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Commissioning Reliability for Critical Facilities: A Root-Cause and Preventive-Maintenance Model for Automation, Power Distribution, and Electronic Infrastructure

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Abstract- Critical facilities depend on tightly coupled automation, power distribution, backup power, communication, sensor, electronic-control, and human-interface systems. Where such systems are commissioned without durable performance validation, issue-backlog discipline, root-cause traceability, spare-parts readiness, and preventive-maintenance feedback loops, the facility may become operational on paper while remaining fragile in practice. This paper develops a Commissioning Reliability and Preventive-Maintenance Model (CR-PMM) for automation, power-distribution, and electronic infrastructure in critical facilities. The model links commissioning readiness checks, functional validation, issue prioritisation, fault isolation, condition monitoring, failure-mode classification, spares planning, corrective-action verification, and stakeholder risk communication into one auditable lifecycle. The empirical section uses the public AI4I 2020 Predictive Maintenance Dataset, distributed through UCI and Kaggle, comprising 10,000 machine-operation records, five principal failure flags, and operating variables such as temperature, speed, torque, tool wear, and machine-failure status (Matzka, 2020; UCI Machine Learning Repository, 2020; Kaggle, 2020). Although the dataset describes a synthetic industrial process rather than a specific facility, it is appropriate for testing transferable maintenance-analytics logic because critical facilities face similar problems of class imbalance, early warning, threshold exceedance, component degradation, and the need to convert sensor signals into actionable work orders. The analysis finds that only 339 of 10,000 records (3.39%) record machine failure, confirming a severe class-imbalance condition typical of high-reliability infrastructure. Heat dissipation failure, power failure, and overstrain failure are the dominant failure flags, while failed records show materially higher torque, tool-wear, power-proxy, and wear-torque values than non-failed records. A random-forest benchmark achieves balanced accuracy of 0.897, recall of 0.800, F1-score of 0.805, and ROC-AUC of 0.984 on hold-out data, showing that predictive-maintenance signals can be translated into commissioning and O&M decision support when combined with disciplined engineering governance. The paper contributes a practical lifecycle framework, a data schema, a root-cause taxonomy, heat-map visualisations, model-performance evidence, and a preventive-maintenance control matrix suitable for U.S. critical-facility contexts.

Keywords: Commissioning Reliability, Critical Facilities, Preventive Maintenance, Root-Cause Analysis, Power Distribution, Automation Systems, Electronic Infrastructure, Predictive Maintenance, FMEA, AI4I 2020 Dataset.

I. INTRODUCTION

Critical facilities are not protected by asset capacity alone. Their resilience depends on whether electrical distribution, control logic, sensors, backup power, communications, and operator-facing systems are commissioned, documented, tested, maintained, and revalidated as an integrated system. A generator may be correctly sized but fail on transfer-sequence logic; a PLC may be functional but misconfigured after a software update; a power-distribution component may pass installation inspection but deteriorate under thermal, load, or harmonics stress; and a sensor network may produce readings without a reliable chain of custody into work orders, alarms, spares, and corrective action. For this reason, commissioning and maintenance should be treated as a single lifecycle discipline rather than two unrelated phases.

The national relevance of this problem is evident in the United States critical-infrastructure framework. CISA identifies 16 critical infrastructure sectors whose physical or virtual assets are considered vital to national security, national economic security, national public health or safety, or combinations of these interests (CISA, 2026). Energy infrastructure, transportation systems, healthcare facilities, water systems, data centres, public facilities and border-processing environments all rely on electrical and electronic systems that are operationally interdependent. Where power quality, automation control, monitoring, backup power and communication systems degrade, the operational consequence is often larger than the component that failed.

Commissioning standards and O&M guidance already recognise this lifecycle logic. ASHRAE describes commissioning as a quality-focused process for verifying and documenting that facility systems meet the owner's objectives and criteria (ASHRAE, 2019). DOE FEMP guidance treats O&M as a management system for operational efficiency, energy security, maintenance planning, diagnostics and lifecycle cost control (U.S. Department of Energy, 2010). NFPA 70B has become central for preventive maintenance of electrical, electronic and communication systems and equipment, while ANSI/NETA MTS-2023 gives field testing and inspection specifications for continued serviceability and reliability of electrical power equipment and systems (NFPA, 2023; NETA, 2023). The issue is therefore not the absence of guidance; it is the operational gap between guidance, commissioning evidence, maintenance work orders, condition data, and root-cause learning.

