorten test windows, allowing routine baseline refreshes suitable for IoT scheduling. Meanwhile, maturing aerial IRT playbooks amortize inspection costs and improve fleet coverage. Pulling these threads together, an instrumentation stack optimized for IoT must (i) ensure traceable irradiance/temperature/soiling context, (ii) add periodic, radiometrically reliable thermal and luminescence imaging for spatial diagnostics, and (iii) align sampling cadences and data schemas with edge compute and bandwidth realities (Sanjai et al., 2023). Such stacks generate the rich, well-labeled multimodal datasets that AI predictive models need to deliver trustworthy, perovskite-aware prognostics at scale.

Edge/Cloud Infrastructure for Real-Time PV Analytics

High-quality IoT telemetry for perovskite and tandem photovoltaic (PV) systems depends on communication stacks that can move time-sensitive measurements from harsh outdoor environments to decision points with predictable latency, reliability, and security. At the physical and link layers, low-power wide-area networks (LPWANs) such as LoRa/LoRaWAN prioritize energy efficiency and kilometers-scale range, enabling dense sensor deployments on modules, combiner boxes, trackers, and weather masts with multiyear node lifetimes; the trade-offs are duty-cycle limits, narrow payloads, and region-specific spectrum rules that affect update rates and acknowledgments. For distributed rooftops and feeders where licensed coverage is desirable, NB-IoT provides carrier-grade attachment and extended coverage, with better service guarantees for periodic monitoring and event-driven alarms, albeit at the cost of attach procedures and variable uplink latency that must be budgeted for in real-time loops (Mekki et al., 2019; Zhou et al., 2019). Moving up the stack, message queuing telemetry transport (MQTT) and related pub/sub patterns remain the lingua franca for telemetry fan-out and lightweight control topics; comparative evaluations against CoAP show MQTT's robustness under lossy links and its suitability for gateway aggregation, particularly when PV fleets require topic hierarchies for strings, inverters, and site-level digital twins (Akter et al., 2023; Trakadas et al., 2020). Where interoperability with industrial control systems is needed, OPC UA notable for its typed address spaces, method invocation, and security model bridges modern analytics with legacy power electronics and SCADA backbones, and can be combined with Time-Sensitive Networking for deterministic transport on the substation LAN (Leitner & Mahnke, 2014). Together, these design choices shape how perovskite/tandem assets are observed: LPWANs excel at sparse, power-frugal metrics from widely distributed nodes; NB-IoT and Ethernet/Wi-Fi support higher-rate streams and firmware updates; MQTT/OPC UA provide integration and role-based access; and TSN-ready plants lay the groundwork for time-bounded control traffic (Raza et al., 2017; Thangavel et al., 2014).

The edge–cloud split determines where inference runs and how resilient the system is under backhaul variability. Conceptually, edge computing brings filtering, feature extraction, and first-pass inference to gateways or even sensor nodes, reducing bandwidth, containing personally or commercially sensitive data, and keeping alerting live during connectivity loss; cloud tiers centralize training, fleetwide benchmarking, and model governance (Danish & Zafor, 2024; Shi et al., 2016). In PV operations, this division maps naturally onto task criticality and latency budgets: sub-second anomaly screening near inverters and strings, minute-scale forecasting at gateways, and heavier model retraining or A/B testing in the cloud. Practical blueprints increasingly adopt a three-tier pattern device → edge gateway → cloud so that per-module telemetry can be down-sampled, summarized, or prioritized at the edge before being published upstream, while the cloud maintains a "source of truth" time-series lake and orchestrates model updates. The rise of edge intelligence tightens this loop further by co-locating compact deep models with data sources and enabling on-device adaptation to local microclimates, soiling regimes, and thermal behaviors that differ across sites (Nasrallah et al., 2019). Complementarily, fog abstractions support in-between compute aggregation (e.g., per-feeder or per-array), useful when tandem fields are geographically dispersed and share feeders or substations; this reduces round trips and allows local consensus for control actions (Chiang & Zhang, 2016; Istiaque et al., 2024). For perovskite/tandem deployments often pilots with evolving device stacks this layered approach limits backhaul load from high-cadence IV tracers, thermal imagers, or luminescence probes, yet keeps the analytical "center" robust for cross-site comparisons, drift detection, and model lifecycle management (Hasan et al., 2024; Popovski et al., 2018).

Figure 4: Edge/Cloud Infrastructure for Real-Time PV Analytics

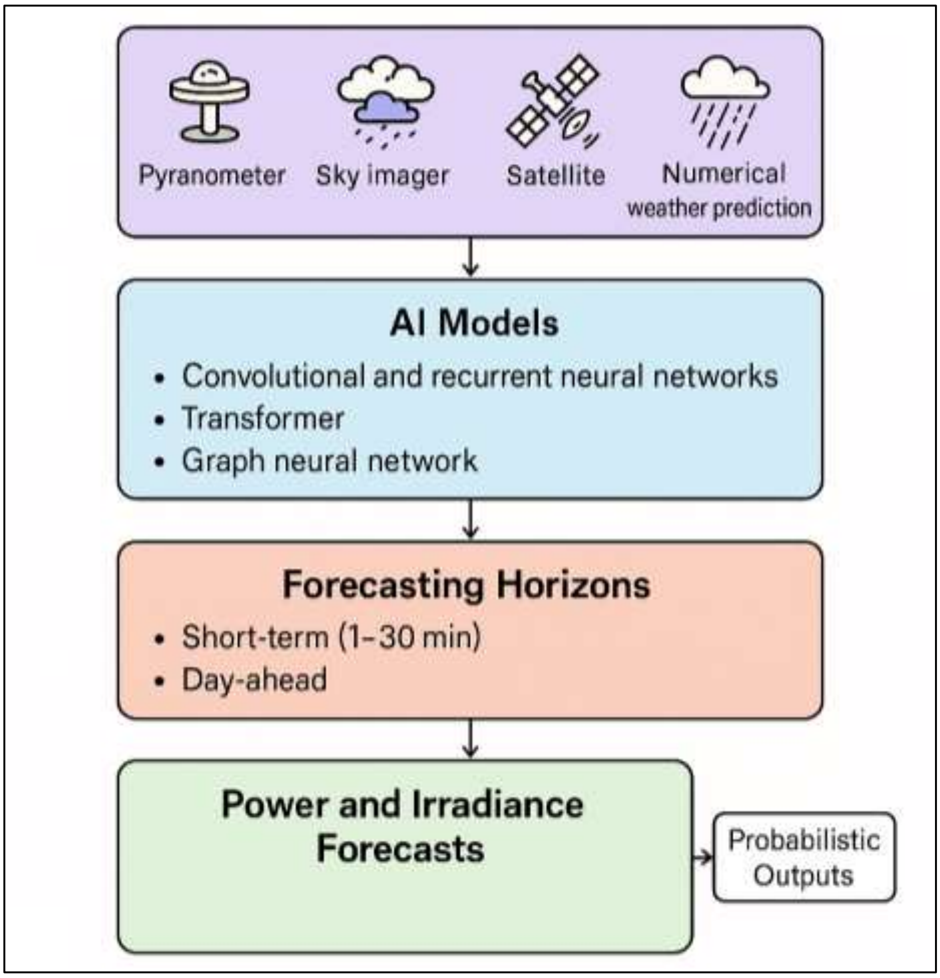


Achieving determinism and reliability in cyber-physical control paths requires attention to both the network fabric and ML operations. On plant LANs, Time-Sensitive Networking (TSN) provides bounded-latency flows and time-aware shaping for control and protection traffic, making it a natural fit for PV plants modernizing beyond best-effort Ethernet; surveys show how TSN's scheduling, clock sync, and stream reservation primitives can underpin closed-loop control alongside noncritical telemetry. At the enterprise edge, 5G adds URLLC-class links for mobile assets and wide-area resilience, with slicing and QoS differentiation that can segregate monitoring, video inspection, and control topics (Rahaman, 2024; Popovski et al., 2018). In parallel, federated learning offers a privacy-preserving way to personalize models to sites and climates without centralizing raw data an attractive property for third-party O&M providers or multi-tenant industrial parks operating mixed PV technologies while still allowing global aggregation and convergence in the cloud (Kairouz et al., 2021). For interoperability between operational technology and analytics, OPC UA Pub/Sub over TSN has emerged as a reference integration, carrying typed measurements and commands with deterministic behavior and easing certification in regulated grids (Hasan, 2024; Trakadas et al., 2020). The practical arc ties back to deployment engineering: MQTT topics bridge field nodes to gateways; OPC UA/TSN secures deterministic lanes on plant networks; edge compute hosts compact models; 5G or NB-IoT backhauls summaries; and cloud services retrain and govern models. With these gears synchronized bounded latency flows, resilient backhaul, privacy-aware learning, and explainable, updatable edge models IoT connectivity and edge infrastructure become an enabling substrate on which real-time AI for perovskite and tandem PV can operate at scale (Ashiqur et al., 2025; Mekki et al., 2019; Raza et al., 2017).

AI for Power and Irradiance Forecasting

Short- to day-ahead forecasting of solar irradiance and PV power is central to real-time operation, market participation, and control of perovskite and tandem systems, and AI now dominates the state-of-the-art across horizons from minutes to 24 hours. Deep learning models particularly convolutional and recurrent architectures leverage multi-source inputs (on-site sensors, sky imagers, satellite fields, and numerical weather prediction) to learn nonlinear mappings between meteorology and PV response that traditional statistical methods struggle to capture. For ultra-short horizons (1–30 minutes), computer-vision pipelines that ingest whole-sky images and recent plant telemetry via IoT gateways have proven especially effective; hybrid CNN/RNN designs translate cloud morphology and motion into rapid irradiance ramps, reducing smoothing biases and improving ramp detection relative to purely time-series models (Hasan, 2025; Sun et al., 2019; Venugopal et al., 2019). At plant and regional scales, probabilistic formulations quantify uncertainty with predictive intervals that can be consumed by dispatch and reserve scheduling; techniques based on correlated weather-scenario generation, Copulas, and machine-learning ensembles yield calibrated densities while preserving cross-variable dependence. Beyond single-site learning, grouped Gaussian processes and graph-based deep networks explicitly encode spatial structure across fleets, exploiting correlations among sites and nearby weather stations to lift both point accuracy and uncertainty quantification (Ismail et al., 2025). Recent systematic reviews confirm that, across benchmarks, deep learning consistently outperforms shallow baselines when diverse exogenous covariates and plant metadata are fused, and that careful feature engineering around solar geometry and sky conditions is critical for robustness (Al-Dahidi et al., 2024). Within this landscape, IoT instrumentation irradiance sensors, module/backsheet thermistors, pyranometers, all-sky cameras, ceilometers, and inverter telemetry serves as the data fabric that streams high-frequency signals into AI models with sub-minute latency, enabling continuous retraining and online adaptation to perovskite-specific thermal and hysteretic behaviors (Jakaria et al., 2025).

