

AI-Powered Robotics for Reliable, Stable, and Robust Operation and Maintenance of Power Systems: Architecture, Unified Modeling, and Quantitative Evaluation

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AI-Powered Robotics for Reliable, Stable, and Robust Operation and Maintenance of Power Systems: Architecture, Unified Modeling, and Quantitative Evaluation

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Abstract—Robotic inspection and artificial intelligence (AI) are increasingly used in power-system operation and maintenance (O&M), yet they are usually evaluated in isolation—by image-detection accuracy or robot mobility—rather than by their effect on the quantities utilities are regulated on. This paper proposes AIRO-PS, a standards-aligned six-layer architecture that integrates aerial, line-mounted, substation, and live-line robots with edge AI, zoned communications, and a network digital twin, together with a unified modeling framework that maps each robotic or AI capability to reliability, stability, and robustness parameters: pre-failure detection probability, effective failure rate, restoration-time components, dynamic thermal rating, critical-clearing-time margin, and guaranteed control error. The framework is evaluated through eight coupled simulation studies and a techno-economic appraisal. On an 11-kV test feeder, a 6000-year sequential Monte Carlo simulation shows that AI-robotic O&M reduces SAIFI by 67.3%, SAIDI by 83.8%, and expected energy not supplied by 84.1% relative to conventional O&M, and lowers the 90th-percentile annual SAIDI by 77.1%. Robot-sensed dynamic line rating raises mean ampacity by 36.8% under hot-climate conditions, a multilayer-perceptron transient-stability classifier reaches 98.85% accuracy, Bayesian prognostics with monthly robotic data cut remaining-useful-life error by 86%, a Q-learning maintenance policy performs within 1.5% of the average-cost optimum, and sliding-mode stand-off control reduces unmanned-aerial-vehicle tracking error near live conductors by 89%. A 250-feeder deployment yields an internal rate of return of 31.1%.

Index Terms—Artificial intelligence, digital twin, dynamic line rating, inspection robots, power distribution reliability, predictive maintenance, reinforcement learning, sliding-mode control, transient stability, unmanned aerial vehicles.

I. INTRODUCTION

Power-system operation and maintenance (O&M) is under simultaneous pressure from three directions. A large share of transmission and distribution assets is approaching the end of its design life, so that wear-out mechanisms dominate the hazard function [1]; inverter-based generation reduces inertia and narrows transient and frequency stability margins [2]; and extreme heat, dust, salt contamination, and storms increase both equipment stress and the difficulty of reaching assets safely. The conventional O&M model—periodic patrols, fixed-interval maintenance, manual thermography, and reactive crew dispatch—is labor-intensive, exposes workers to electrical and fall hazards, produces sparse condition data, and responds to failures only after customers have been interrupted.

Robotics and artificial intelligence (AI) have matured enough to change this model. Recent reviews document the transition of unmanned aerial vehicles (UAVs), line-suspended

robots, and multi-robot systems from research prototypes to routine inspection tools [3]–[6], and of deep-learning detectors from benchmark studies to field pipelines for power-line components [7], [8]. Single-stage detectors now exceed 90% mean average precision on insulator-defect data sets [9], [10], and vision-language models are beginning to enable open-vocabulary fault recognition [11], [12]. Live-working robots for distribution networks are standardized in IEEE Std 2991 [13], [14], digital twins are being extended across the equipment lifecycle [15], and deep reinforcement learning (DRL) is being applied to grid operation and maintenance scheduling [16]–[18].

Despite this progress, robotic and AI capabilities are mostly evaluated with component-level metrics—detection accuracy, route length, obstacle-crossing ability, or classifier F1-score. Utilities, however, are regulated and funded on system-level outcomes such as the IEEE Std 1366 indices SAIFI and SAIDI [19], must preserve stability margins as loading rises, and must guarantee clearances from energized conductors defined by IEEE Std 516 [20]. Without a model that links a robot's capability to these outcomes, the value of robotic O&M cannot be compared across technologies, justified to regulators, or used to size a fleet. This paper addresses that gap. Its contributions are as follows:

- **AIRO-PS architecture.** A six-layer reference architecture that integrates heterogeneous robots with edge AI, zoned communications, a network digital twin, and enterprise work management, mapped to IEC 61850, IEC 62443, IEEE Std 516, IEEE Std 2991, and ISO 10218 (Section III).
- **Unified modeling framework.** A capability-to-parameter mapping through which robotic and AI functions enter established models of reliability (effective failure rate and restoration time), stability (dynamic line rating, critical clearing time, and data-driven assessment), and robustness (a sliding-mode error bound that sets a dynamic safety margin) (Section IV).
- **Coupled quantitative evaluation.** Eight simulation studies that share clearly defined baselines, together with analytical verification of the Monte Carlo reliability model and a 15-year techno-economic appraisal (Sections V and VI).

The remainder of the paper is organized as follows. Section II reviews recent related work. Section III presents the architecture and robotic equipment, and Section IV the

modeling framework. Section V describes the case-study design, Section VI reports and discusses the results, and Section VII concludes.

II. RELATED WORK AND RESEARCH GAP

A. Robotic Platforms for Power-System O&M

UAVs are the most widely deployed O&M robots. Ahmed *et al.* [3] and Xu *et al.* [4] survey UAV-based transmission-line inspection, from platform architectures to image-based line detection. Close-range work near conductors is now feasible at low cost: Wang *et al.* [21] inspected an energized 10-kV line from within 2 m using an RGB camera and millimeter-wave radar, with correction modules that maintain the trajectory despite wind and positioning error. For substations, UAV path planning must respect electromagnetic safety thresholds [22], and ground robots increasingly rely on multisensor fusion for navigation [23]. Fleet-level planning has also advanced: Caballero *et al.* [24] formulated multi-UAV inspection as a capacitated min-max multi-depot routing problem and inspected over 10 km of line in 13 min in the field. Line-suspended robots [5], [25] provide contact-level diagnostics that UAVs cannot, and multi-robot systems that combine cooperative perception, planning, and execution are reviewed in [6]. For maintenance rather than inspection, dual-arm insulated robots perform live work on 10-kV networks within a layered safety framework [14], consistent with the IEEE Std 2991 guide [13].

B. AI for Condition Assessment and Decision-Making

Deep learning dominates visual inspection [7], [8]. Recent detectors such as RSP-YOLOv11n report a mean average

precision (mAP@0.5) of 91.2% on a self-built insulator data set and 98.4% on the public CPLID set [9], while vision-language models add open-vocabulary recognition and multimodal reasoning [11], [12]. Partial-discharge (PD) source recognition from phase-resolved PD (PRPD) patterns of apparent charge measured per IEC 60270 [26] exceeds 94% accuracy for four typical defect types [27], [28]. Prognostics combine digital twins with sequence models to estimate transformer health index and remaining life [29]. For decisions, DRL has been surveyed extensively for smart-grid operation [16], [17], applied to integrated grid O&M [30], and used with Shapley-value interpretation to schedule monthly outage maintenance [18]. Data-driven transient stability assessment (TSA) is reviewed in [31]; graph neural networks now reach about 99% accuracy on the IEEE 68-bus system [32]. Dynamic line rating (DLR) is supported by regulation [33] and by the IEEE Std 738 thermal model [34], and its coordination with distributed resources is reviewed in [35]. Large language models are emerging as interfaces for power-system tasks [36].

C. Research Gap

Table I positions this work relative to representative recent studies. Each advances a specific capability—perception, a platform, routing, a scheduler, or a stability classifier—and reports a metric native to that capability. To the author's knowledge, no study evaluates robotic and AI capabilities jointly in terms of distribution reliability indices, stability margins, and control-guaranteed safety clearances, within one standards-mapped architecture and with an economic appraisal. AIRO-PS is designed to close this gap.