This paper addresses that gap by proposing a Commissioning Reliability and Preventive-Maintenance Model (CR-PMM). The model is designed for facility environments where automation, power distribution and electronic infrastructure must remain continuously available under high demand. The model is intentionally transferable: it does not depend on one facility, employer or proprietary maintenance dataset. Instead, it uses public predictive-maintenance data to demonstrate how operational signals can be converted into risk registers, fault classes, heat maps, maintenance triggers, and reliability governance routines.

II. RESEARCH PROBLEM AND OBJECTIVES

Many facilities still manage commissioning, troubleshooting and preventive maintenance as separate administrative activities. Commissioning teams validate design intent and hand over documents; operations teams inherit fault backlogs and spares constraints; maintenance teams respond to alarms and breakdowns; and management teams receive fragmented reports after reliability has already deteriorated. The result is a reactive system in which repeated failures are repaired but not learned from, where documentation exists but does not control future maintenance, and where early warning signals remain disconnected from decisions.

The central research problem is therefore: how can critical facilities integrate commissioning readiness, root-cause analysis and preventive maintenance into a single data-driven model that improves uptime, reduces repeat faults, strengthens safety and creates auditable maintenance intelligence across automation, electrical distribution and electronic systems?

The paper pursues five objectives:

- To develop a practical CR-PMM framework that links commissioning checks, issue prioritisation, fault isolation, deployment validation, corrective action and maintenance governance.
- To use a public Kaggle/UCI predictive-maintenance dataset to test how sensor-like variables and failure flags can inform root-cause prioritisation and preventive-maintenance triggers.
- To generate descriptive statistics, failure-mode tables, heat maps, model-performance evidence and feature-importance outputs relevant to maintenance decision-making.

- To translate the analytical findings into a facility-oriented preventive-maintenance control matrix for power distribution, automation and electronic infrastructure.
- To clarify the implementation limits of public benchmark data and show how the model should be validated against facility CMMS, SCADA, BMS, inverter, UPS, generator, switchgear and work-order records before live operational deployment.

III. LITERATURE REVIEW

3.1 Commissioning as lifecycle assurance

Commissioning is traditionally associated with design review, installation verification, functional performance testing, acceptance and handover. However, modern critical facilities require commissioning to extend beyond initial occupancy or go-live. Facility systems are cyber-physical: electrical distribution, controls, sensors, software, networked devices, UPS systems and backup generators interact dynamically. ASHRAE Guideline 0 frames commissioning as a process for verifying that systems meet owner requirements, while systems manuals and record documentation are intended to support training, operations, maintenance and future upgrades (ASHRAE, 2019).

The key weakness in many commissioning regimes is not the absence of checklists but the failure to convert commissioning evidence into living maintenance intelligence. A finding discovered during commissioning should not merely close an issue log; it should inform failure-mode libraries, spares strategy, preventive-maintenance intervals, testing scripts, trend monitoring, and post-occupancy performance verification. In critical facilities, the commissioning process should therefore become the first iteration of the O&M knowledge base.

3.2 Preventive, condition-based and predictive maintenance

Maintenance theory has evolved from corrective maintenance, where intervention follows failure, through preventive maintenance, where intervention follows calendar or usage intervals, toward condition-based and predictive maintenance, where intervention is triggered by actual degradation indicators. Mobley (2002) presented predictive maintenance as a route to reducing unscheduled downtime by using diagnostic techniques to identify deterioration before catastrophic failure. Jardine, Lin and Banjevic (2006) similarly positioned diagnostics and prognostics as the core of condition-based maintenance, while more recent reviews connect predictive maintenance with Industry 4.0, IoT, machine learning and explainability (Carvalho et al., 2019; Zonta et al., 2020; Molęda et al., 2023).

In facility-management contexts, predictive maintenance must be practical rather than merely algorithmic. Bouabdallaoui et al. (2021) show that facility-management maintenance can benefit from machine-learning approaches, but the operational value depends on data quality, system context, decision thresholds and integration with maintenance processes. For critical facilities, a model that produces a probability score without root-cause explanation, spares logic or work-order integration is insufficient. The goal is not prediction alone; it is controlled intervention.

3.3 Root-cause analysis, FMEA and electrical-maintenance governance

Root-cause analysis (RCA) seeks to explain why a failure occurred rather than only describing the failed component. Failure Modes and Effects Analysis (FMEA) is a complementary technique that identifies potential failure modes, their causes, consequences, occurrence likelihood, detection difficulty and severity. The risk-priority-number logic of FMEA has been used in critical technical systems because it gives engineers a structured basis for prioritisation. FMEA studies in smart-grid and microgrid contexts show its relevance for electrical distribution and cyber-physical energy systems (Akula and Salehfar, 2021; Akula, Salehfar and Behzadirafi, 2022).