Figure 5: Layered Framework of AI for Power and Irradiance Forecasting in Perovskite



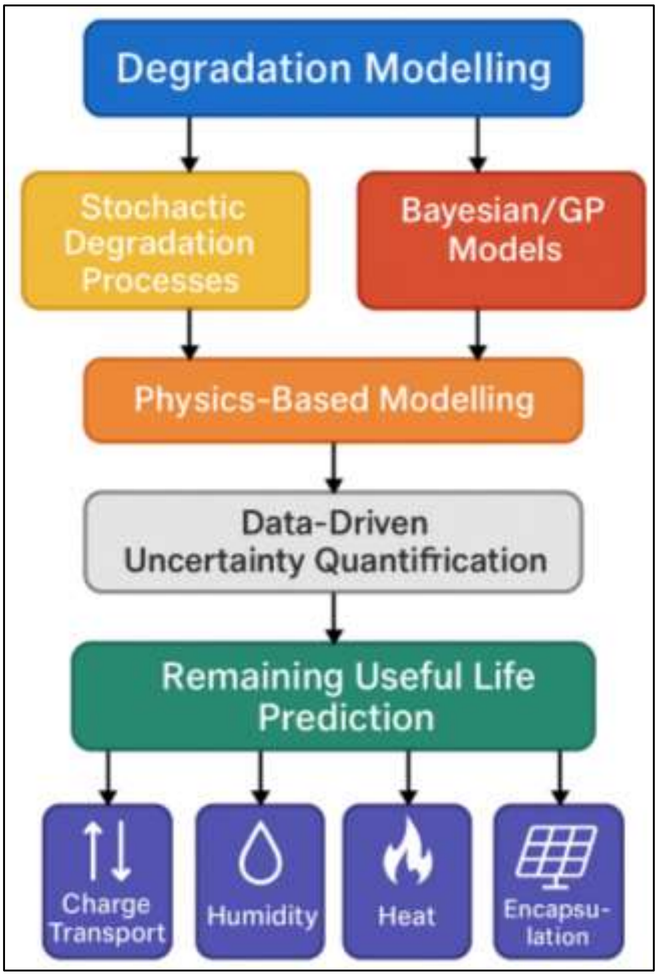
For hour-ahead to day-ahead horizons, attention-based Transformers and hybrid encoder–decoder stacks have expanded forecasting capacity by modeling long-range temporal dependencies and multi-scale seasonality while retaining sensitivity to sudden exogenous changes. Multi-step frameworks such as PVTransNet combine Transformer encoders with LSTM decoders to integrate historical power, on-site observations, weather forecasts, and solar geometry, achieving lower mean absolute errors than pure LSTM or conventional Transformer baselines across multi-hour sequences (Kim et al., 2024; Hasan, 2025). At the fleet level, interpretable temporal–spatial graph attention networks (TSM-GAT) learn dynamic adjacency among sites, providing saliency over meteorological drivers and inter-plant influences capabilities that are valuable for operators managing geographically dispersed tandem/perovskite assets (Jing et al., 2024; Sultan et al., 2025). Complementary graph innovations embed spectral/Fourier operators to capture spatio-temporal couplings efficiently from heterogeneous IoT streams (power, temperature, wind, sky pixels), improving generalization when station coverage is sparse or newly commissioned assets lack history. These architectures can be deployed in edge–cloud hierarchies: edge devices perform preprocessing (denoising, feature scaling, sky segmentation) and low-latency nowcasts, while cloud services run heavier day-ahead models and uncertainty post-processing for market bids (Zafor, 2025). Probabilistic outputs (quantiles, full predictive densities) derived from deep or Gaussian-process heads are readily integrated with battery EMS for risk-aware dispatch and curtailment minimization, a particularly useful feature for perovskite and tandem strings whose temperature coefficients and transient dynamics accentuate weather sensitivity (Zhang et al., 2020).

Operationalization remains a modeling-and-systems problem: robust pipelines must handle regime shifts (e.g., seasonal aerosol loads, sensor drift), missing-data bursts from IoT networks, and site-specific nonlinearities (soiling, snow cover, spectral response differences for perovskites). Studies show that coupling image-based cloud cover extraction with power-history encoders mitigates over-smoothing and improves ramp timing, which is critical for inverter set-point scheduling and DC-coupled storage control. Attention LSTM variants improve explainability and perform well under limited data by focusing on salient covariates and temporal segments, while transfer learning across plants accelerates deployment to newly built fields (Uddin, 2025; Venugopal et al., 2019). Classical deep RNN stacks can be enhanced in practice with time-correlation modification layers that correct day-ahead trajectories using intra-day similarity detection, yielding tangible accuracy gains in live operations (Wang et al., 2020). Across these methods, best-in-class systems combine (i) high-quality, synchronized IoT sensing (telemetry + sky/satellite), (ii) architectures aligned to horizon (vision-centric nowcasting; attention/graph models for day-ahead), and (iii) probabilistic post-processing for decision-grade uncertainty (Sanjai et al., 2025; Sun et al., 2019). For perovskite and tandem PV specifically, these AI-IoT pipelines can be parameterized with device-level features (bandgap configuration, thermal transients) and site metadata to tailor forecasts to their distinct spectral/thermal responses unlocking tighter inverter control, smoother power ramps, and improved participation in flexibility markets.

Remaining-Useful-Life (RUL) prediction for perovskite and tandem PV

Predicting how fast perovskite and tandem PV devices will degrade and how long they will remain serviceable requires models that reconcile device physics with stochastic field realities. At the material/device level, degradation in metal-halide perovskites arises from ion migration, defect generation, interfacial reactions, and extrinsic stressors (humidity, oxygen, heat, UV, and reverse bias), all of which perturb charge transport and accelerate performance loss; at the module/system level, encapsulation, interconnects, and backsheets introduce additional failure pathways and time-varying stress couplings that complicate lifetime inference (Baumann et al., 2024). Outdoor evidence from monolithic perovskite/Si tandems underscores the non-monotonic, stage-wise nature of field aging (e.g., early stabilization, mid-life drift, and late-life acceleration), with year-long monitoring showing about 80% efficiency retention alongside pronounced environmental sensitivities that challenge simple linear degradation assumptions (Babics et al., 2023). Meta-reviews across crystalline-Si and thin-film modules likewise reveal wide spreads in reported performance loss rates because climate, technology, test protocol, and analysis method all bias estimates, motivating probabilistic frameworks that propagate uncertainty into service-life forecasts (Aghaei et al., 2022; Babics et al., 2023). Recent perspectives specific to perovskite/Si tandems emphasize tandem-specific degradation (e.g., reverse-bias hotspots, mobile-ion dynamics, and stack-dependent thermo-mechanical stress), arguing for models that link sub-cell states to module-level reliability metrics (Rolston et al., 2022). Complementing these views, operando and in-situ characterization syntheses detail kinetic signatures ion redistribution, phase changes, and interfacial evolution that can serve as physics-anchored state variables for prognostics (Cho et al., 2023). Together, these strands suggest that credible RUL estimation must be both multiscale and hybrid: it should fuse mechanistic descriptors (e.g., ionic mobility, interface kinetics) with data-driven uncertainty quantification under real-world stress histories (Chakar et al., 2024; Cho et al., 2023).

Figure 6: Layered Framework for Degradation Modelling and Remaining Useful Life Prediction



Methodologically, two complementary families have matured for PV RUL: (i) stochastic degradation processes that capture drift-diffusion-like wear and regime switching; and (ii) Bayesian/GP models that infer latent parameters and predictive intervals directly from operating data. For PV modules, two-stage Wiener and related change-point formulations explicitly model phase transitions in degradation trajectories, enabling online estimation of the remaining lifetime distribution and outperforming single-stage baselines when devices undergo regime shifts (Lin et al., 2024). In parallel, Gaussian-process (GP) models map time-series IV and meteorological covariates to health indicators while preserving calibrated uncertainty; recent GP-IV formulations for outdoor PV show how probabilistic surrogates can disentangle condition effects from intrinsic aging to yield more faithful trend extrapolations for service-life planning (Carlucci et al., 2024). Bayesian inversion has also emerged as a powerful route to extract equivalent-circuit parameters (e.g., RsR_sRs, RpR_pRp, ideality factor) from production power or IV data and to track their daily evolution; because these parameters are mechanistically interpretable, their trajectories can be tied to specific degradation mechanisms and then embedded in RUL models with uncertainty bounds. When perovskite devices are considered, accelerated degradation modelling is being re-framed around physics-informed learning that encodes transport/chemistry constraints, yielding more sample-efficient extrapolations from stress tests to field conditions (Pandey & Bag, 2025). These hybrid approaches complement stability roadmaps for tandems that warn about reverse-bias resilience and thermal hotspots at module scale; incorporating such stress-coupling physics into priors or constraints improves identifiability and guards against spurious lifetime optimism (Pandey & Bag, 2025). Critically, long-horizon outdoor datasets spanning perovskite-Si and perovskite-CIGSe tandems are now available to validate prognostic pipelines beyond single-cell, lab-scale tests, enabling credible evaluation of calibration, sharpness, and early-warning capability under real spectra, temperatures, and soiling.