TABLE I
POSITIONING OF THIS WORK RELATIVE TO REPRESENTATIVE RECENT STUDIES

Ref.	Year	Scope	Headline result reported	Pillar(s) addressed
[7]	2025	Review: deep learning for power-line inspection	Taxonomy of component detection and fault diagnosis	Perception
[3]	2024	Review: UAS for line inspection	Methods, challenges, and status of UAS	Perception, platforms
[6]	2026	Review: multi-robot power inspection	Cooperative perception, planning, execution	Platforms, planning
[9]	2025	Insulator-defect detector (RSP-YOLOv11n)	mAP@0.5 = 91.2% (own data); 98.4% (CPLID)	Perception
[11]	2026	Vision-language line-fault detection	Open-vocabulary detection with corridor geo-prior	Perception
[21]	2023	Low-cost close-range UAV	Inspection within 2 m of an energized 10-kV line	Platform, robustness
[24]	2025	Multi-UAV route planning	> 10 km inspected in 13 min (−67% time)	Planning
[14]	2026	10-kV live-working robot	13-DOF dual-arm robot, layered safety framework	Platform, safety
[18]	2025	Interpretable RL maintenance scheduling	Fewer voltage violations and lower losses	Decision-making
[32]	2023	GNN-based transient stability assessment	99.17% accuracy, IEEE 68-bus system	Stability
[29]	2025	Transformer health index (digital twin, LSTM-GRU)	Health-index and life prediction, 940 units	Prognostics
[35]	2025	Review: DLR, DER, and EV coordination	Hybrid optimization/ML coordination framework	Thermal capacity
This work	2026	Integrated AI-robotic O&M (AIRO-PS)	SAIDI −83.8%; TSA 98.85%; SMC error −89%; IRR 31.1%	Reliability, stability, robustness, economics

III. AIRO-PS ARCHITECTURE AND EQUIPMENT

A. Six-Layer Reference Architecture

The AI-driven Robotic Operation and maintenance framework for Power Systems (AIRO-PS) follows five design principles: standards-first interoperability, edge-first intelligence (safety-critical perception and control run on the robot so that loss of wide-area connectivity degrades

performance but never safety), safety by design, defense-in-depth cybersecurity, and human-in-the-loop governance for high-consequence actions. Fig. 1 shows the resulting six layers, and Table II lists their functions and governing standards. Data flow upward from assets and robots to enterprise systems; missions, commands, and work orders flow downward. Functional safety, AI governance and explainability, and time synchronization are cross-cutting concerns.

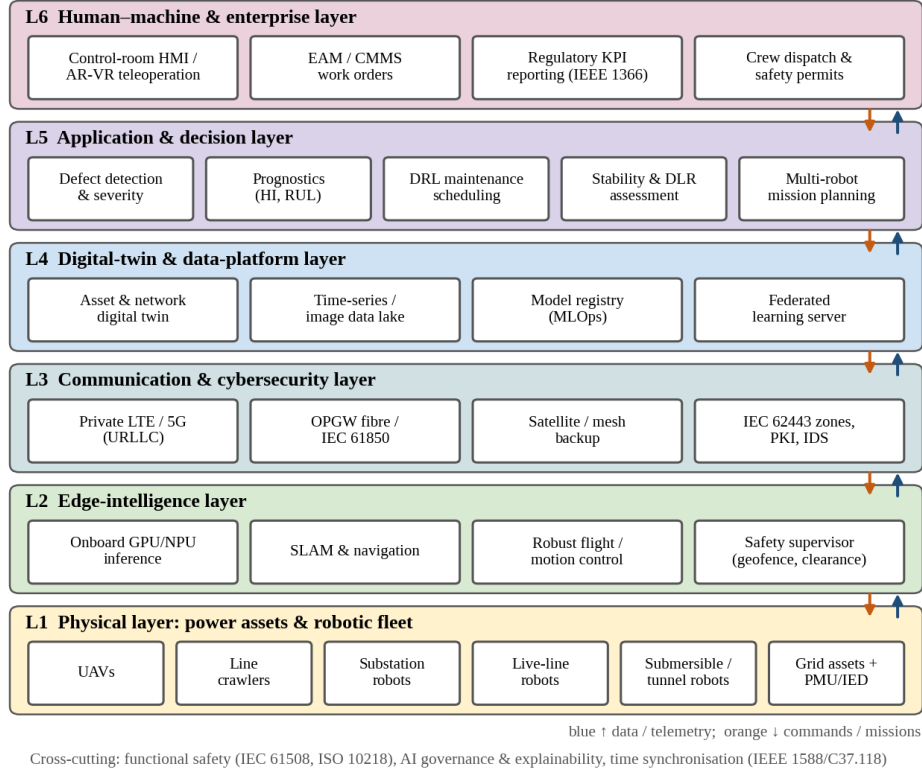


Fig. 1. Six-layer AIRO-PS reference architecture. Blue arrows denote upward data and telemetry flow; orange arrows denote downward commands, missions, and work orders.

TABLE II
FUNCTIONS AND GOVERNING STANDARDS OF THE AIRO-PS LAYERS

Layer	Principal functions	Enabling technologies	Key standards
L1 Physical	Power assets; UAVs, line crawlers, substation, live-line, and tunnel robots; PMUs and online monitors	Multirotor/VTOL UAVs, legged and wheeled robots, CT energy harvesters, online DGA	IEEE 516, IEEE 2991, ISO 10218-1
L2 Edge intelligence	On-board inference, SLAM, robust motion control, independent safety supervisor	GPU/NPU modules (≥ 100 TOPS), RTOS controllers, RTK-GNSS, LiDAR	IEC 61508 (SIL 2 target)
L3 Communication & security	Low-latency command links, bulk backhaul, zoning, PKI, intrusion detection	Private LTE/5G slices, OPGW fiber, mesh and satellite backup, TLS 1.3	IEC 61850, IEC 62443, IEC 62351, IEEE 1686
L4 Digital twin & data	Probabilistic asset and network state, time-series and image lake, model registry, federated learning	Graph/time-series databases, MLOps pipelines	IEC CIM (61970/61968)
L5 Application & decision	Defect detection, PD recognition, prognostics, RL scheduling, DLR, AI-TSA, mission planning	CNN/transformer detectors, Bayesian RUL, Q-learning/PPO, VRP solvers	IEEE 738, IEEE 1366, IEC 60270
L6 Human-machine & enterprise	Control-room HMI, tele-operation, EAM/CMMS work orders, regulatory KPIs	Explainable dashboards (Grad-CAM, SHAP), AR tele-operation, EAM APIs	IEEE 1366

B. Closed-Loop Operation and Time Scales

AIRO-PS operates as a sense-analyze-decide-act loop around a network digital twin that maintains a probabilistic state for every asset (health index, degradation-model posterior, recent robotic observations, and loading) [15]. Recommendations reach operators with explanations—Grad-CAM saliency maps for visual detections [37] and SHAP attributions for tabular models [38]—and with calibrated confidence. Two nested time scales coexist. The *fast loop* (milliseconds to seconds) comprises robot motion control, protection-coordinated switching, and real-time stability screening; the *slow loop* (hours to months) comprises inspection planning, prognostics, and maintenance scheduling. A typical fault response illustrates the loop: protection trips a

feeder breaker; AI fault localization ranks candidate sections and dispatches a docked UAV; on-board detection confirms the fault and streams geo-tagged evidence; the distribution management system proposes isolation and back-feed switching, which the operator approves; and the enterprise asset-management system raises a repair order with the correct spares. These steps shorten the fault-location and switching times that appear explicitly in the reliability model of Section IV.

C. Communications, Cybersecurity, and Safety

Robots introduce mobile, wireless entry points into operational-technology networks. AIRO-PS therefore places them in IEC 62443 zones with defined conduits [39]; inter-zone traffic is authenticated and encrypted (IEC 62351 for IEC

61850 messaging and TLS 1.3 for telemetry) [40], [41], robots hold hardware-rooted identities, and device hardening follows IEEE Std 1686 [42]. Commands from the robot-operations zone never reach protection devices directly; switching is always mediated by SCADA with operator approval. Safety relies on three independent layers: inherent measures (insulated airframes and tools), a deterministic safety supervisor that is logically separate from the AI stack and enforces geofences, clearance, battery, and link-quality limits, and procedural controls per IEEE Std 516 [20] and ISO 10218-1 [43]. An IEC 60812 failure-mode and effects analysis [44] identified clearance violation in gusts, missed defects, and cyber intrusion through robot links as the highest-risk failure modes; the mitigations include the robust controller of Section IV-E, multispectral fusion with active learning, and zoning.