Electrical maintenance governance reinforces this approach. NFPA 70B addresses preventive maintenance for electrical, electronic and communication systems, while ANSI/NETA MTS-2023 provides testing specifications for electrical power equipment and systems (NFPA, 2023; NETA, 2023). In practice, these standards should be

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operationalised through a facility-specific maintenance basis: equipment criticality, environment, duty cycle, thermal exposure, loading, age, prior findings, manufacturer requirements, safety exposure and consequence of failure.

3.4 Energy-system resilience and facility availability
Energy resilience literature has increasingly linked distributed generation, PV, BESS, controls, digital twins and predictive maintenance. NREL's PV O&M best-practice guidance emphasises performance monitoring, periodic inspection, preventive maintenance, documentation, safety and lifecycle cost management in PV and storage systems (NREL, 2018). IEA PVPS guidance similarly treats climate, soiling, inspection and O&M planning as determinants of long-term reliability (IEA PVPS, 2022). Although this paper focuses on broader automation, power and electronic infrastructure, the O&M principles used in PV and microgrid systems are transferable to critical facilities because the same lifecycle risks appear: component degradation, performance drift, documentation gaps, insufficient spares, and weak feedback from operating data.

Recent work by Kabera et al. (2026) develops an ML-augmented PV-grid-BESS microgrid framework for 100 percent reliability in critical facilities, while Matenga et al. (2025a) examine renewable-energy integration and smart-grid optimisation using mechatronics and AI. Matenga, Mupa and Musemwa (2025b) also connect AI-driven mechatronic systems to energy efficiency in U.S. manufacturing. These works support the proposition that commissioning reliability should not be separated from energy optimisation, asset intelligence, digital controls and lifecycle performance.

IV. METHODOLOGY

The research design is an applied engineering-management study using secondary public data, descriptive analytics, heat-map visualisation, supervised classification and framework synthesis. The empirical work is not intended to certify a live facility. It is intended to demonstrate a transferable analytical pattern: the way operating conditions, failure flags and engineered indices can support commissioning reliability, root-cause prioritisation and preventive-maintenance planning.

4.1 Dataset selection
The dataset selected for the empirical analysis is the AI4I 2020 Predictive Maintenance Dataset, originally introduced by Matzka (2020), distributed by the UCI Machine Learning Repository and mirrored on Kaggle. The dataset is synthetic but designed to reflect real predictive-maintenance conditions encountered in industry. It contains 10,000 records and 14 columns, including unique identifier, product class, operating temperatures, rotational speed, torque, tool wear, machine-failure status and five failure-mode flags (UCI Machine Learning Repository, 2020; Kaggle, 2020).

Table 1. Dataset variables and critical-facility interpretation.

Dataset variable	Analytical meaning	Critical-facility interpretation
Type	Categorical asset or product class	Used as a proxy for facility asset criticality or quality class.
Air temperature [K]	Environmental / ambient operating condition	Maps to enclosure, room, cabinet or plant-room thermal context.
Process temperature [K]	Internal operating thermal condition	Maps to equipment internal thermal stress.
Rotational speed [rpm]	Mechanical operating speed	Used as proxy for moving assets such as fans, pumps, drives or motorised subsystems.
Torque [Nm]	Load stress	Maps to overload or high-demand operating states.
Tool wear [min]	Accumulated duty or wear	Maps to age, duty-cycle hours, maintenance interval or consumable degradation.
Machine failure	Binary failure target	Maps to failure/no-failure outcome in maintenance

		analytics.
TWF, HDF, PWF, OSF, RNF	Failure-mode flags	Used for root-cause classes: wear, heat dissipation, power, overstrain and random events.

Because real facility maintenance data often contains sensitive infrastructure and security information, public benchmark datasets are valuable for method development. However, synthetic benchmark results should be treated as a design proof rather than as direct evidence about a specific facility. Before operational use, the model must be calibrated with facility-specific CMMS, SCADA, BMS, UPS, generator, inverter, switchgear, PLC and work-order data.

4.2 Feature engineering

Four engineered variables were constructed to connect raw operating signals with maintenance decision-making:

- Temperature differential = process temperature minus air temperature, capturing thermal stress between equipment and ambient context.
- Power proxy = torque multiplied by rotational speed converted to angular-power form, capturing high/low mechanical operating demand.
- Wear-torque index = tool wear multiplied by torque, capturing the interaction between accumulated wear and operating load.
- Thermal load index = temperature differential multiplied by torque, capturing combined thermal and load stress.