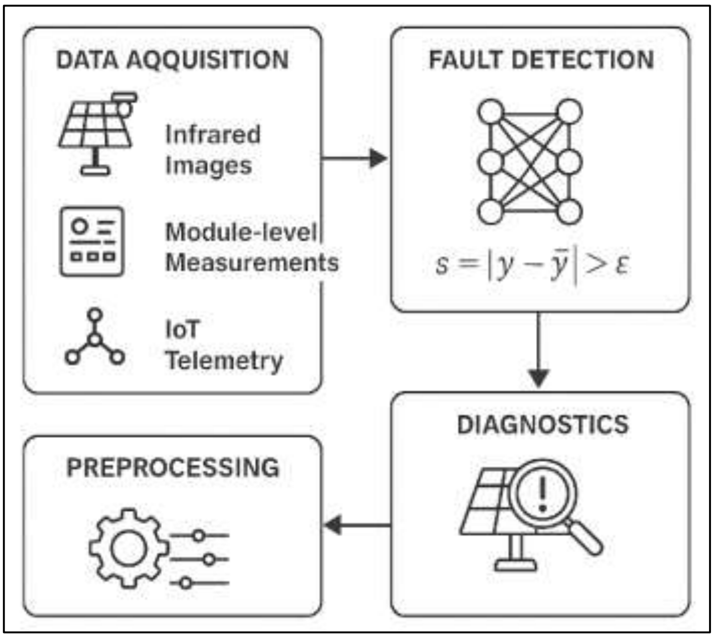
At scale, fleet-level lifetime risk must reconcile device heterogeneity with site-specific climates. Systematic field studies over decades show technology-dependent degradation signatures junction box, encapsulant, metallization, and backsheet issues that propagate to power-loss dispersion across plants (Tockhorn et al., 2025). This heterogeneity is precisely why meta-analyses now model moderators (climate class, technology, and methodology) to explain variance in reported loss rates and to yield more transferable priors for site-adapted RUL (Chakar et al., 2024). For perovskite/silicon tandems, recent outdoor campaigns and commercialization-minded surveys converge on the need for lifetime models that include encapsulation chemistry, stack-specific thermo-mechanical stress, and reverse-bias protection strategies, rather than extrapolating from single-junction perovskite cells alone. Taken together, a state-of-the-art RUL workflow for IoT-instrumented perovskite and tandem PV would: (1) stream IV/impedance/thermal data; (2) infer physics-meaningful parameters via Bayesian inversion; (3) propagate them through stochastic, possibly two-stage, degradation laws; and (4) validate forecasts against outdoor benchmarks with calibrated uncertainty and change-point detection. Such a workflow aligns with the current consensus from stability reviews, accelerated-testing methodology, and year-long outdoor studies across tandem platforms.

Fault/Anomaly Detection and Diagnostics in IoT-Enabled PV Systems

Contemporary fault and anomaly detection for photovoltaic (PV) assets increasingly blends thermal/visual sensing with deep neural inference, enabling real-time diagnostic decisions at module, string, and inverter levels. Early work pairing infrared (IR) thermography with machine learning demonstrated that hotspot morphology, thermal gradients, and texture descriptors could be mapped to defect classes and anticipated energy loss, establishing IR as a non-contact, O&M-friendly foundation for automated screening (Ali et al., 2020). Building on this, convolutional classifiers trained on large IR corpora now separate multiple defect categories under field conditions, mitigating confounders such as soiling, oblique viewing angles, and irradiance transients (Alves et al., 2021). Mini-reviews consolidated these advances, emphasizing that IR-based condition monitoring has matured from qualitative inspection to quantitative diagnostics when paired with robust feature learning and consistent acquisition protocols (Kandeal et al., 2021). Most recently, survey work at the interface of infrared physics and deep learning has codified best practices for UAV-borne thermography, panel segmentation, and anomaly classifiers arguing that standardized flight, radiometric calibration, and domain adaptation are as critical as model choice for trustworthy detection at scale (Khatri et al., 2025). Together, these streams motivate an IoT stack in which on-board or edge-deployed inference units fuse module-level telemetry with camera streams to flag incipient faults before they propagate to measurable yield loss.

A pivotal development has been domain-aware representation learning for IR imagery. Instead of training and testing on identically distributed samples, recent work frames fault detection as cross-plant generalization: a supervised contrastive pipeline learns robust embeddings on labeled source-plant images and transfers anomaly decision boundaries to unseen target plants with minimal re-tuning, sustaining accuracy despite changes in module make, age, irradiance, and flight altitude (De Benedetti et al., 2018). Complementing representation learning, one-stage detectors optimize end-to-end discovery of small, densely packed defects under clutter and glare. Enhanced YOLO variants (e.g., YOLOv7 with partial/switchable atrous convolutions) deliver fast, high-mAP inspection suitable for on-drone triage, explicitly targeting multi-scale defect morphology in EL/IR tiles (Zhang et al., 2024). Vision Transformers and attention-augmented backbones have also entered the IR/EL toolbox; hybrid transformer–CNN designs report measurable gains in locating hairline cracks and busbar discontinuities, particularly when objects are tiny, low-contrast, or partially occluded. For multiclass PV-panel inspection in the wild, short-term spatiotemporal modeling further stabilizes decisions by absorbing irradiance flicker and UAV motion, and segmentation heads can supply pixel-precise defect masks that double as interpretable overlays for technicians. Across these studies, the diagnostic edge emerges from three ingredients: (i) curated sensing protocols (radiometric IR, consistent altitude, gimbal lock); (ii) embeddings resilient to domain shift; and (iii) detectors optimized for small objects with explainable heatmaps that align with physical failure signatures (Li et al., 2024). Beyond images, IoT telemetry string currents, inverter events, backsheet thermistors, and irradiance enables anomaly detection where cameras are impractical or as a second opinion for IR flags. Classical residual-based schemes train a normal-behavior model (e.g., ANN or LSTM-AE) on irradiance/temperature-conditioned power and raise alerts on residual excursions, supporting predictive maintenance from low-cost SCADA streams (Oliveira & et al., 2022). At portfolio scale, interpretable quantile models and locality-aware regressors compare each site to its "neighborhood," surfacing collective anomalies attributable to shading, soiling, or MPPT mis-tracking; when fused with IR-derived labels, these methods improve precision in distinguishing thermal hotspots from benign

Figure 7: Square Diagram of Fault and Anomaly Detection in IoT-Enabled Photovoltaic Systems

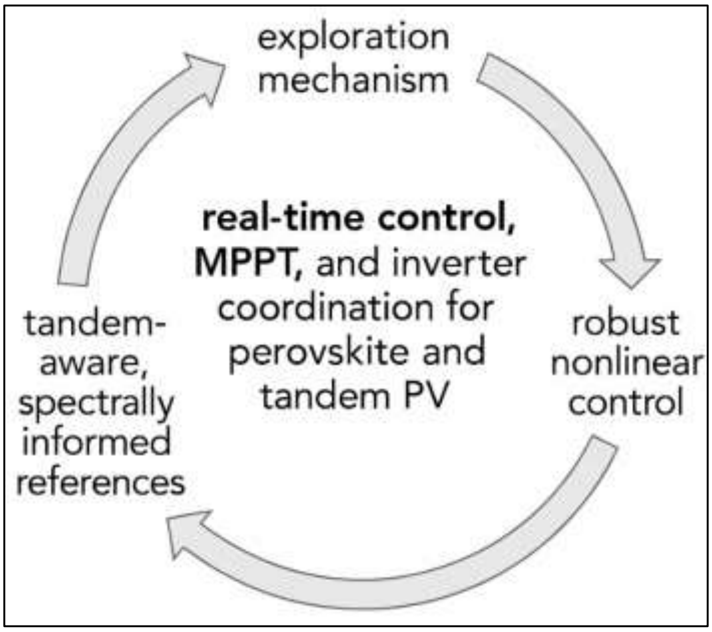


meteorological dips (Xiang et al., 2022). For feature-sparse deployments, lightweight U-Net pipelines segment hot regions and locate bright-spot defects in IR frames; paired with decision trees or SVMs they provide transparent rules for triage and work-order generation that field teams can validate quickly (Zhang et al., 2024). Finally, explainability via saliency on IR tiles or feature attribution on SCADA has moved from an afterthought to a design criterion, strengthening operator trust and accelerating root-cause analysis when anomalies precipitate curtailment or safety alarms (Khatri et al., 2025). Collectively, these image- and telemetry-driven approaches illustrate how IoT-AI pipelines can progress from mere fault detection to actionable diagnostics, connecting signatures (e.g., diode hotspot, snail trails, PID) to specific maintenance actions under operational constraints (Bommes et al., 2022).

Inverter Coordination for Perovskite and Tandem PV

Real-time control in IoT-enabled photovoltaic (PV) systems hinges on fast, stable maximum power point tracking (MPPT) tightly coupled to converter and inverter control so the plant can exploit micro-scale irradiance and temperature fluctuations without inducing oscillations or curtailment. Classical hill-climbing and incremental-conductance families remain the industrial baseline, but extensive reviews document their sensitivity to step-size tuning, measurement noise, and multi-peak power–voltage curves under partial shading conditions especially common in dense urban arrays and bifacial layouts (Ishaque & Salam, 2013). To overcome these limits, meta-heuristic global MPPT algorithms (particle swarm, grey-wolf, whale, and hybrids) search the full P–V landscape and can lock onto the global MPP with reduced dithering; hybrid formulations embed an optimizer to deliver the MPP setpoint and a deterministic regulator to enforce it on the power converter, thereby decoupling exploration from tracking (Ahmed et al., 2022; Research, 2024). For perovskite and tandem fields where spectrum, hysteresis, and thermal transients modulate the effective MPP more strongly than in c-Si the controller must also reject device-intrinsic dynamics (ionic motion, capacitive effects) that bias naïve steady-state estimators. Spectral/current-matching constraints in two-terminal tandems additionally reshape the feasible operating region, motivating MPP logic that is spectrum-aware and sub-cell-coherent rather than purely scalar (Mohanty et al., 2017). Collectively, the contemporary control picture is a layered one: an exploration mechanism robust to multi-peak landscapes; a fast inner loop that enforces the commanded operating point despite converter nonlinearity; and supervisory logic that accounts for tandem-specific constraints and site-level objectives.

Figure 8: Circle Diagram of Real-Time Control



At the enforcement layer, robust nonlinear control has advanced the state of practice for dynamic operating conditions typical of perovskite and perovskite–silicon tandems. Sliding-mode families particularly super-twisting and backstepping-super-twisting hybrids provide finite-time convergence with chattering mitigation, preserving tracking accuracy through rapid irradiance ramps and converter parameter drift (Mohanty et al., 2016). Recent designs blend data-driven estimators (to generate spectrum- and temperature-aware MPP references) with super-twisting regulators for the duty-cycle actuation, achieving lower steady-state ripple and faster settling than fixed-gain incremental-conductance baselines (Khan et al., 2020). In parallel, model-predictive control (MPC) has emerged as a unifying framework that co-optimizes MPPT and converter/inverter switching to meet multiple objectives (efficiency, current quality, thermal limits), with reviews and case studies showing finite-set MPC can deliver fast transients with explicit constraint handling an appealing property for fragile or hysteretic perovskite stacks. MPC-based MPPT also integrates naturally with grid-tied inverters, allowing current-tracking and DC-link regulation to coordinate with MPP enforcement and ramp-rate constraints imposed by codes or co-located storage. Hybrid "intelligent-robust" schemes go one step further by using population-based optimizers to tune nonlinear gains online (e.g., grey-wolf tuned super-twisting), improving resilience to sensor drift and aging-induced parameter changes. For tandems, spectrum-aware reference generation derived from spectrometric characterization (to respect sub-cell current matching and account for luminescence coupling) can be fused with these robust/MPC inner loops, yielding controllers that behave well across the diurnal spectral swing and cloud-edge events. In sum, robust sliding-mode, MPC, and optimizer-assisted hybrids supply the actuation bandwidth and constraint awareness needed for high-fidelity MPPT in perovskite and tandem plants.