D. Robotic Fleet and Equipment

The fleet deliberately combines complementary platforms (Table III). Docked multirotor UAVs deliver wide-area

coverage at low cost per kilometer; line crawlers deliver contact-level diagnostics of strands, joints, and corrosion; wheeled and legged robots provide high-frequency, time-registered substation surveillance; and insulated manipulators perform live-line maintenance [13], [25]. Fig. 2 illustrates the transmission-inspection configuration, in which a docked UAV carries RGB, long-wave infrared, and ultraviolet cameras, uses RTK-GNSS and LiDAR for navigation, and continuously verifies its minimum approach distance to energized conductors. Thermal findings are graded by the temperature rise over a similar reference component, normalized to rated current, following NETA practice [45]. For hot, dusty, and saline climates, AIRO-PS specifies IP54 (aerial) and IP65 (ground) protection, operation at 55 °C with solar load, salt-fog qualification, and conditioned docks for battery management.

TABLE III
REPRESENTATIVE SPECIFICATIONS OF THE AIRO-PS ROBOTIC FLEET (DESIGN TARGETS)

Platform	Mobility and endurance	Primary payload	Principal O&M tasks
Docked multirotor UAV	6–9 kg, IP54; 35–45 min; 12 m/s cruise	RGB 45 MP, LWIR 640 × 512, UV corona, LiDAR	Insulator and fitting inspection, fault patrol, thermography
VTOL fixed-wing UAV	12–20 kg; 2–4 h; 80–150 km	Corridor LiDAR, oblique RGB	Vegetation and clearance survey, post-storm assessment
Line crawler	25–100 kg on conductor; days with CT harvesting	Strand/corrosion sensor, micro-ohm joint test, RGB/IR	Close inspection, strand repair, damper and spacer replacement
Substation wheeled / legged robot	30–250 kg, IP65–67; 2–8 h, auto-docking	PTZ IR/RGB, acoustic camera, gas sensor, 3-D LiDAR	Routine patrol, hotspot, PD and SF ₆ -leak detection, gauge reading
Live-line manipulator	Insulated boom, dual 6-DOF arms; tele-operated or semi-autonomous	Insulated tools, force/torque sensing, stereo vision	Jumper, fuse, and insulator replacement on energized MV lines

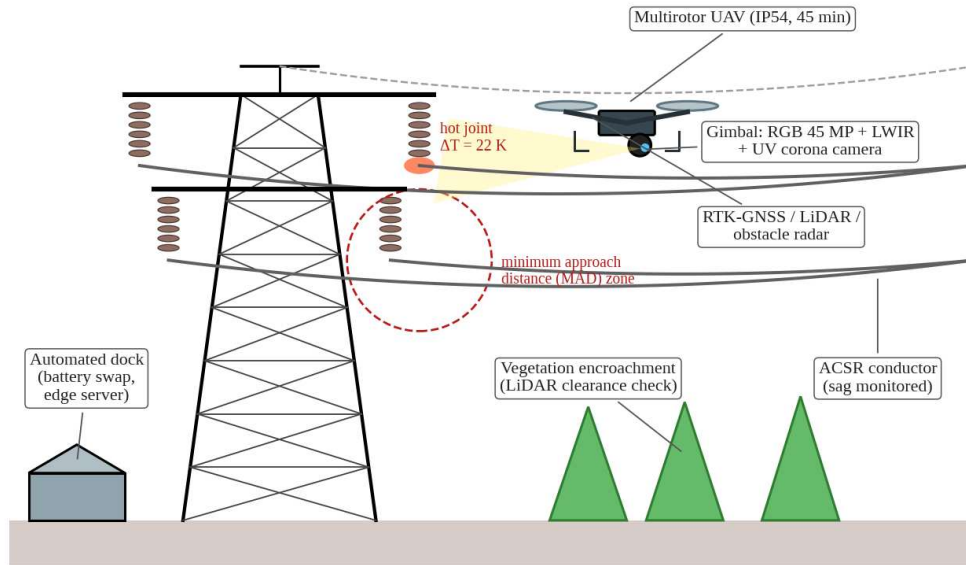


Fig. 2. Docked multirotor inspection UAV with a multispectral gimbal, RTK-GNSS/LiDAR navigation, hot-joint detection, and vegetation-encroachment checking while maintaining the minimum approach distance (MAD) to energized conductors.

IV. UNIFIED MODELING FRAMEWORK

The central idea of the framework is that every robotic or AI capability must be traced to a small set of physically meaningful parameters, so that its effect can be evaluated with

established power-engineering methods rather than asserted. Table IV, at the end of this section, summarizes the mapping.

A. Reliability

A defect is intercepted only if an inspection falls inside its P–F interval τ_{PF} —the time between the point at which an incipient defect becomes detectable and functional failure—and that inspection detects it. With inspection frequency f_i and per-inspection detection probability q , the probability of pre-failure detection is

$$p_{\text{det}} = 1 - (1 - q)^n, \quad n = \lfloor \tau_{PF} f_i \rfloor. \quad (1)$$

Robotics raises f_i by one to two orders of magnitude, while multispectral sensing and learned detectors raise q and lengthen τ_{PF} . Only a fraction p_{inc} of failures is preceded by an observable incipient stage, so the effective unplanned failure rate becomes

$$\lambda_{\text{eff}} = \lambda (1 - p_{\text{inc}} p_{\text{det}}), \quad (2)$$

because each detected defect is converted into planned—and, with live-line robots, interruption-free—work. For a radial feeder, the restoration time seen by load point j after a failure of component i on main section k is

$$r_{ij} = T_{\text{loc}} + \mathbf{1}_{ij}^{\text{up}} T_{\text{sw}} + \mathbf{1}_{ij}^{\text{dn}} [(1 - \chi_k) T_{\text{rep}} + \chi_k (T_{\text{sw}} + T_{\text{tie}})], \quad (3)$$

where the indicators $\mathbf{1}_{ij}^{\text{up}}$ and $\mathbf{1}_{ij}^{\text{dn}}$ denote that j lies upstream, or on/downstream, of i , and $\chi_k = 1$ if a normally open tie can back-feed the downstream section. UAV fault patrol shortens the location time T_{loc} , remote switching shortens T_{sw} and T_{tie} , and prognostics-driven spares with robot-assisted repair shorten T_{rep} . The load-point indices and the IEEE Std 1366 system indices [1], [19] follow as

$$\lambda_j = \sum_{i \in \Omega_j} \lambda_{\text{eff}, i}, \quad U_j = \sum_{i \in \Omega_j} \lambda_{\text{eff}, i} r_{ij}, \quad (4)$$

$$\text{SAIFI} = \frac{\sum_j \lambda_j N_j}{\sum_j N_j}, \quad \text{SAIDI} = \frac{\sum_j U_j N_j}{\sum_j N_j}, \quad (5)$$

$$\text{CAIDI} = \frac{\text{SAIDI}}{\text{SAIFI}}, \quad \text{ASAI} = 1 - \frac{\text{SAIDI}}{8760}, \quad \text{EENS} = \sum_j L_j U_j, \quad (6)$$

where Ω_j is the set of components whose failure interrupts j , and N_j and L_j are its customers and average load. Because regulators increasingly penalize poor years, not only poor averages, these indices are also evaluated by sequential Monte Carlo simulation, which yields their full annual distribution [1].

B. Stability

Robotics affects stability through fault frequency (vegetation, cracked insulators, and hot joints are dominant precursors of line faults), through thermal margin (DLR), and through the speed of assessment. For the benchmark single-machine infinite-bus (SMIB) system, the swing equation [46] is

$$\frac{2H}{\omega_s} \frac{d^2 \delta}{dt^2} = P_m - P_{\text{max}} \sin \delta - D \Delta \omega, \quad (7)$$

with inertia constant H , synchronous speed ω_s , mechanical power P_m , and damping D . For a bolted fault that reduces electrical power to zero and a post-fault characteristic $P_{\text{max, post}}$,

the equal-area criterion gives the critical clearing angle and time

$$\delta_0 = \sin^{-1} \frac{P_m}{P_{\text{max, pre}}}, \quad \delta_{\text{max}} = \pi - \sin^{-1} \frac{P_m}{P_{\text{max, post}}}, \quad (8)$$

$$\cos \delta_c = \frac{P_m (\delta_{\text{max}} - \delta_0)}{P_{\text{max, post}}} + \cos \delta_{\text{max}}, \quad (9)$$

$$t_{cc} = \sqrt{\frac{4H(\delta_c - \delta_0)}{\omega_s P_m}}.$$

The margin $t_{cc} - t_{\text{clr}}$ is what AI-based TSA must predict in real time. The surrogate is a multilayer perceptron (MLP) that maps the operating point and contingency descriptor $\mathbf{x}$ to the probability of instability,

$$\hat{y} = \sigma(\mathbf{w}_3^T \phi(\mathbf{W}_2 \phi(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + \mathbf{b}_2) + b_3), \quad (10)$$

with ReLU activations ϕ , trained by binary cross-entropy on labels generated with (7). The conductor thermal rating follows the IEEE Std 738 heat balance [34], in which convective and radiative cooling equal solar and Joule heating:

$$q_c + q_r = q_s + I^2 R(T_c), \quad I_{\text{max}} = \sqrt{\frac{q_c + q_r - q_s}{R(T_{c, \text{max}})}}, \quad (11)$$

where the convection term q_c depends strongly on wind speed and direction (forced- and natural-convection correlations as in [47]). Static ratings assume simultaneous worst-case weather; robot- and tower-mounted sensors measure local conditions, and the resulting DLR is passed to the energy management system and to TSA [33], [35].

