SECTION 9.
ENERGY AND POWER ENGINEERING

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AI-DRIVEN PREDICTIVE MAINTENANCE FOR SOLAR PV PLANTS

Utility-scale PV performance is increasingly determined not by nominal equipment ratings but by how quickly latent defects are detected and mitigated. In real operation, losses often emerge from combinations of minor issues: local hotspot development, connector degradation, string mismatch, elevated contact resistance, partial shading, and non-uniform soiling. When these conditions are not identified early, they accumulate and evolve into costly failure scenarios. For this reason, AI-driven predictive maintenance is becoming a core mechanism for improving availability, stabilizing output, and protecting long-term asset value across large solar portfolios [1], [2].

Conventional O&M strategies rely on calendar-based inspections or response after a clear failure event. While administratively simple, this logic does not capture equipment-specific degradation dynamics and often triggers intervention too late. Operators then face avoidable downtime, emergency dispatch of service teams, and weak prioritization of maintenance effort. Predictive maintenance changes the decision model: work is scheduled based on risk forecasts and expected energy-loss impact, rather than on fixed intervals. This shift improves resource allocation and aligns maintenance planning with actual technical condition of the plant [1], [3].

A practical predictive-maintenance architecture should fuse at least three data channels. The first is high-frequency SCADA telemetry, including electrical and thermal indicators. The second is RGB/IR visual evidence from drone surveys or fixed imaging systems. The third is contextual information: weather behavior, soiling conditions, cleaning history, maintenance logs, and curtailment events. Multi-source fusion increases sensitivity to weak degradation signals that may be invisible in isolated channels. It also reduces false alarms and improves confidence in intervention prioritization, which is essential for field operations at scale [2], [4], [5].

In telemetry analytics, label scarcity often favors anomaly-detection approaches such as autoencoders, isolation forest, and statistical boundary methods supported by domain rules. In computer vision, segmentation and defect classification models can detect hotspots, microcracks, delamination signatures, local shading, and severe soiling zones. The key requirement is cross-channel integration: outputs should be translated into a unified risk score that includes not only defect probability but also expected energy-loss impact, urgency horizon, and severity class. This allows maintenance teams to execute targeted, economically justified interventions [1], [4], [6].

Industrial value depends on workflow integration. If model outputs remain in standalone dashboards, operational behavior typically does not change. In a mature setup, every high-risk event should automatically create a CMMS/ERP work order with priority, inspection route, and closure feedback fields. This closed-loop process creates reliable post-maintenance labels, enabling continuous model improvement and reduction of false recommendations over time. Therefore, the effectiveness of AI in maintenance is not a model-only property; it emerges from the interaction of data, algorithms, and operational process design [2], [5].

Evaluation should focus on operational and financial KPIs rather than classification accuracy alone. Relevant indicators include mean time to detection, prevented unplanned outages, avoided energy losses, maintenance cost per critical event, false dispatch rate, and post-repair recovery time. These metrics translate model quality into business outcomes and provide a consistent basis for comparing alternative pipeline configurations. A KPI-centered framework also improves governance discussions by linking technical adjustments to measurable economic and reliability effects, which is critical for portfolio-level decision making [1], [2], [6].

At portfolio scale, a centralized MLOps framework is required. Core functions include feature-drift monitoring, risk-distribution stability checks, scheduled retraining, and cross-site quality audits. Without such governance, models that perform well on one plant can degrade quickly when transferred to sites with different hardware, climates, or operating procedures. Centralized lifecycle management also accelerates dissemination of newly discovered failure patterns across all assets, turning local incident knowledge into portfolio-wide preventive capability. This significantly improves learning speed and consistency of maintenance quality [3], [6].

Cybersecurity and data integrity are equally critical. Predictive systems depend on continuous high-frequency telemetry, and corrupted or delayed data streams can trigger unsafe maintenance priorities. Practical safeguards include role-based access control, audit logging, redundant storage, and integrity checks on key sensor pipelines. These controls protect trust in model outputs and reduce operational risk. In critical energy infrastructure, robust data governance is not optional; it is a prerequisite for safe automation of decision support and sustainable scaling of AI-driven maintenance practices [2], [5], [6].

In conclusion, AI-based predictive maintenance is a realistic pathway to improve PV performance without immediate capacity expansion. The strongest results are achieved when telemetry analytics and computer vision are jointly deployed and embedded in real O&M workflows. For Ukraine, this approach is especially valuable because it supports reliability growth under constrained service resources and accelerated infrastructure modernization. With standardized data practices, robust governance, and proper system integration, predictive maintenance can become a baseline operational standard for solar portfolios [1], [2], [6].

A robust pilot for predictive maintenance should include sites with different climates, equipment ages, and inverter configurations. This is necessary to test model transferability and avoid overestimating performance on homogeneous datasets. During the pilot, teams must establish a formal defect taxonomy, annotation protocol, and objective criteria for incident severity. Without consistent semantics, failure knowledge remains fragmented and models become team-specific rather than scalable. Standardized labeling is therefore a prerequisite for reliable cross-site learning and for converting pilot success into portfolio-wide operational capability [1], [2], [6].

Another high-impact area is optimization of inspection logistics. When risk scores are linked to geolocated asset maps, maintenance routes can be generated automatically based on severity and expected energy-loss impact. This reduces field logistics cost and shortens response times for critical issues. Additional gains are achieved by aligning maintenance windows with short-term weather forecasts, shifting non-urgent interventions to low-irradiance periods to minimize production losses. In this way, AI contributes beyond diagnostics: it directly supports planning efficiency in day-to-day O&M execution and improves utilization of limited service resources [2], [5].

Long-term effectiveness requires a structured after-action review loop. After each intervention, teams should record confirmed root cause, recovered capacity, downtime duration, and deviation from predicted risk. Feeding this information back into model training improves calibration and reduces recurring recommendation errors. Without such feedback, model quality deteriorates and operational trust declines. Predictive maintenance should therefore be treated as a continuous organizational learning process rather than a one-time software deployment. The feedback loop is what transforms algorithmic output into compounding reliability gains over time [1], [3], [6].

At strategic level, predictive analytics can be integrated with spare-parts planning and contractor management to create additional economic value. If likely failure classes are known in advance, operators can optimize inventory, shorten procurement lead times for critical components, and reduce emergency purchasing costs. This elevates AI from a local technical tool to a lifecycle asset-management capability. For Ukrainian PV portfolios, such integration is especially important because service resources are constrained and reliability improvements must be achieved without large immediate capital expansion [2], [4], [6].

References:

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