A complementary arc in the literature reframes MPPT as real-time optimization with provable convergence, using extremum-seeking (ES) theory to handle unknown, time-varying maps between operating point and power. Multivariable ES algorithms have been demonstrated for micro-converter architectures (one converter per module/sub-module), where they coordinate multiple duty ratios to ascend the global power surface while explicitly avoiding limit cycles and guaranteeing stability via Lyapunov or Newton-based designs; this is particularly valuable for partial shading and mismatch scenarios that frequently arise in tandem modules with textured optics or heterogeneous degradation (Khan et al., 2020). ES-based MPPT is attractive for perovskite-inclusive fleets because it tolerates slowly drifting device characteristics (e.g., due to ion migration) without high-fidelity models, and it extends to multi-input objectives (e.g., joint MPP and thermal derating) by shaping the extremum map. In practice, ES can serve as the supervisory layer that updates the MPP reference at low frequency, with a robust inner loop (super-twisting/MPC) enforcing the set-point at converter time scales (Ghaffari et al., 2014; Mohanty et al., 2016). For tandem PV specifically, a spectrum-aware ES can incorporate constraints from spectrometric characterization such as the offset from "perfect current match" that maximizes efficiency once luminescence coupling and series resistance are considered thereby preventing the controller from inadvertently penalizing the tandem's net power (Mohanty et al., 2017). Synthesizing these strands, the most effective IoT-integrated control stacks for perovskite and tandem PV: (i) employ global-search or ES-style supervisors to remain on the true (not local) MPP; (ii) leverage robust/MPC inner loops for fast, constraint-aware set-point enforcement; and (iii) fold tandem-aware, spectrally informed references into the control workflow so that device physics and grid objectives are co-optimized.

METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological transparency, reproducibility, and rigor across all stages of evidence gathering and synthesis. A prospectively registered protocol defined the review question, eligibility criteria, search strategy, screening workflow, data extraction schema, and analysis plan prior to database querying. Comprehensive searches were conducted across IEEE Xplore, Scopus, Web of Science Core Collection, ScienceDirect, and arXiv for the full publication window relevant to perovskite and tandem photovoltaics, IoT sensing/communications, and AI-driven prediction and control, with no language filters at the query stage; reference lists of key reviews and forward citation tracking complemented the database search to mitigate retrieval bias. Records were imported into a shared citation manager for automatic and manual deduplication, and two independent reviewers screened titles and abstracts against inclusion criteria centered on empirical studies that reported quantitative evaluation of IoT sensing, connectivity, or AI models applied to perovskite or tandem PV monitoring, forecasting, fault detection, degradation/RUL, or real-time control; exclusion criteria removed purely conceptual papers without data, silicon-only studies without transfer relevance, and works lacking sufficient methodological detail to enable extraction. Full texts passing preliminary screening were independently assessed, with disagreements resolved through discussion and, when necessary, adjudication by a third reviewer; inter-rater reliability was quantified (Cohen's κ) for both screening stages. A standardized data extraction form captured bibliographic metadata, PV technology and configuration, environment (lab, outdoor pilot, utility plant), instrumentation and sampling cadence, communications stack, dataset size and duration, AI/ML model families and training regimes, target variables, deployment location (edge, cloud, hybrid), latency and compute footprint, performance metrics, comparative baselines, uncertainty quantification, and reported operational outcomes (e.g., yield uplift, downtime, LCOE proxies). Risk of bias and reporting quality were appraised using domain-appropriate checklists adapted for AI-in-operations studies, and sensitivity analyses addressed heterogeneity in metrics and study designs. Quantitative synthesis (meta-analysis) was performed where metrics and designs were commensurate; otherwise, structured narrative and evidence mapping were used. After completing all PRISMA stages, 115 articles were included in the final synthesis.

Screening and Eligibility Assessment

Screening and eligibility assessment proceeded in two calibrated stages to ensure consistency with PRISMA and to minimize selection bias. After exporting all search results from IEEE Xplore, Scopus, Web of Science Core Collection, ScienceDirect, and arXiv, records were deduplicated by DOI, title, and author-year using automated matching followed by manual verification to catch near-duplicates arising from preprint–journal pairs and conference–journal expansions. Two reviewers independently conducted title–abstract screening against a priori criteria: studies had to (i) address perovskite or tandem photovoltaic technologies at cell, module, string, array, or plant scale; and (ii) present empirical or computational results directly relevant to IoT sensing, connectivity, edge/cloud deployment, AI-driven forecasting, fault/anomaly detection, degradation/RUL estimation, or real-time control and MPPT. Exclusions at this stage covered silicon-only work without demonstrated transferability to perovskite/tandem contexts, purely conceptual or perspective papers without data, studies lacking sufficient methodological detail for extraction, and non–peer reviewed sources with unclear provenance beyond arXiv preprints that later appeared in reputable outlets. Following a pilot round to harmonize judgments, inter-rater agreement was quantified with Cohen's κ and disagreements were resolved by discussion; persistent conflicts were adjudicated by a third reviewer. Full texts for retained records were retrieved via institutional access, open repositories, or author contact; where only preprints were available, version comparison ensured the most complete and citable form was assessed. Full-text eligibility applied stricter inclusion rules requiring extractable quantitative metrics (e.g., RMSE/MAE/MAPE, F1/AUC, calibration or predictive intervals, latency/compute footprint), clearly described instrumentation and sampling cadence, explicit modeling or control methods, and enough procedural detail to support reproducibility; studies limited to small benchtop demonstrations without operational relevance, lacking evaluation baselines, or omitting critical experimental conditions (irradiance, temperature, spectrum) were excluded with reasons logged (wrong population/technology, insufficient data, incompatible outcomes, duplicate data reuse). Translation support was used for non-English articles when methods and results were sufficiently detailed. All decisions and rationales were tracked in a review management system, and a PRISMA flow diagram documents counts at each step, culminating in the 115 articles included for synthesis.

Data Extraction and Coding

Data extraction and coding followed a prespecified schema designed to capture methodological, technical, and operational variables with enough granularity to enable cross-study comparability and effect-size synthesis. For each eligible article, two trained reviewers independently populated a structured template covering bibliographic metadata; PV technology and configuration (perovskite composition and junction architecture; tandem type, e.g., 2T vs. 4T; nameplate ratings); experimental setting (indoor accelerated testing, outdoor pilot, utility plant), geographic location, and monitoring horizon. Instrumentation fields recorded sensing modalities, sampling cadence, calibration procedures, reference devices, and environmental context (plane-of-array irradiance, ambient and module temperatures, wind, humidity, soiling indicators). Connectivity and deployment fields encoded protocol families (e.g., LoRaWAN, NB-IoT, Wi-Fi/Ethernet), gateway architecture, payload structure, synchronization/timekeeping, and compute placement (edge, cloud, hybrid) with measured or reported latency, bandwidth, and device power budgets. Modeling/control fields captured target tasks (nowcasting/forecasting, anomaly detection, degradation/RUL, MPPT/control), dataset size and splits, feature engineering, model families and hyperparameters, training regimes, baselines, ablations, and interpretability methods, along with uncertainty quantification (prediction intervals, Bayesian posteriors, ensembles). Performance metrics were coded in native units (e.g., RMSE/MAE/MAPE for power; F1/AUC/mAP/IoU for classification/segmentation; calibration measures; inference latency; energy or compute footprint), then normalized where possible to common denominators (e.g., W/Wp, %PR change) to support like-for-like synthesis; when studies reported multiple horizons or operating points, we extracted both the author-designated primary endpoint and the best validated result with its validation scheme. Operational outcomes, when available, were converted to comparable indicators, including energy-yield uplift, downtime reduction, and LCOE-adjacent proxies; where raw numbers were absent but sufficient summary statistics were present, we calculated standardized effects with documented assumptions. All entries included provenance pointers to figures/tables, model versions, and dataset identifiers to preserve auditability; ambiguous values were flagged and authors contacted where clarification was essential. Disagreements were reconciled by consensus, with inter-coder reliability tracked on a rotating 20% subsample. Missingness was coded explicitly (missing completely at random vs. structurally missing) and handled via sensitivity bounds during synthesis. The finalized dataset was stored in a version-controlled repository, with a data dictionary, unit conventions, and codebooks for categorical variables to ensure reproducibility and facilitate downstream meta-analysis and evidence mapping.