C. Robotic Mission Energy and Routing

For a UAV sortie r of length L_r that inspects n_r assets, with cruise energy e_{km} per kilometer and hover energy e_a per asset, the battery constraint is

$$E_r = e_{\text{km}} L_r + n_r e_a \leq E_u, \quad (12)$$

where E_u is the usable battery energy. Multi-sortie inspection is a capacitated vehicle routing problem. A route-first, cluster-second heuristic [48] builds a giant tour by nearest-neighbor construction and 2-opt improvement [49] and then splits it optimally into energy-feasible sorties by dynamic programming over tour positions,

$$V(j) = \min_{0 \leq i < j} \{ V(i) + C(i+1, j) : E(i+1, j) \leq E_u \}, \quad (13)$$

with $V(0) = 0$ and $C(i+1, j)$ the length of the sortie depot $\rightarrow a_{i+1} \rightarrow \dots \rightarrow a_j \rightarrow$ depot. The split is exact for a given tour and runs in $O(n^2)$ time.

D. Prognostics and Maintenance Decisions

Following [50], a normalized degradation signal $d(t)$ is modeled as exponential with random parameters, which becomes linear after a logarithmic transform:

$$\ln d(t_k) = \ln \theta + \beta_d t_k + \varepsilon_k, \quad \varepsilon_k \sim \mathcal{N}(0, \sigma^2). \quad (14)$$

With a Gaussian prior (μ_0, Σ_0) on $(\ln \theta, \beta_d)$, observations $\mathbf{y}$, and design matrix $\Phi = [\mathbf{1}, \mathbf{t}]$, the posterior and the remaining useful life (RUL) at a failure threshold D_{th} are

$$\Sigma_k = \left(\Sigma_0^{-1} + \Phi^T \Phi \right)^{-1}, \quad \mu_k = \Sigma_k \left(\Sigma_0^{-1} \mu_0 + \frac{\Phi^T \mathbf{y}}{\sigma^2} \right), \quad (15)$$

$$\text{RUL}_k \approx \frac{\ln D_{th} - \hat{\mu}_{\theta,k}}{\hat{\mu}_{\beta,k}} - t_k. \quad (16)$$

The posterior covariance shrinks with the number of observations and with $1/\sigma^2$; robotic sensing increases the former (monthly rather than annual sampling) and reduces the latter (repeatable sensor pose and calibrated payloads). Maintenance is then posed as a Markov decision process with condition states S_0 (good) to S_3 (severe) and S_f (failed), actions {none, minor, major}, and per-period cost c that includes maintenance, failure, and monitoring costs [51]. Tabular Q-learning [52] updates

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha_t \left[c_t + \gamma \min_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right], \quad (17)$$

and relative value iteration (RVI) provides the exact average-cost optimum against which the learned policy is benchmarked. Fleet-scale variants replace the table with a neural approximator and add a safety layer that masks infeasible actions [16], [30].

TABLE IV
MAPPING OF AI-ROBOTIC CAPABILITIES TO MODEL PARAMETERS

Capability	Model parameter(s)	Eq.	Pillar
Robotic inspection with learned detection	$f_i, q, \tau_{PF} \rightarrow p_{\text{det}}, \lambda_{\text{eff}}$	(1), (2)	Reliability, stability
UAV fault patrol and AI fault localization	T_{loc}	(3)	Reliability
Remote and automated switching	$T_{\text{sw}}, T_{\text{tie}}$	(3)	Reliability
Live-line robotic repair; prognostics-driven spares	T_{rep} ; planned-outage duration and share	(3), (4)	Reliability
Weather and sag sensing for DLR	$V_w, T_a, Q_{\text{sc}} \rightarrow I_{\text{max}}$	(11)	Stability, capacity
AI-based transient stability assessment	Fast estimate of $t_{\text{cc}} - t_{\text{clr}}$	(9), (10)	Stability
Robotic condition monitoring and prognostics	Sampling rate, $\sigma \rightarrow \text{RUL posterior}$	(15), (16)	Reliability, cost
RL maintenance scheduling	Policy $\pi(a s)$	(17)	Robustness, cost
Sliding-mode stand-off control	Error bound $\Phi/\Lambda \rightarrow d_{\text{MAD}}^{\text{robot}}$	(18)–(20)	Robustness, safety

V. CASE-STUDY DESIGN

A. Scenarios and Baselines

Eight studies instantiate the models of Section IV with three O&M scenarios that are held fixed across all studies, so that results are directly comparable. *S1, conventional O&M (baseline)*: periodic manual patrols, fixed-interval maintenance, manual fault location, and crew-operated switching. *S2, robotic inspection*: UAV and substation-robot inspection with conventional analysis and decision-making, and limited live-line work. *S3, AI-robotic O&M (AIRO-PS)*: docked robots with AI perception, prognostics, RL scheduling, automated fault localization, remote switching, and extensive robotic live-line maintenance. Table V lists the scenario parameters, which operationalize (2) and (3). They are engineering estimates informed by [25], [55] and are intended to be recalibrated with utility data.

E. Robustness: Guaranteed Clearance near Energized Conductors

A UAV holding a stand-off distance from a live conductor is subject to matched uncertainty from unknown payload mass, drag, and gusts. For the stand-off error $e = x - x_d$ of the model $m\ddot{x} = u - c\dot{x} + d(t)$, sliding-mode control (SMC) [53], [54] uses

$$s = \dot{e} + \Lambda e, \quad u = \hat{m}(\ddot{x}_d - \Lambda \dot{e}) + \hat{c}\dot{x} - K \text{sat}(s/\Phi), \quad (18)$$

with nominal estimates $\hat{m}$ and $\hat{c}$, surface bandwidth Λ , switching gain K , and boundary layer Φ . With $V = \frac{1}{2}s^2$, the reaching condition holds if K exceeds the lumped uncertainty bound:

$$K \geq |\tilde{m}(\ddot{x}_d - \Lambda \dot{e}) + \tilde{c}\dot{x}| + \bar{d} + \eta_r \Rightarrow s\dot{s} \leq -\eta_r |s|, \quad (19)$$

where $\tilde{m} = m - \hat{m}$, $\tilde{c} = c - \hat{c}$, and $\bar{d} \geq |d(t)|$. Inside the boundary layer the error is bounded by $|e| \leq \Phi/\Lambda$. AIRO-PS uses this bound to set a dynamic minimum approach distance for robots,

$$d_{\text{MAD}}^{\text{robot}} = d_{\text{MAD}}^{516} + \Phi/\Lambda + 3\sigma_{\text{loc}}, \quad (20)$$

where d_{MAD}^{516} is the IEEE Std 516 distance for the voltage class [20] and σ_{loc} the localization standard deviation. A controller with a tighter guaranteed bound therefore permits closer, higher-resolution inspection at the same risk.