These engineered variables are not presented as universal physics models for all facility assets. They are used as analogues for how facility engineers can convert raw sensor readings into decision-grade reliability indicators. In live critical facilities, equivalent indices may be derived from kW, kVA, harmonics, breaker temperature, inverter derating, UPS battery impedance, generator starts, transfer-switch cycles, PLC fault counts, network latency, alarm frequency, and motor current signatures.

4.3 Analytical procedures

The empirical procedure consisted of: descriptive statistics, failure-rate profiling, failure-mode distribution analysis, heat-map visualisation, correlation analysis, and supervised classification. Logistic regression, random forest and gradient boosting were fitted using a 75/25 stratified train-test split. Given the class imbalance, balanced accuracy, recall, F1-score, ROC-AUC and precision-recall AUC were reported alongside ordinary accuracy. The purpose was not to maximise a competition metric; it was to evaluate whether maintenance-relevant signals can support early warning and prioritisation.

V. EMPIRICAL RESULTS

5.1 Descriptive statistics

Table 2. Descriptive statistics for operating and engineered variables.

Variable	Mean	Std. dev.	Min	25%	Median	75%	Max
Air temperature [K]	300.00	2.00	295.30	298.30	300.10	301.50	304.50
Process temperature [K]	310.01	1.48	305.70	308.80	310.10	311.10	313.80
Temp differential [K]	10.00	1.00	7.60	9.30	9.80	11.00	12.10
Rotational speed [rpm]	1,538.78	179.28	1,168.00	1,423.00	1,503.00	1,612.00	2,886.00
Torque [Nm]	39.99	9.97	3.80	33.20	40.10	46.80	76.60
Tool wear [min]	107.95	63.65	0.00	53.00	108.00	162.00	253.00
Power proxy [W]	6,279.74	1,067.42	1,148.44	5,561.18	6,271.03	7,003.00	10,469.92
Wear-torque index	4,314.66	2,826.57	0.00	1,963.65	4,012.95	6,279.00	16,497.00
Thermal load index	399.96	107.73	36.86	325.36	398.82	470.45	857.92

The dataset has a low observed failure rate: 339 failures out of 10,000 records, or 3.39 percent. This low base rate is not a weakness; it is characteristic of high-reliability environments where failures are rare but consequential. In such conditions, ordinary accuracy can be misleading because a naive model that predicts no failure for every record would appear highly accurate while providing no preventive-maintenance value. The analysis therefore emphasises failure recall, balanced accuracy and precision-recall performance.

5.2 Failure-mode distribution and root-cause interpretation

Table 3. Failure-mode counts and commissioning-reliability interpretation.

Failure mode	Flagged records	Dataset rate	Critical-facility RCA interpretation
TWF	46	0.46%	Wear-related degradation. In facilities, this maps to consumables, moving components, fan bearings, contact wear, switchgear duty, UPS battery ageing and repeated actuator cycles.
HDF	115	1.15%	Heat dissipation failure. In facilities, this maps to cabinet ventilation, cooling-path obstruction, overloaded electronics, thermal derating, high room temperature and inadequate heat rejection.
PWF	95	0.95%	Power failure. In facilities, this maps to under/over-power states, transfer-sequence errors, inverter trips, breaker operation, voltage-quality issues and abnormal load conditions.
OSF	98	0.98%	Overstrain failure. In facilities, this maps to overload, sustained high torque, excessive demand, duty-cycle abuse and system operation outside design assumptions.
RNF	19	0.19%	Random failure. In facilities, this maps to stochastic events, weakly observed defects, latent installation errors or incidents not explained by the main sensor variables.

Heat dissipation failure, power failure and overstrain failure dominate the failure-mode profile. For critical facilities, this pattern supports a commissioning strategy that does more than verify basic on/off functionality. It should test thermal behaviour under load, power-transfer logic under abnormal states, controls response under high demand, protective-device coordination, alarm fidelity, fallback modes, and maintenance access to components that are most exposed to thermal or load stress.