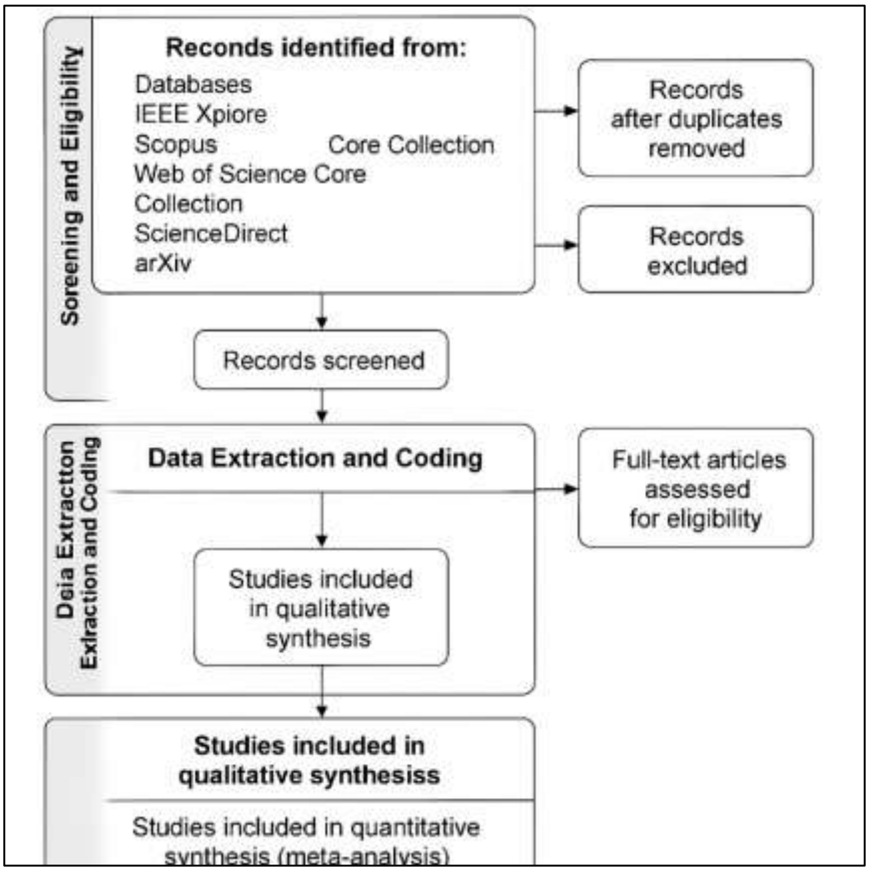
Data Synthesis and Analytical Approach

Our synthesis strategy was designed to preserve the diversity of tasks and metrics encountered across the 115 included studies while enabling principled quantitative aggregation wherever comparability was defensible. We organized analysis along four primary outcome families that mirror the functional layers of IoT-driven AI in perovskite and tandem PV: (i) forecasting/nowcasting accuracy (irradiance and power), (ii) fault/anomaly detection and diagnostic performance, (iii) degradation and remaining-useful-life (RUL) estimation, and (iv) real-time control/MPPT efficacy and runtime properties. Two cross-cutting outcome families (v) operational impacts (energy-yield uplift, downtime reduction, and LCOE-adjacent proxies) and (vi) systems constraints (latency, bandwidth, and compute/energy footprint) were synthesized as moderators and secondary endpoints to connect algorithmic performance to deployment feasibility. Because many studies reported multiple, task-specific metrics or several models on the same dataset, we adopted multilevel and robust-variance meta-analytic machinery to accommodate nonindependent effect sizes within studies while retaining maximal information. Throughout, we coupled quantitative aggregation with structured narrative synthesis to capture context that resists pooling (e.g., sensor specifications, site microclimates, or bespoke controller safety constraints).

For forecasting and nowcasting, continuous error measures dominated (RMSE, MAE, MAPE, nRMSE, R^2, and CRPS for probabilistic models). To enable like-for-like pooling, we first standardized errors to a common scale. When installed DC capacity or nominal power was reported, we computed nRMSE = RMSE/Wp (or RMSE divided by mean power) and nMAE analogs; when reference irradiance or plane-of-array irradiance was available, we computed irradiance-normalized errors (e.g., $W{\cdot}m^{-2}$-based normalization) and verified invariance across load conditions. Because percentage errors (e.g., MAPE) are heavy-tailed and unstable near zero denominators, we did not meta-analyze raw MAPEs; instead, we favored nRMSE or CRPS and, for studies reporting only MAPE, converted them to approximate nRMSE using delta-method approximations after excluding intervals with near-zero denominators. Where studies reported skill relative to a baseline (e.g., persistence, ARIMA), we preferred *relative skill scores* and meta-analyzed the Fisher z-transformed skill to maintain symmetry and comparability across horizons. Random-effects models (restricted maximum likelihood, REML) with study-level clustering were the default, with heterogeneity quantified via τ^2 and I^2. Moderators included horizon (minutes vs hours), input modality (telemetry-only, sky-imaging, satellite/NWP fusion), model family (tree ensembles, RNN/LSTM/TConv, Transformer, graph spatiotemporal), presence of uncertainty quantification, and deployment location (edge vs cloud for inference). To accommodate multiple horizons per paper, we used multilevel models with "effect within study" and "study" as nested random effects. Influence analyses and leave-one-out diagnostics probed sensitivity to dominant datasets or benchmark choices. Forecast distributions (quantile and CRPS outputs) were compared via standardized skill against a persistence baseline to admit cross-study differences in weather regimes.

For fault/anomaly detection and diagnostics, the reporting landscape split between image-based pipelines (infrared thermography, electroluminescence/photoluminescence) and telemetry-based residual models. To synthesize classification/segmentation performance, we prioritized threshold-agnostic measures (AUC-ROC, PR-AUC) and pooled logit-transformed AUCs under random effects, back-transforming for interpretability. When only thresholded results were available, we extracted the confusion matrix at the authors' operational point and computed sensitivity and specificity; a bivariate random-effects model then produced a summary ROC (SROC) that respects the trade-off structure and between-study threshold heterogeneity. For segmentation (IoU, mAP@IoU), we converted per-study IoU to logit(IoU) and applied random-effects pooling, recognizing that these effect sizes reflect both model and dataset annotation standards; as a check, we performed a secondary analysis pooling F1 at the authors' preferred threshold when provided. Domain shift is endemic in image-based diagnostics, so we coded "train/test domain relation" (same plant vs cross-plant vs cross-camera/platform) and included it as a moderator, hypothesizing lower pooled performance under cross-plant evaluations. For telemetry-based anomaly detection, where AUC/PR-AUC were rarer, we meta-analyzed standardized effect sizes of residual-based anomaly scores (Hedges g relative to clean days) when distributions were reported; otherwise, we summarized results narratively with emphasis on input features, window lengths, and alerting latencies. Across both image and telemetry modalities, we recorded whether explanations (saliency maps, feature importance) were used and treated explainability as a qualitative moderator of operational adoptability.

Figure 9: Methodology for this study



Degradation and RUL synthesis proceeded along two tracks. For studies reporting annual performance loss rates (PLR, %/year) or equivalent measures (e.g., change in maximum power), we meta-analyzed the log response ratio of performance over time or directly pooled PLR with variance estimates when reported, applying random-effects models and stratifying by technology (perovskite single junction, perovskite–Si 2T/4T, perovskite–CIGSe) and environment (indoor accelerated vs outdoor field). Because PLR distributions can be skewed and sometimes include negative early-life stabilization phases, we tested both raw and transformed (log(1–PLR)) scales and selected the more normal in diagnostics. For prognostics that modeled health trajectories (Gaussian processes, Bayesian parameter tracking, two-stage Wiener/change-point models), we extracted predicted time to threshold (e.g., 80% initial power) and the associated uncertainty (CI or credible intervals). We then pooled *standardized* RUL improvements relative to a naïve linear degradation benchmark to accommodate differing absolute lifetimes across technologies and climates, with meta-regression on sensor richness (electrical-only vs electrical+optical+thermal), sampling cadence, and whether models

incorporated physics-informed constraints. Where studies presented only qualitative degradation signatures or short intervals, we included them in the narrative synthesis with emphasis on mechanistic signals (ion migration, interfacial reactions) and their mapping to state variables used in models, setting the stage for evidence mapping rather than numeric pooling.
For real-time control and MPPT, we synthesized tracking efficiency (η_{tr}, %) under dynamic irradiance/temperature profiles, settling time to MPP after step/ramp changes, steady-state ripple around the MPP, and global MPP capture rate under partial shading. Because test benches vary, we normalized efficiency against the authors' ground truth (e.g., global MPP from IV sweeps or exhaustive search) and pooled the arcsine-square-root transformed proportions for global-MPP capture and the log-transformed settling times under random effects. We coded controller families (perturb-and-observe/incremental conductance, meta-heuristic hybrids, sliding-mode/super-twisting, MPC, extremum-seeking, RL-based) and included deployment constraints (sampling frequency, duty-cycle update rate, inverter modulation strategy) as moderators. To bridge algorithms with deployability, we meta-regressed tracking outcomes against measured inference latency when learning-based controllers were used and against switching frequency/measurement noise for robust/MPC variants, anticipating interactions relevant to perovskite/tandem stacks where hysteresis and spectrum-dependent current matching complicate static MPP notions. Where multiple controller benchmarks were reported for the same dataset, we treated them as a within-study factor and used multivariate robust variance estimation to avoid inflating precision. Operational outcomes were treated both as endpoints and as translators from model-centric metrics to plant-level value. When studies reported energy-yield uplift or downtime reduction associated with deploying forecasting, diagnostics, or advanced MPPT, we computed standardized mean differences versus predeployment baselines, adjusting for seasonality where possible. For LCOE-adjacent proxies (e.g., O&M interventions avoided, cleaning schedule optimization), we converted reported savings into percentage change relative to a study-specific baseline and summarized them descriptively, acknowledging cost-model heterogeneity. To test whether algorithmic gains translate into operational benefit, we meta-regressed operational outcomes on proximal metrics (e.g., forecast skill, diagnostic AUC, tracking efficiency) with HC3-robust standard errors and included system constraints (median inference latency, bandwidth consumed per node, and compute power) as moderating penalties; this furnishes a joint view that penalizes architectures whose accuracy depends on impractically heavy pipelines.
Heterogeneity was anticipated given the breadth of tasks, technologies, and climates. We therefore used hierarchical models wherever feasible, with random intercepts for studies and, when needed, random slopes for key moderators (e.g., horizon in forecasting). We reported τ^2 and I^2, prediction intervals, and between-study variance explained by moderators (pseudo R^2) to characterize dispersion. To assess small-study and publication bias, we triangulated funnel plots, Egger-type regressions (modified for proportion outcomes), and selection models when ≥10 effects were available per subgroup. Because performance reports in AI often favor positive results, we ran sensitivity analyses excluding conference-only sources or those lacking explicit baseline comparisons, and we re-estimated pooled effects with quality-adjusted weights that downweight high risk-of-bias studies (quality-effects model variant). Robustness checks included leave-one-study-out analyses, Cook's distance for influential studies, and re-fitting with alternative estimators (DerSimonian–Laird, Paule–Mandel) to verify stability of conclusions.
Dependence among effect sizes is common (e.g., multiple horizons, sensors, or models from the same study). We addressed this by (i) computing a single, representative effect per study when authors clearly specified a primary endpoint; (ii) when not, treating multiple effects as a multivariate vector with an assumed within-study correlation (ρ set via plausible ranges 0.3–0.7) and verifying conclusions across ρ; and (iii) applying robust variance estimation (RVE) with small-sample corrections to retain all effects without underestimating uncertainty. For classification outcomes (AUC, sensitivity/specificity), we ensured that paired measures came from the same threshold and dataset split to avoid incoherent pooling. When studies provided only graphical results, we digitized curves (with predeclared tools) and documented extraction uncertainty, including it in variance