TABLE V
SCENARIO PARAMETERS OF THE RELIABILITY STUDY (MEAN VALUES; TIMES IN HOURS)

Parameter	S1	S2	S3
Pre-failure detection probability p_{det}	0.25	0.45	0.75
Fault location, main feeder, T_{loc}	1.50	0.80	0.35
Fault location, lateral	1.20	0.70	0.30
Switching and isolation, T_{sw}	1.00	0.60	0.15
Tie transfer, T_{tie}	0.50	0.30	0.10
Line repair, T_{rep}	5.0	4.5	3.5
Transformer replacement	10.0	9.0	7.0
Planned-outage duration, T_{plan}	4.0	3.0	2.0
Planned work performed live-line	0%	30%	80%

B. Test Systems and Data

Distribution reliability: the 11-kV radial feeder of Fig. 3, built in the spirit of the Roy Billinton test system [56], has four main sections (0.75, 0.80, 0.70, and 0.75 km) separated by sectionalizing switches, seven fused laterals (5.15 km in total) supplying load points LP1–LP7 with 1013 customers and 4.69 MW of average load, and a normally open tie to an adjacent feeder. Line sections fail at 0.065 f/km·yr with $p_{\text{inc}} = 0.7$; distribution transformers at 0.015 f/yr with $p_{\text{inc}} = 0.8$; and each lateral has 0.5 planned outages per year. Restoration times are gamma distributed (shape 2) with the means of Table V, and

6000 years are simulated per scenario with a convergence criterion of a coefficient of variation below 2%. The expected

indices are also computed analytically from (4)–(6) for verification.

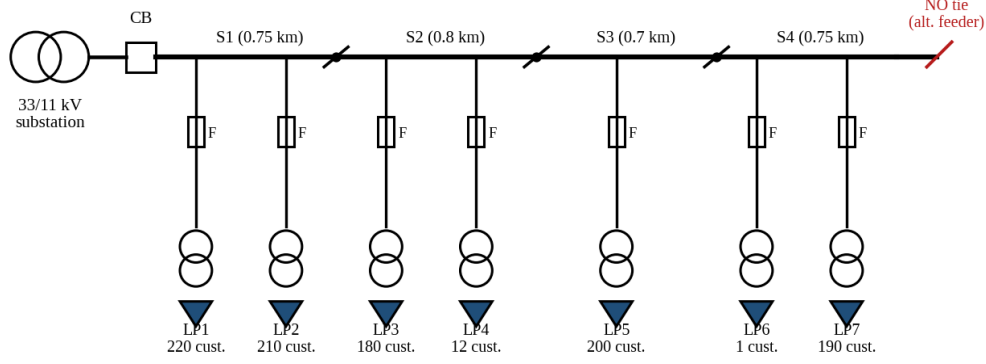


Fig. 3. Radial 11-kV test feeder with circuit breaker (CB), sectionalizing switches, four main sections, seven fused laterals with load points LP1–LP7, and a normally open (NO) tie to an adjacent feeder.

Dynamic line rating: ACSR Drake ($D_0 = 28.14$ mm, $R_{25} = 7.284 \times 10^{-5}$ Ω /m, $R_{75} = 8.688 \times 10^{-5}$ Ω /m, emissivity and absorptivity 0.8, $T_{c,max} = 75$ $^{\circ}$ C). The static rating assumes 45 $^{\circ}$ C ambient, 0.61 m/s perpendicular wind, and 1000 W/m² solar irradiance; the DLR uses a synthetic 24-h Abu Dhabi summer profile at 15-min resolution.

Transient stability: a 50-Hz SMIB system with $H = 5$ s, $X_d = 0.30$ p.u., $E' = 1.10$ p.u., transformer reactance 0.15 p.u., and a double-circuit line of 0.50 p.u. per circuit, delivering $P_m = 0.8$ p.u.; a three-phase fault is cleared by tripping one circuit. For AI-TSA, 5236 feasible cases (2143 unstable) are generated by sampling $P_m \in [0.3, 1.1]$ p.u., $H \in [3, 8]$ s, $E' \in [1.0, 1.2]$ p.u., $X_L \in [0.3, 0.9]$ p.u., $t_{clr} \in [0.05, 0.40]$ s, and $D \in [0, 2]$ p.u., and labeling each by fourth-order Runge–Kutta integration (1-ms step, 3-s horizon; unstable if δ exceeds 180 $^{\circ}$). An MLP with two hidden layers of 64 ReLU units (Adam optimizer [57]) is compared with random-forest [58] and gradient-boosting classifiers on a stratified 70/30 split.

PD recognition: 700 synthetic PRPD feature vectors per class (corona, surface, internal void, floating electrode), each with half-cycle phase centroids, mean log-charges, phase spread, repetition rate, a shape descriptor, and polarity asymmetry; stratified 70/30 split; random-forest, gradient-boosting, and RBF support-vector classifiers [59]. *Prognostics:* 60 degradation trajectories drawn from (14) with prior means (ln 0.02, 0.035 month⁻¹), end of life at a health index of 0.3, and predictions at 50%, 70%, and 90% of life, comparing robotic monitoring (monthly, $\sigma = 0.10$) with manual testing (annual, $\sigma = 0.20$). *Maintenance:* monthly degradation probabilities 0.04, 0.06, 0.10, and 0.20 from S_0 to S_3 , random-shock failure probability 0.003 per month, costs of 1.5, 8, and 120 units for minor maintenance, major maintenance, and failure, robotic monitoring at 0.05 units per month versus manual inspection at 0.5 units per year; Q-learning with $\gamma = 0.995$ over 4000 episodes of 240 months.

UAV routing: 81 assets on three branched feeders, cruise at 12 m/s and 420 W (9.72 Wh/km), 45-s hover at 480 W per asset (6 Wh), and 320 Wh of usable energy per sortie. *Robust control:* a 5-m stand-off with nominal mass 2.5 kg but actual

mass 3.2 kg (+28%), drag 0.35 N·s/m, a 6-N gust between 5 and 12 s on Ornstein–Uhlenbeck turbulence ($\sigma = 1.2$ N), ± 15 N thrust limits, and filtered noisy measurements; PID ($K_p = 14$, $K_i = 5$, $K_d = 8$) versus SMC ($\lambda = 2.5$ s⁻¹, $K = 4.5$ N, $\Phi = 0.15$ m/s). All studies were implemented in Python (NumPy, SciPy, and scikit-learn) with fixed random seeds.

VI. RESULTS AND DISCUSSION

A. Distribution Reliability

Table VI and Fig. 4 summarize the reliability results. Robotic inspection alone (S2) reduces SAIFI by 23.7%, SAIDI by 42.4%, and EENS by 42.9%, mainly through faster fault location and switching. Full AI-robotic O&M (S3) reduces SAIFI by 67.3% (0.725 to 0.237 interruptions per customer-year), SAIDI by 83.8% (3.03 to 0.49 h), CAIDI by 50.3%, and EENS by 84.1% (14.2 to 2.25 MWh/yr), and cuts unplanned failures by 44.8%; ASAI improves from 0.99965 to 0.99994. The improvement is nearly uniform across load points (failure frequency –66% to –68%, annual outage time –83% to –85%) because main-feeder faults, which are cleared only by the breaker, interrupt every customer. The final coefficients of variation were 1.01%, 1.19%, and 1.96% for S1–S3, and the Monte Carlo means agree with the analytical values of (4)–(6) (S1: 0.736, 3.064 h, 14.28 MWh; S2: 0.554, 1.732 h, 8.05 MWh; S3: 0.235, 0.487 h, 2.25 MWh) to within 1.4%, which verifies the implementation.