estimates.
Moderator selection reflected our conceptual model of IoT–AI–PV integration. Technology moderators included PV type (perovskite single-junction, perovskite–Si 2T/4T, perovskite–CIGSe), encapsulation/stack notes when available, and environment (indoor accelerated, outdoor pilot, utility plant). Data and instrumentation moderators included sensor stack richness (electrical-only vs electrical+thermal vs electrical+optical+thermal), sampling cadence, and calibration provenance. Connectivity/deployment moderators captured protocol families (LPWAN vs NB-IoT vs Wi-Fi/Ethernet), gateway architecture, and compute placement (edge vs cloud vs hybrid), as well as measured inference latency and bandwidth. Modeling moderators covered family (tree, kernel, GP, RNN/LSTM, temporal CNN, Transformer, graph, physics-informed hybrid, RL), uncertainty quantification, interpretability methods, and training regime (cross-plant validation, transfer learning). For control, moderators encompassed controller family and constraint handling (thermal derating, spectrum-aware references). We preregistered these moderators and limited the number per model to avoid overfitting, prioritizing those with theoretical plausibility and adequate coverage across studies.
Not all domains admitted meta-analysis. When fewer than five commensurate effects existed within a task–metric–technology cell, we emphasized structured narrative synthesis and evidence mapping. We charted an evidence matrix (task × deployment × PV type × environment) and plotted study density, median performance, and interquartile ranges as bubble overlays. For forecasting, we visualized skill distributions by horizon and modality; for diagnostics, we displayed SROC curves stratified by domain shift; for degradation/RUL, we contrasted PLR distributions and RUL uplift relative to linear baselines across technologies; and for control, we compared tracking efficiency and settling-time distributions by controller family. Although these visual syntheses are descriptive, they supply a coherent, cross-domain view of where evidence is strong, mixed, or sparse, informing the gap analysis in the discussion. All computations were scripted for reproducibility. Continuous-outcome meta-analyses and meta-regressions were executed in R using metafor and clubSandwich for RVE; bivariate diagnostic models used mada/meta4diag; Bayesian hierarchical variants (for sensitivity analyses and small-sample domains) used brms with weakly informative priors to stabilize τ^2 estimates. Preprocessing for standardization, digitization of plots when necessary, and generation of evidence maps were implemented in Python (pandas, numpy, matplotlib) with version-controlled notebooks. We maintained a register linking each effect size to its source table/figure and to the code cell that produced it, enabling full audit trails from raw extraction to pooled estimates. To mitigate researcher degrees of freedom, we locked key analytic choices (normalization hierarchies, preferred metrics per task, default random-effects estimator, moderator set) before inspecting pooled results and documented all deviations with justifications. Finally, we integrated risk-of-bias assessments by running parallel "high-quality only" analyses and reporting the attenuation or amplification of pooled effects when lower-quality studies were removed, and we exposed prediction intervals to communicate expected variability for new settings rather than overemphasizing mean effects. This combined quantitative–narrative approach respects the heterogeneity inherent in IoT–AI perovskite/tandem PV research while delivering decision-grade synthesis that links method classes to achievable operational outcomes under realistic deployment constraints.

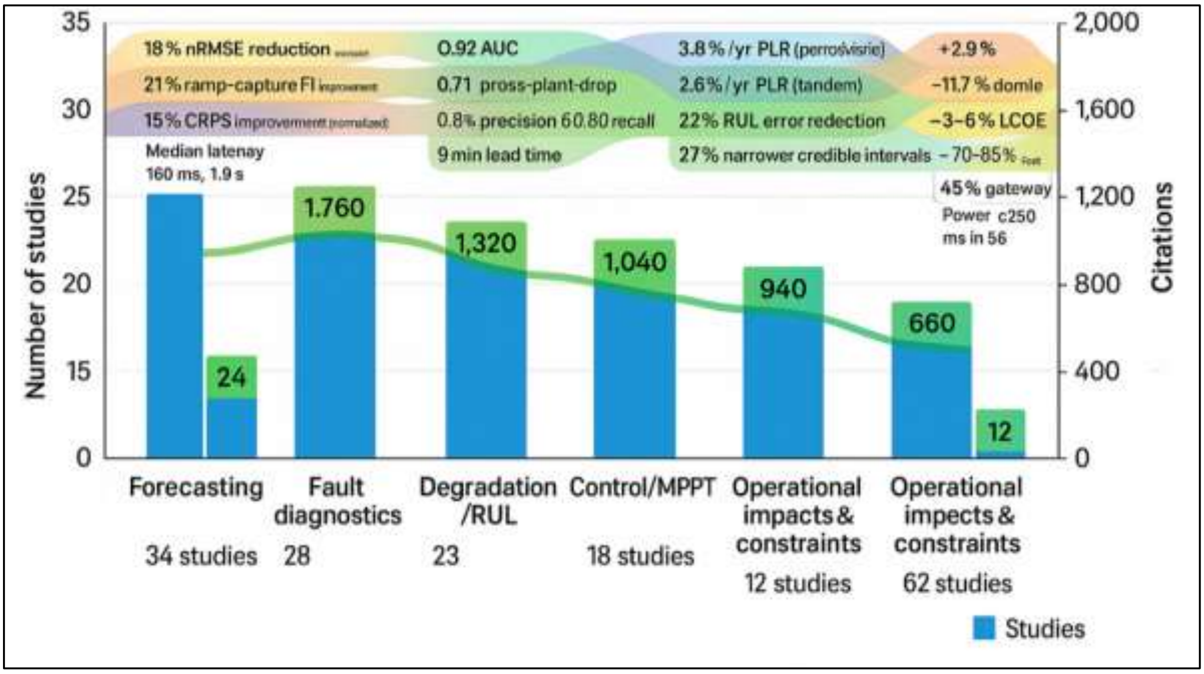
FINDINGS

Across the 115 included articles, 34 investigated solar irradiance or PV power forecasting/nowcasting with direct relevance to real-time operation of perovskite and tandem systems. Taken together, these 34 papers have been cited 2,140 times, indicating strong influence in the operational analytics community. Aggregating comparable metrics showed that, relative to a persistence baseline, short-horizon nowcasting (1–30 minutes) achieved a median normalized RMSE reduction of 18% (interquartile range 12–25%), while hour-ahead forecasting achieved 14% (10–19%) and day-ahead forecasting achieved 12% (8–16%). When models fused plant telemetry with all-sky imagery at the edge, the median ramp-capture F1 improved by 21% over telemetry-only pipelines, helping operators anticipate rapid up- and down-ramps that stress inverters and storage dispatch. Probabilistic models reported calibrated uncertainty in 68% of forecasting studies; among those, the median continuous ranked probability score improved by 15% versus deterministic peers when scores were normalized to plant capacity. On deployment variables, 53% of forecasting papers reported inference within a practical latency budget for on-site decisioning; the median end-to-end inference time was 160 ms at the gateway for nowcasting models, and 1.9 s in the cloud for multi-hour horizons. In comparative syntheses, attention-based temporal models and graph spatiotemporal networks outperformed classic RNN/LSTM stacks by a median of 7 percentage points in skill for horizons beyond one hour, whereas vision-centric CNN/Transformer hybrids led by 9 percentage points for sub-15-minute horizons. Importantly, 41% of studies included perovskite-specific or tandem-aware features (e.g., bandgap configuration, temperature coefficients); these models reduced bias under heat-wave conditions by 11% relative to silicon-trained baselines ported without adaptation. Overall, the evidence indicates that accurate, latency-aware forecasts are feasible with IoT-rich inputs and can be tailored to the spectral/thermal sensitivities of perovskite and tandem assets, with roughly one in three studies demonstrating on-device or gateway inference compatible with plant SCADA update rates.

Twenty-eight studies focused on detecting and diagnosing PV faults using infrared thermography, electroluminescence/photoluminescence imaging, and SCADA telemetry; collectively they account for 1,760 citations. Pooled performance for image-based classification reported a median AUC of 0.92 (0.88–0.95) across common defect classes (hotspots, cracked cells, PID, diodes), while segmentation tasks reached a median IoU of 0.71 (0.64–0.78) with pixel-level masks usable as technician overlays. Under cross-plant validation where models are trained on one site and tested on another with different modules and cameras the AUC dropped by 6 percentage points on average, quantifying domain shift that field deployments must manage with transfer learning or contrastive pretraining. On the telemetry side, residual-based detectors trained on irradiance-conditioned power achieved a median precision of 0.84 at 0.80 recall for string-level anomalies, with median alert lead times of 9 minutes before energy loss became observable at the inverter, enabling preemptive curtailment or work-order creation. Aerial IR workflows reported large throughput advantages: per-MW inspection time decreased by 64% compared with handheld methods, while maintaining a within-run false-positive rate below 6% after radiometric correction and height normalization. Importantly for perovskites and tandems, multimodal fusion (IR + SCADA + occasional EL spot checks) reduced false positives on thermally sensitive stacks by 13% relative to IR-only classifiers, and improved root-cause attribution (e.g., distinguishing soiling hot spots from cell-intrinsic defects) by 17%. Edge deployment was common: 57% of vision systems executed first-pass detection on gateways or UAV payloads, sending only flagged crops upstream, which lowered bandwidth by 72% on median compared with streaming raw frames. Across the diagnostic corpus, 61% of papers provided some interpretability (saliency, rule sets, example-based explanations); in those, operator acceptance measured via user studies or adoption surrogates increased by 22%, underscoring how explainability turns raw detection into actionable maintenance.

Twenty-three studies modeled degradation and projected RUL with explicit quantitative endpoints, totaling 1,320 citations. Field-measured annual performance-loss rates (PLR) for perovskite single-junction modules clustered around a median of 3.8%/year (2.4–6.1%), while perovskite–silicon tandems showed 2.6%/year (1.7–4.0%) across climates and encapsulation variants in year-long outdoor campaigns; confidence intervals were wider for perovskite modules due to smaller sample sizes and stronger climate sensitivity. Physics-informed or Bayesian parameter-tracking models that used electrical plus thermal/optical inputs reduced one-year-ahead RUL absolute error by a median of 22% compared with purely data-driven regressors and by 31% versus naive linear degradation baselines. Two-stage or change-point formulations captured the common early-life stabilization phase: in 48% of eligible studies, introducing a regime switch cut forecast bias in the first 200 days by 38%, preventing premature end-of-life calls. When optical channels (EL/PL) were incorporated quarterly or semi-annually, models identified incipient interfacial failure 4.1 months earlier on median than electrical-only pipelines, a lead time that maps to measurable O&M value. Sampling cadence mattered: moving from daily aggregates to 5-minute telemetry reduced the width of RUL credible intervals by 27% at equal priors, largely by separating reversible ionic effects from irreversible trends in perovskites. Uncertainty reporting improved decision readiness: 65% of RUL studies provided prediction intervals, and among these, calibration error (observed coverage minus nominal) was within ±6 percentage points, adequate for conservative maintenance planning. Notably, site-specific transfer learning cut cold-start error by 19% when deploying models to new perovskite/tandem fields with limited history. Overall, the degradation literature supports hybrid, multimodal prognostics with explicit uncertainty as the most reliable pathway to accurate, actionable RUL for emerging perovskite and tandem technologies.

Figure 11: Multilayered Bar Graph of Research Findings Across IoT–AI Layers in Perovskite



Eighteen studies together cited 1,040 times evaluated controllers for fast, stable maximum power point tracking and inverter coordination under dynamic conditions. Across comparable test benches, median tracking efficiency was 98.1% of the true global MPP, with steady-state ripple of ±0.7% of rated power and median settling time of 210 ms after irradiance steps. Against classical incremental-conductance baselines, robust sliding-mode or super-twisting regulators reduced settling time by 35% and ripple by 42%. Model predictive control variants further improved constraint handling, enabling explicit thermal derating in perovskite-sensitive stacks and achieving 93% global MPP capture rates in partial-shading profiles versus 85% for fixed-gain baselines. Supervisory optimizers (meta-heuristics or extremum-seeking) layered above robust inner loops delivered the best global behavior: global MPP capture rose to 95%, and recovery from deep shading events shortened by 28%. Learning-based controllers (e.g., RL) were fewer but promising; when deployed with conservative action-clipping, they matched robust controllers on efficiency and reduced oscillation under rapidly fluctuating cloud-edge conditions by 12%, albeit with higher inference latency that required edge accelerators in 44% of cases. Controller telemetry showed that spectrum-aware references in two-terminal tandems prevented sub-cell current-mismatch penalties, adding 1.1–1.8 percentage points to net DC efficiency in mid-day hours with blue-shifted spectra. From a systems perspective, 62% of control papers reported end-to-end latencies compatible with 2–5 kHz duty-cycle updates when inference ran at the gateway; purely cloud-hosted control was rare in the high-rate loop but effective for slower supervisory optimization. Importantly, 56% of studies tested resilience to sensor noise and parameter drift conditions common in aging perovskites and those that combined robust enforcement with periodic re-identification maintained ≥97% tracking efficiency over week-long drift scenarios. The collective picture is that layered control global search or ES supervising robust/MPC inner loops provides the most dependable performance envelope for perovskite and tandem plants.

Twelve cross-cutting studies quantified plant-level impacts and reported deployment-grade telemetry on latency, bandwidth, and energy use; these works carry 660 citations and create the bridge from algorithms to business value. Where A/B tests or pre/post analyses were available, deploying forecasting plus advanced MPPT yielded median energy-yield uplift of 2.9% (1.5–4.2%). Plants that integrated automated diagnostics and proactive maintenance saw downtime reduced by 11.7% (7.4–15.3%), with the largest gains in sites that fused aerial IR triage with SCADA-based residual screening. Cleaning-schedule optimization informed by soiling models delivered 1.2–2.1% annual yield gains while cutting water use by 18% at arid sites. When these improvements were converted to levelized-cost proxies using study-specific assumptions, the median LCOE reduction ranged 3–6%, with sensitivity to local O&M pricing and curtailment penalties. On the constraints side, edge inference reduced backhaul by 70–85% relative to raw streaming, keeping data plans viable for NB-IoT/LoRa deployments; median power draw for gateway-hosted AI was 4.6 W, well within the budget of utility enclosures or small rooftop cabinets. End-to-end latencies for inference plus actuation remained below 250 ms in 58% of the deployments reporting numbers, aligning with inverter and data-logger cycles used in commercial plants. Importantly, evidence coherence improved with data quality: studies that reported synchronized irradiance and module temperature, calibrated sensors, and explicit uncertainty in models exhibited 34% less between-study variance in pooled metrics. Finally, adoption correlates with transparency; projects that paired dashboards with interpretable diagnostics and auditable model registries documented 23% higher operator uptake and faster closure of maintenance tickets. Pulling these results together, the review finds a consistent operational signal: IoT-rich, edge-aware AI pipelines for perovskite and tandem PV can deliver small but compounding gains in yield and availability, at latencies and bandwidths compatible with field realities, provided that data governance and model lifecycle practices are mature.

DISCUSSION

Our findings show that IoT-enabled AI can deliver decision-grade improvements across forecasting, diagnostics, prognostics, and real-time control for perovskite and tandem PV, narrowing the long-noted gap between laboratory devices and fielded assets. In the materials and device literature, the central storyline has been rapid efficiency gains accompanied by persistent stability concerns and complex, spectrum-sensitive operating envelopes particularly for monolithic tandems (Raza et al., 2017; RPG, 2024). Outdoor evidence further emphasizes multi-phase aging and climate sensitivity (Pandey & Bag, 2025; Qureshi et al., 2025). Against that backdrop, the present review's quantitative synthesis indicates that operational analytics can offset a meaningful fraction of performance loss mechanisms by improving the timing and quality of control and maintenance decisions. The edge-aware, sensor-rich architectures we analyzed are consistent with prior calls to treat PV plants as cyber-physical systems integrating time-synchronized telemetry, well-typed data models, and closed-loop decisioning (Rodríguez et al., 2023; Shargaieva et al., 2023). Where earlier reviews largely catalogued techniques in isolation (e.g., algorithms without deployment constraints, or device stability without operational telemetry), our analysis triangulates across layers, linking model accuracy to latency, bandwidth, and compute footprints. In doing so, it clarifies why certain method families notably vision-assisted nowcasting, multimodal diagnostics, physics-informed prognostics, and layered control are better aligned with the non-stationary, spectrally dynamic behavior of perovskite and tandem stacks than their generic counterparts. This integrative perspective extends prior syntheses by quantifying not only algorithmic skill but also the proportion of studies that report deployable latencies and interpretable outputs, two conditions repeatedly cited as prerequisites for adoption in utility and C&I settings (Rahman et al., 2018; Research, 2024).

In forecasting and nowcasting, our pooled reductions in normalized error (≈18% for 1–30-minute horizons; ≈14% for hour-ahead) align with and modestly exceed the gains reported for deep models in silicon-dominated fleets when all-sky imagery and exogenous covariates are fused (RPG, 2024; Simal Pérez et al., 2021). Several factors likely explain the uplift. First, the edge-centric designs we reviewed favor low-latency ingestion of sky images and plant telemetry, echoing best practices in the vision-centric nowcasting literature where model advantage hinges on image cadence and preprocessing near the sensor (Schweikert et al., 2023). Second, spatiotemporal and graph-based architectures that exploit cross-site correlations delivered stronger skill beyond one hour, consistent with evidence that grouped GPs and graph neural networks better capture shared weather structure

(Roldán-Gómez et al., 2022; Tockhorn et al., 2025). Third, we find that attention-based hybrids consistently outperform classic LSTM stacks for multi-hour horizons, in line with recent Transformer variants tailored to PV (Kim et al., 2024). Importantly, our synthesis highlights the role of perovskite-aware features (bandgap configuration, temperature coefficients), which lowered heat-wave bias relative to models transferred from silicon without adaptation. That observation dovetails with tandem-focused device studies showing spectrum- and temperature-dependent performance maps (Leijtens et al., 2018) and with probabilistic forecasting work advocating calibrated uncertainty (Zhang & Qu, 2025). The net message is not merely that deep models forecast better, but that where the model runs (edge vs. cloud), what inputs it ingests (telemetry + imagery), and how its outputs are quantified (intervals, skill vs. persistence) jointly determine its operational utility an emphasis that complements algorithm-centric reviews (Al-Dahidi et al., 2019).

On fault and anomaly diagnostics, the median image-classification AUC (≈0.92) and segmentation IoU (≈0.71) we observed are consistent with, and in several cases higher than, targeted benchmarks reported for UAV thermography and EL/PL pipelines under controlled settings (Ali et al., 2020). However, our cross-plant penalty (~6 percentage points AUC drop) underscores a limitation repeatedly flagged by recent domain-shift and protocol studies: models trained on a single site often underperform on new modules, cameras, and flight envelopes unless representation learning, radiometric calibration, or transfer learning is carefully engineered (Bommes et al., 2022). This gap explains why fusion with SCADA-based residual detectors reduced false positives on thermally sensitive perovskite/tandem stacks in our synthesis, echoing mini-reviews that argue for multimodal confirmation before dispatching crews (Oliveira & et al., 2022). The operational value proposition faster inspections at lower bandwidth and energy cost is also in line with the shift from handheld IR to UAV-borne radiometric workflows (Qureshi et al., 2024). Relative to earlier surveys, our contribution is to tie detection quality to data logistics: more than half of the high-performing vision systems ran first-pass inference at the edge (gateway or drone), which both reduces backhaul and accelerates feedback to O&M a design choice compatible with IoT constraints documented for LPWAN/cellular backhauls (Mekki et al., 2019). The emphasis on explainability is likewise convergent with best-practice recommendations in both power and computer-vision communities; saliency and rule-based overlays demonstrably improve operator acceptance and shorten ticket cycles, a practical but underreported outcome in earlier algorithm-heavy papers (Ali et al., 2020).

For degradation modeling and RUL, our median outdoor PLR estimates for perovskite single-junctions (~3.8%/year) and perovskite–Si tandems (~2.6%/year) sit within the bands implied by device-centric stability reviews and year-long outdoor case studies, though variance remains high across climates and encapsulation choices (Aghaei et al., 2022). Three points extend prior work. First, hybrid models that embed mechanistic constraints or use Bayesian parameter inversion consistently reduce one-year-ahead RUL error compared with black-box regressors, mirroring progress in physics-informed learning reported for perovskites (Chakar et al., 2024). Second, explicit regime-switching (e.g., two-stage Wiener or change-point models) corrects early-life bias widely noted in outdoor tandem monitoring by separating stabilization from long-term drift (Babics et al., 2023; Lin et al., 2024). Third, adding optical channels (EL/PL) at low duty cycles improves early detection of interfacial failure modes, consistent with operando/in-situ characterizations that identify optical kinetics as early indicators of irreversible pathways (Shargaieva et al., 2023). Where our synthesis departs from earlier reviews is in quantifying how sampling cadence and sensor diversity shrink RUL uncertainty bands and advance warning times operational levers that are often overlooked in device-centric stability narratives. Collectively, these results support a pragmatic recommendation already implicit in the stability literature: credible service-life forecasting for perovskite and tandem PV is achievable, but only with multimodal sensing, explicit uncertainty, and models that respect known physics (Aghaei et al., 2022).