TABLE VI
RELIABILITY INDICES OF THE TEST FEEDER (6000-YEAR SEQUENTIAL MONTE CARLO)

Index	S1	S2	S3	S3 vs. S1
SAIFI (int./cust.·yr)	0.725	0.553	0.237	–67.3%
SAIDI (h/cust.·yr)	3.034	1.747	0.493	–83.8%
CAIDI (h/int.)	4.18	3.16	2.08	–50.3%
ASAI (p.u.)	0.99965	0.99980	0.99994	+0.029 pp
EENS (MWh/yr)	14.16	8.08	2.25	–84.1%
Unplanned failures (f/yr)	0.528	0.428	0.291	–44.8%
Std. dev. of annual SAIDI (h)	2.38	1.61	0.75	–68.5%
P90 of annual SAIDI (h)	6.24	3.83	1.43	–77.1%

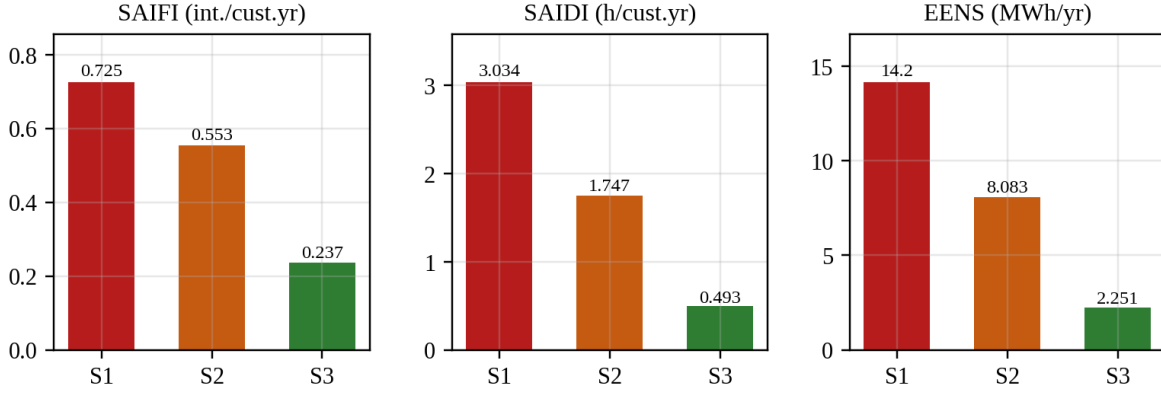


Fig. 4. SAIFI, SAIDI, and EENS of the test feeder under conventional (S1), robotic-inspection (S2), and AI-robotic (S3) O&M.

Fig. 5 shows the exceedance probability of annual SAIDI. Under conventional O&M, one year in ten exceeds 6.24 h per customer; under AI-robotic O&M the 90th percentile is 1.43 h, and the probability of exceeding 4 h falls from about 30% to below 1%. The 68.5% reduction in the standard deviation of

annual SAIDI shows that AI-powered robotics improves not only expected reliability but also its robustness against unfavorable years—an outcome that matters under performance-based regulation.

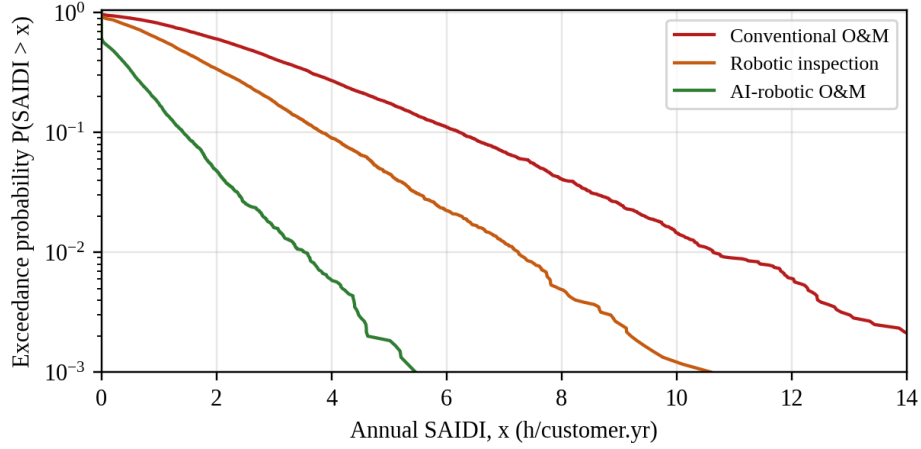


Fig. 5. Exceedance probability of annual SAIDI for the three O&M scenarios (6000 simulated years each).

B. Robot-Sensed Dynamic Line Rating

The static rating of the ACSR Drake conductor is 646 A. Fig. 6(a) confirms the dominant influence of wind: at 40 °C ambient, ampacity rises from about 650 A at 0.6 m/s to over 1500 A at 8 m/s. Over the summer day (Fig. 6(b)), with ambient temperature between 32.0 and 46.9 °C and wind between 0.25 and 4.15 m/s, the DLR averages 884 A (+36.8%), ranges from

627 to 1120 A, and exceeds the static value 97.9% of the time. During a brief hot, low-wind interval, however, the DLR falls to 627 A—below the static rating, where the static value is unsafe. Measurement-based rating therefore improves both capacity and safety, but because higher loading reduces the critical clearing time, AIRO-PS couples DLR with AI-TSA rather than deploying it alone.

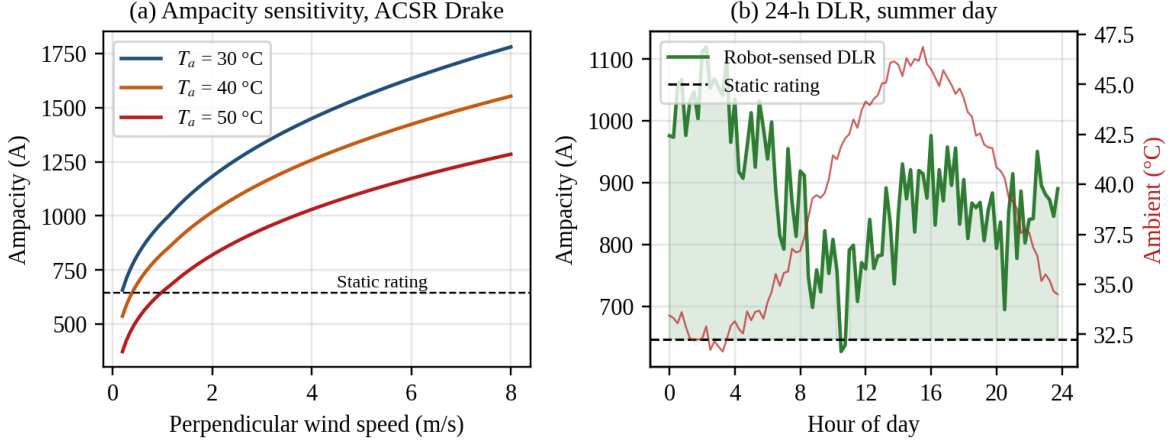


Fig. 6. Dynamic line rating of ACSR Drake: (a) ampacity versus perpendicular wind speed at 30, 40, and 50 °C ambient; (b) robot-sensed 24-h DLR on a summer day compared with the static rating.

C. Transient Stability and AI-Based Assessment

For the SMIB benchmark, (8) and (9) give $P_{\max, \text{pre}} = 1.571$ p.u., $P_{\max, \text{post}} = 1.158$ p.u., $\delta_0 = 30.6^\circ$, $\delta_{\max} = 136.3^\circ$, and $\delta_c = 56.5^\circ$, so the critical clearing time is 189.7 ms. Time-domain

simulation (Fig. 7(a)) confirms stability for clearing at 100 and 180 ms and loss of synchronism at 200 ms, and Fig. 7(b) shows how the critical clearing time decreases with loading and increases with inertia.

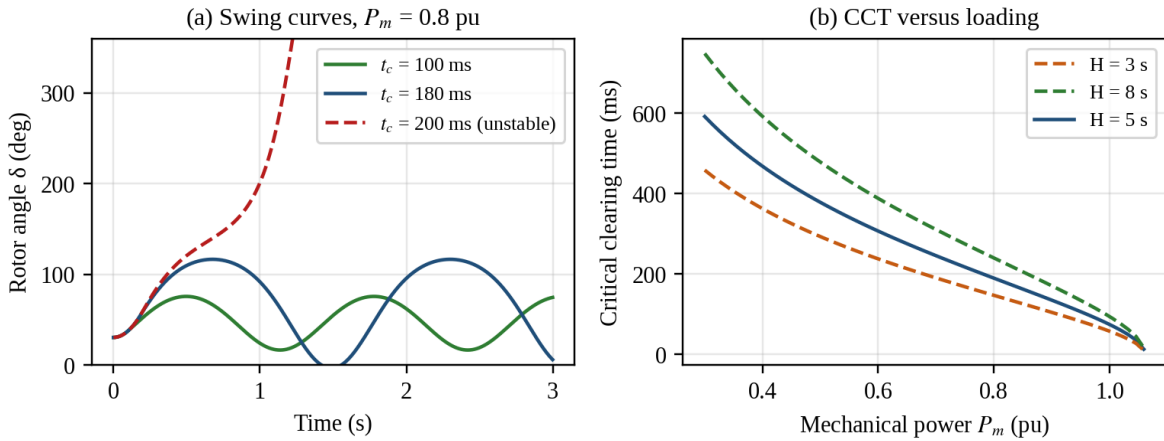


Fig. 7. SMIB transient stability: (a) rotor-angle swing curves for clearing times of 100 ms and 180 ms (stable) and 200 ms (unstable); (b) critical clearing time versus mechanical loading for $H = 3, 5$, and 8 s.