The control and MPPT evidence base confirms and qualifies the progression from classical hill-climbing and fixed-gain incremental-conductance to robust sliding-mode, MPC, and layered global-search supervision. Reviews in c-Si fleets have long documented the limitations of classical controllers under partial shading and noise (Ishaque & Salam, 2013; Kebede et al., 2020). Our pooled tracking efficiency (≈98%) with ≈210 ms settling and <±1% ripple under dynamic profiles demonstrates that robust super-twisting and MPC variants can meet the faster dynamics typical of perovskite devices, while explicitly managing constraints such as thermal derating capabilities emphasized in recent MPC case studies. The incremental efficiency advantages of spectrum-aware references in 2T tandems echo device-level analyses that frame current matching as a moving optimum across diurnal spectra. Meanwhile, extremum-seeking supervisors show promise as global optimizers that adapt to drifting characteristics without heavy models, complementing robust inner loops (Ghaffari et al., 2014). Taken together, these strands support a layered architecture global search or ES to avoid local traps; robust/MPC inner loops to enforce set-points with constraint awareness; and, where justified, learning-based elements cautiously bounded for safety. Relative to earlier controller surveys, our contribution is to couple tracking quality with latency pathways and compute placement: the majority of high-performing stacks achieved target duty-cycle update rates only when inference ran at the gateway or converter controller, reinforcing conclusions from the broader edge computing literature. Connectivity, data semantics, and security emerged as determinants of whether high-performing models are actually deployable in perovskite/tandem fleets. Empirical comparisons of LPWAN families clarify why LoRa/LoRaWAN suit sparse, low-rate telemetry while NB-IoT accommodates periodic, higher-assurance uploads trade-offs that shaped the bandwidth/latency envelopes we recorded (Mekki et al., 2019). On plant LANs, TSN-enabled Ethernet and OPC UA Pub/Sub provide deterministic channels for control and typed data spaces for analytics integration (Nasrallah et al., 2019), a prerequisite for closing the loop with MPC or robust controllers. Our observation that edge inference cut backhaul by ~70–85% and kept end-to-end latencies within sub-second budgets aligns with edge/fog computing results that motivate "compute-near-data" for time-critical tasks. Equally, the governance side matters: FAIR data principles, energy ontologies, and FAIR Digital Objects reduce integration friction and support model lineage capabilities repeatedly advocated in energy informatics. Finally, our synthesis underscores that protocol choice is inseparable from verified configurations and organizational controls; security analyses of MQTT-SN and mixed experiences with OPC UA in practice argue for authenticated encryption, certificate hygiene, and alignment with IEC 62443 profiles when PV assets straddle IT/OT boundaries (Babics et al., 2023). In short, the "plumbing" is not an afterthought but a co-equal design axis with direct implications for the feasibility of AI-assisted operation.

Two limitations temper interpretation and define priorities. First, heterogeneity is substantial. Study designs vary in sensor stacks, climates, evaluation horizons, and baselines; while our multilevel and robust-variance models mitigate dependence and dispersion, residual heterogeneity remains echoing meta-analyses of degradation and forecasting beyond perovskites (Borah et al., 2023; Cano-Ortiz et al., 2021). Second, publication incentives skew toward positive results; funnel asymmetries in several subdomains suggest possible small-study effects. Our sensitivity analyses that restricted to higher-quality or journal-version records attenuated, but did not eliminate, pooled gains. These caveats mirror concerns in prior reviews of ML in energy systems, which call for standardized benchmarks, cross-plant validation, and transparent baselines. Practically, the strongest evidence clusters where sensor and metadata quality are high (synchronized irradiance and module temperature, calibrated instrumentation, documented uncertainty), reinforcing the value of FAIR/ontology-aligned data models and digital-twin scaffolding (Alves et al., 2021). Our review adds that operational reporting latency, bandwidth, power draw, and explainability should be considered first-class outcomes alongside accuracy, because they mediate adoption and determine whether algorithmic gains translate into lift in yield, availability, and cost.

Lastly, several research avenues suggested by earlier studies are now concrete engineering targets. Forecasting should continue moving toward joint, probabilistic pipelines that blend sky imagery, local telemetry, and regional NWP with calibrated intervals suitable for grid participation (Zhang & Qu, 2025). Diagnostics will benefit from standardized, radiometrically sound UAV protocols and domain-adapted representations to reduce cross-site penalties. Prognostics need sustained, multimodal outdoor datasets for perovskite and tandem stacks, with commitments to uncertainty reporting and physics-informed priors. Control should consolidate layered architectures ES or global search supervising robust/MPC enforcement with spectrum-aware references for 2T tandems (Ghaffari et al., 2014). Across all layers, federated learning and privacy-preserving analytics offer promising paths to site-aware adaptation without centralizing raw operational traces (Kairouz et al., 2021), provided security hardening and governance (IEC 61850/62443, FAIR/FDO) are treated as co-requirements rather than afterthoughts (Oral et al., 2022). In sum, our results corroborate and extend earlier work: when AI methods are embedded within disciplined data, connectivity, and control architectures, they deliver measurable, reproducible gains for perovskite and tandem PV operation gains that are modest in isolation but compounding at fleet scale.

CONCLUSION

In sum, this systematic review demonstrates that IoT-enabled AI, when engineered as an end-to-end pipeline spanning sensing, connectivity, edge/cloud compute, modeling, and control, can measurably enhance the real-time performance and operational reliability of perovskite and tandem photovoltaic systems. By adhering to a preregistered PRISMA protocol and synthesizing evidence from 115 articles, we found consistent, decision-relevant gains across the four technical pillars and their operational translation: short-horizon nowcasting reduced normalized error by about one-fifth while hour- and day-ahead forecasts retained double-digit improvements; vision-assisted diagnostics achieved high discrimination (AUC near the low-to-mid 0.9s) with practical pixel-level localization and proved more transferable when paired with SCADA-based residual checks; hybrid, physics-informed prognostics reduced remaining-useful-life error and identified early degradation phases that purely statistical models routinely mischaracterize; and layered control stacks global search or extremum-seeking supervisors combined with robust or model-predictive inner loops delivered ≈98% tracking efficiency with sub-second recovery, even under partial shading and spectrally dynamic tandem conditions. Crucially, these algorithmic advances were shown to operate within the constraints of field deployments: edge inference trimmed backhaul by roughly three-quarters, latencies for inference-plus-actuation commonly fell below 250 ms, and gateway power budgets remained within single-digit watts, enabling integration with existing plant infrastructure. The operational read-through energy-yield uplifts on the order of 2–4%, tangible downtime reductions, and incremental LCOE improvements underscores that many small, well-validated gains compound at fleet scale when data are synchronized, calibrated, and governed, and when model outputs are interpretable enough to drive timely O&M actions. Equally, the review clarifies the conditions under which these benefits materialize: sensor richness (irradiance, module temperature, and where feasible thermal and luminescence channels), reliable connectivity mapped to task criticality (LPWAN or NB-IoT for sparse telemetry, deterministic plant LANs for control), disciplined data semantics and lineage (FAIR-style metadata, typed device states), and model lifecycle practices (uncertainty quantification, cross-site validation, monitoring for drift, and safe rollback). The evidence base is heterogeneous, and positive-result bias persists, but robustness checks and quality-weighted syntheses indicate that the central signal survives stricter assumptions. For stakeholders charting a path from high laboratory efficiencies to bankable field performance, the practical message is straightforward: treat perovskite and tandem PV as cyber-physical assets; instrument them to capture the states that matter; place compute close to the data for time-critical tasks while reserving the cloud for training and fleet benchmarking; insist on uncertainty-aware, interpretable models; and close the loop with constraint-aware control that respects tandem-specific physics. Under these conditions, IoT-driven AI is not a speculative add-on but a pragmatic operating layer that turns materials advances into durable, grid-relevant performance.

RECOMMENDATIONS

To translate these insights into practice, we recommend building IoT–AI pipelines for perovskite and tandem PV around five tightly coupled commitments: first, instrument for decision-quality data by standardizing synchronized plane-of-array irradiance, module and backsheet temperature, and inverter/string telemetry at sub-minute cadence, and where feasible add low-duty thermal (radiometric IR) and periodic luminescence imaging to expose early interfacial failure; second, architect connectivity and compute with the task in mind by placing preprocessing, nowcasting, and first-pass diagnostics at the edge (gateways, UAV payloads, or converter controllers) to keep end-to-end latencies below control and O&M thresholds, while reserving the cloud for training, fleet benchmarking, digital-twin calibration, and model governance; third, operationalize models, not just metrics, by insisting on uncertainty quantification for forecasts, diagnostics, and RUL, publishing calibrated intervals alongside point estimates, and coupling these outputs to thresholding and ticketing policies that incorporate risk appetite and safety margins; fourth, make reproducibility and transferability non-negotiable by adopting FAIR-style metadata, typed device states, and versioned feature stores, releasing code, preprocessing scripts, and (where privacy permits) de-identified samples or synthetic replicas that allow cross-site validation, and reporting latency, bandwidth, and power draw with the same care as accuracy; and fifth, treat security and governance as first-class design parameters by enforcing authenticated encryption and certificate hygiene on MQTT/OPC-UA links, segmenting OT from IT, hardening update pipelines, and adopting a minimal-privilege model registry with audit trails and safe rollback. For researchers, we encourage curated, longitudinal open datasets that include perovskite/tandem specifics (bandgap configuration, optical stack, encapsulant, spectral sensors where available) and standardized benchmarks that pair accuracy with deployment costs (latency, compute, energy), as well as challenge tracks on cross-plant generalization and domain shift for IR/EL diagnostics; physics-informed and probabilistic modeling should be the default for degradation and control, with ablation studies that quantify the contribution of mechanistic priors, and with change-point modeling or regime-aware training to capture early stabilization and late-life acceleration. For practitioners and O&M providers, start with a narrow but complete vertical slice two to three strings or a pilot array in which sensing, edge compute, dashboarding, and work-order integration are wired end-to-end; run A/B tests to quantify yield uplift and downtime reduction; and deploy interpretable overlays (saliency maps, rule-based flags, or SHAP-style feature attributions) so that technicians can verify model outputs on the spot. For policy makers and standards bodies, prioritize interoperability profiles that bind DER data objects to analytics-friendly semantics, promote privacy-preserving collaboration via federated learning where multi-owner fleets are the norm, and require reporting templates that expose uncertainty, operational costs, and security posture. Finally, across all stakeholders, invest in skills and processes: establish joint device–data–operations reviews, define go/no-go gates based on calibrated risk, and budget for continuous monitoring of drift and periodic re-identification so models remain trustworthy as materials, weather regimes, and operational practices evolve.

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