Table VII reports the AI-TSA results on the 1571 test cases. The MLP achieves 98.85% accuracy and an F1-score of 98.60%; only 8 of 643 unstable cases (1.24%) are missed, and 10 of 928 stable cases (1.08%) raise false alarms. Random-forest feature importance is physically consistent—the pre-fault rotor angle (0.343), clearing time (0.261), and loading (0.228) dominate—which, together with SHAP explanations [38], supports operator trust. One MLP assessment requires about 4.7×10^3 multiply-accumulate operations, orders of magnitude fewer than a time-domain simulation, which enables continuous screening of large contingency sets. The accuracy is comparable to that of recent graph-based TSA on larger systems [32], although the SMIB setting is simpler.

TABLE VII
PERFORMANCE OF THE AI CLASSIFIERS ON THE TEST SETS

Task / classifier	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
TSA — MLP (2×64)	98.85	98.45	98.76	98.60
TSA — gradient boosting	97.39	97.48	96.11	96.79
TSA — random forest	96.44	97.11	94.09	95.58
PD — random forest	94.88	94.99	94.88	94.86
PD — gradient boosting	94.05	94.29	94.05	94.02
PD — SVM (RBF)	93.45	93.56	93.45	93.44

D. Partial-Discharge Recognition

For PD source recognition (840 test samples; macro-averaged precision, recall, and F1 in Table VII), the random forest attains 94.88% accuracy. Corona and floating-electrode discharges are recognized almost perfectly (F1 of 1.000 and 0.995), whereas surface and internal-void discharges, whose PRPD clusters overlap in phase, reach F1 of 0.896 and 0.904. The accuracy is consistent with the $> 94\%$ reported for image-

based PRPD recognition in gas-insulated switchgear [27]; the residual confusion motivates fusing UHF and acoustic localization on substation robots.

E. Prognostics with Robotic Condition Data

Fig. 8 illustrates one degradation trajectory and its Bayesian RUL forecast. Across the 60 units, robotic monitoring reduces

the RUL root-mean-square error from 10.65 to 1.49 months (-86.0%) and the mean absolute error from 7.93 to 1.08 months, and raises the fraction of predictions within the $\pm 20\%$ α - λ accuracy cone [60] from 41.1% to 99.4%. Maintenance can therefore be scheduled within weeks rather than within about a year, which is the precondition for just-in-time, prescriptive maintenance.

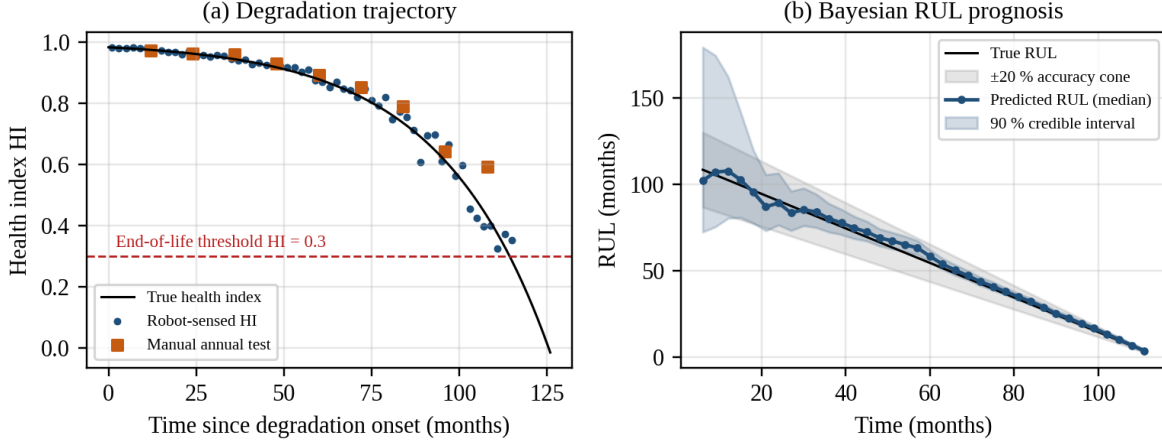


Fig. 8. Prognostics: (a) degradation trajectory with robot-sensed (monthly) and manual (annual) observations; (b) Bayesian RUL prediction with 90% credible interval and $\pm 20\%$ accuracy cone.

F. Maintenance Policy Optimization

Fig. 9(a) shows that Q-learning converges within about 1500 episodes, and Table VIII compares the long-run performance of the policies over 240 000 simulated months. The learned policy is operationally identical to the RVI optimum—no action in S_0 , robot-guided minor maintenance as soon as degradation is detected in S_1 – S_3 , and replacement after failure—and its simulated cost (0.480 units per month) is within 1.5% of that of the RVI policy under the same

simulation (0.473; analytical gain 0.470), the difference being sampling noise. Relative to run-to-failure, the best time-based policy (replacement every 18 months), and annual condition-based maintenance, the AI-robotic policy reduces long-run cost by 79.7%, 57.3%, and 20.8%, respectively, and reduces failures by 84.3% relative to run-to-failure and by 20.5% relative to annual condition-based maintenance. The gain over condition-based maintenance comes entirely from continuous robotic observability, which lets degradation be arrested one state earlier.

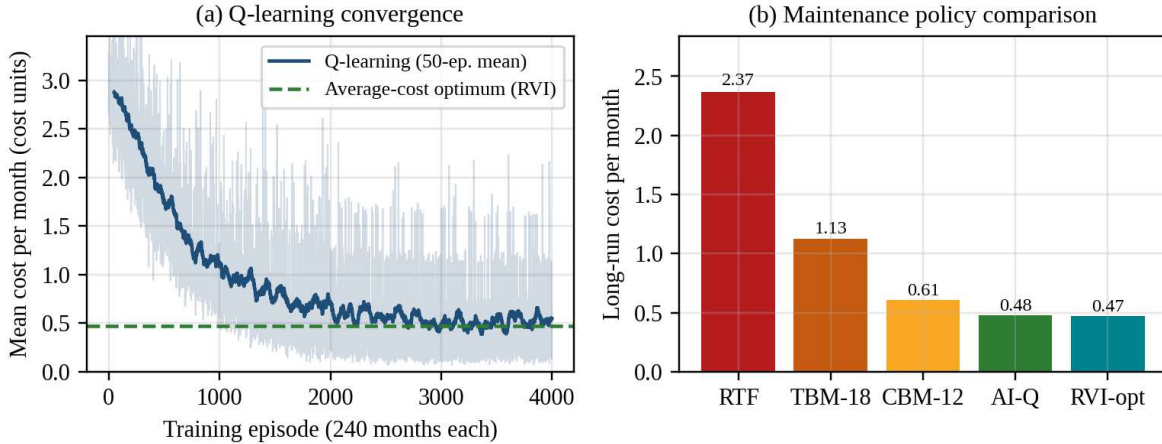


Fig. 9. Maintenance optimization: (a) Q-learning convergence toward the average-cost optimum of relative value iteration (RVI); (b) long-run cost per month of run-to-failure (RTF), time-based (TBM-18), annual condition-based (CBM-12), AI-robotic Q-learning (AI-Q), and optimal (RVI-opt) policies.

TABLE VIII
LONG-RUN PERFORMANCE OF MAINTENANCE POLICIES

Policy	Cost/month	Failures/yr	Availability
Run-to-failure	2.368	0.237	0.9803
Time-based (every 18 months)	1.126	0.069	0.9943
Condition-based (annual manual)	0.607	0.047	0.9961
AI-robotic (Q-learning)	0.480	0.037	0.9969
Optimal (RVI)	0.473	0.036	0.9970

G. Multi-Sortie UAV Mission Planning

For the 81-asset inspection task (Fig. 10), splitting the survey order optimally requires 42.66 km, four sorties, 900.7 Wh, and

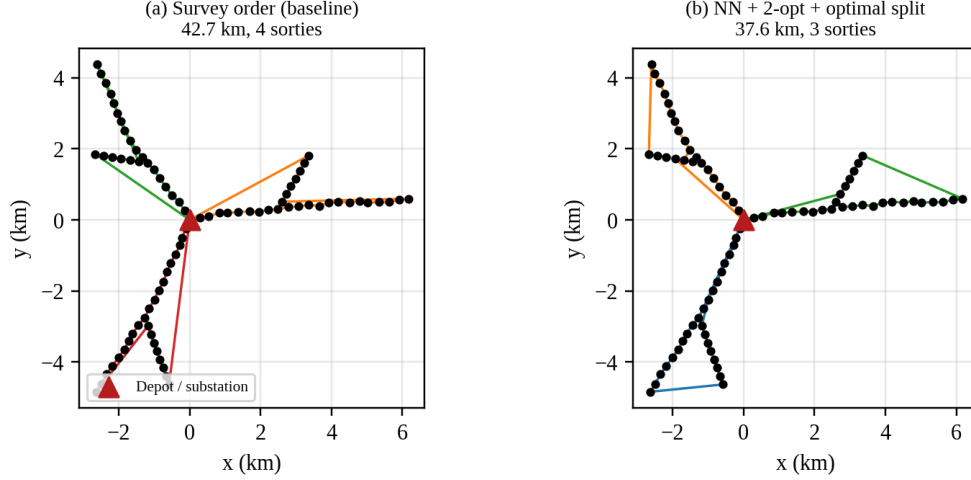


Fig. 10. UAV inspection routing for 81 assets: (a) survey order split into four sorties; (b) nearest-neighbor tour with 2-opt improvement and optimal dynamic-programming split into three sorties.

H. Robust Stand-Off Control

Under a 28% payload-mass error, gust, and turbulence (Fig. 11), the SMC reduces the RMS stand-off error from 17.6 to 1.95 cm (−88.9%) and the maximum deviation from 41.6 to 4.27 cm (−89.7%), keeping the minimum clearance at 4.957 m

instead of 4.652 m, with slightly lower RMS control effort (3.79 versus 3.88 N). The worst-case SMC deviation lies within the 6-cm bound $\Phi/1$ implied by (18) and (19), which validates the dynamic-clearance rule (20): the PID controller would require a margin almost ten times larger, forcing the UAV farther from the conductor and reducing image resolution.

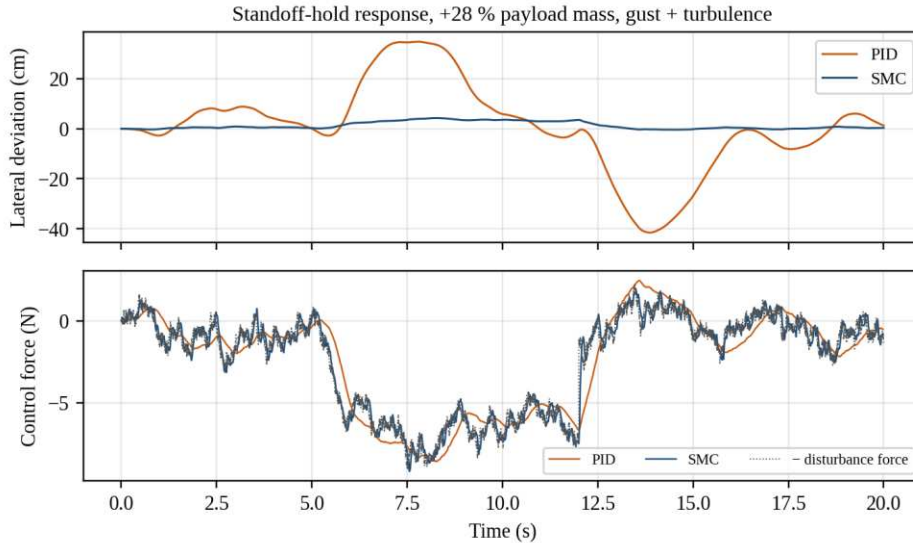


Fig. 11. Stand-off hold under a +28% payload-mass error, gust, and turbulence: lateral deviation (top) and control force with the disturbance force (bottom) for PID and sliding-mode control.

I. Techno-Economic Appraisal

A 15-year appraisal at an 8% real discount rate was performed for deployment on 250 feeders similar to the test feeder, with a capital cost of USD 6.5 million and a USD 2.0 million technology refresh in year 8. Corrective-maintenance costs scale with the simulated failure counts (132 versus 73 events per year across the fleet), and lost energy sales are valued at USD 100/MWh. Table IX shows that annual cost falls from USD 6.93 million to 4.80 million, a saving of USD 2.13 million per year, giving a utility net present value (NPV) of USD 10.65 million, an internal rate of return of 31.1%, and a discounted payback of 3.65 years. The NPV remains positive with 60% higher capital and refresh costs (USD 6.10 million) or 40% lower savings (USD 3.36 million); the break-even saving is USD 0.89 million per year. Valuing avoided customer interruptions at USD 6/kWh adds USD 17.87 million per year of societal benefit and raises the societal NPV to USD 163.6 million.

TABLE IX
ANNUAL COSTS AND INVESTMENT METRICS (250 FEEDERS, USD MILLION)

Item	Conventional	AI-robotic
Inspection (patrols / robot operations)	2.40	1.40
Preventive-maintenance crews	1.80	1.30
Corrective maintenance	2.37	1.09
Lost energy sales	0.35	0.06
AI platform, licenses, connectivity	—	0.95
Total annual cost	6.93	4.80
NPV / IRR / discounted payback	—	10.65 / 31.1% / 3.65 yr
Societal NPV (VoLL USD 6/kWh)	—	163.6

J. Integrated Discussion

Four observations emerge. First, the largest reliability gains come from combining robotics with AI and automation, not from robots alone: S2 captures about half of the SAIDI improvement, and the remainder requires AI-based early detection, automated fault localization and switching, and live-line robotic work. Second, the pillars reinforce each other: early defect detection lowers fault rates (reliability), which also reduces stability-threatening disturbances, whereas DLR raises capacity but must be co-assessed with TSA because higher loading reduces the critical clearing time. Third, robustness appears at three levels—guaranteed control error near conductors, lower variance of annual reliability, and maintenance policies that remain near-optimal. Fourth, the economic case is dominated by customer benefits, which suggests that performance-based regulation is the most effective enabler of adoption.

K. Limitations

The results should be read in light of the following limitations. The feeder, PRPD, degradation, and cost data are synthetic or estimated, and the scenario parameters (notably p_{det} and restoration times) are engineering judgments; field calibration is required before the magnitudes are used for investment decisions. The stability study uses an SMIB model, whereas systems with high shares of inverter-based resources exhibit converter-driven and frequency-stability phenomena [2] that require multi-machine models. The control study is one-dimensional; six-degree-of-freedom simulation with

tower-induced aerodynamics would refine the margins. The economic appraisal excludes regulatory approval, cybersecurity-incident, and organizational-change costs. Finally, classifiers trained on synthetic data may not transfer directly to field data; the active-learning and federated-learning mechanisms of the architecture [61] are intended to close this gap. These limitations qualify the magnitudes of the benefits but not the modeling framework itself.

VII. CONCLUSION

This paper has proposed AIRO-PS, a standards-aligned architecture and unified modeling framework that expresses the value of AI-powered robotics in the native terms of power engineering: failure and restoration parameters for reliability, thermal margin and critical-clearing-time margin for stability, and guaranteed control error and safety clearance for robustness. Eight coupled studies on common baselines indicate that AI-robotic O&M can reduce SAIFI by 67.3%, SAIDI by 83.8%, and EENS by 84.1%, compress the tail of the annual SAIDI distribution, release about 37% additional thermal capacity while exposing unsafe static-rating intervals, assess transient stability with 98.85% accuracy, cut RUL error by 86%, bring maintenance policies within 1.5% of the optimum, and hold UAVs within a 6-cm guaranteed band near live conductors, with an internal rate of return of 31.1%. Future work will calibrate the framework with utility outage and inspection records, extend AI-TSA and the stability-risk assessment to inverter-rich multi-machine systems, develop six-degree-of-freedom adaptive controllers validated in flight tests, and coordinate heterogeneous robot fleets with safe multi-agent reinforcement learning.

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