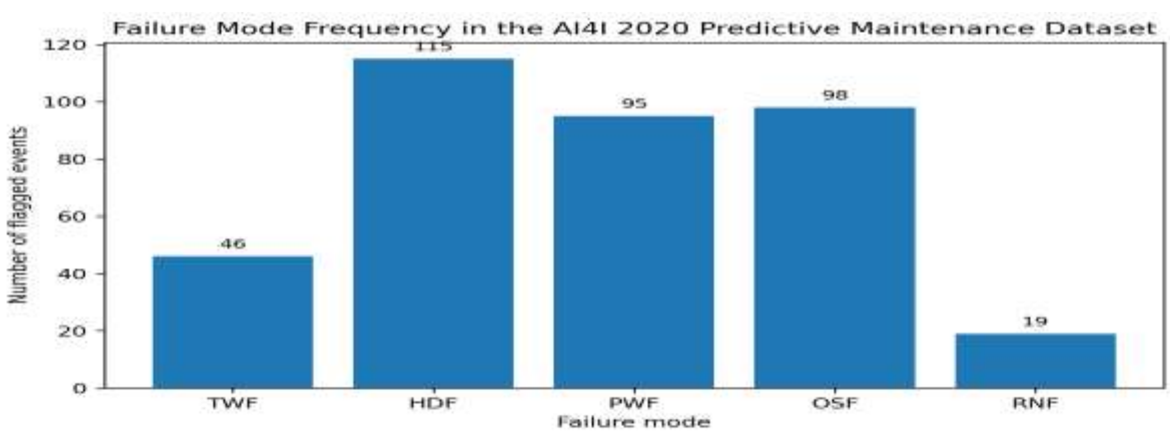

Figure 1. Failure-mode frequency in the AI4I 2020 predictive-maintenance dataset

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5.3 Failure rate by class and operating-condition comparison

Table 4. Failure rate by product / asset class.

Class	Records	Failures	Failure rate
H	1,003	21	2.09%
L	6,000	235	3.92%
M	2,997	83	2.77%

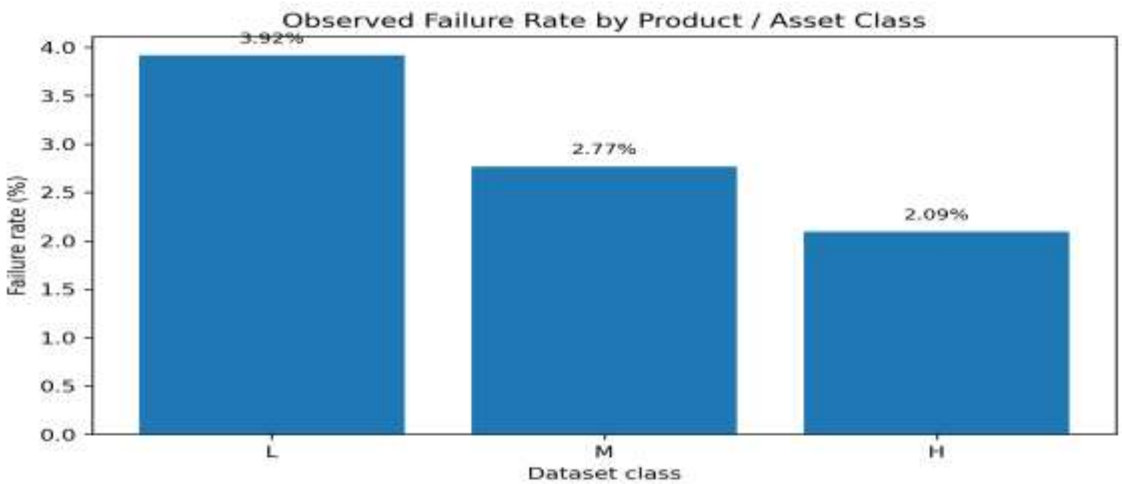

Figure 2. Observed failure rate by product / asset class.

Table 5. Operating-condition means in non-failed versus failed records.

Variable	No-failure mean	Failure mean	Difference	% difference
Air temperature [K]	299.97	300.89	0.91	0.3%
Process temperature [K]	310.00	310.29	0.29	0.1%
Temp differential [K]	10.02	9.40	-0.62	-6.2%
Rotational speed [rpm]	1,540.26	1,496.49	-43.77	-2.8%
Torque [Nm]	39.63	50.17	10.54	26.6%
Tool wear [min]	106.69	143.78	37.09	34.8%
Power proxy [W]	6,244.55	7,282.82	1,038.27	16.6%
Wear-torque index	4,213.84	7,187.94	2,974.10	70.6%

The clearest separation between failed and non-failed records appears in torque, tool wear, power proxy and wear-torque index. Failed records also show lower average rotational speed but far higher speed dispersion, which is consistent with both low-speed/high-torque stress and high-speed/high-power stress being important operating regimes. A facility maintenance model should therefore avoid one-dimensional thresholds. The interaction between load, speed, thermal behaviour, accumulated duty and component class is more useful than any isolated signal.

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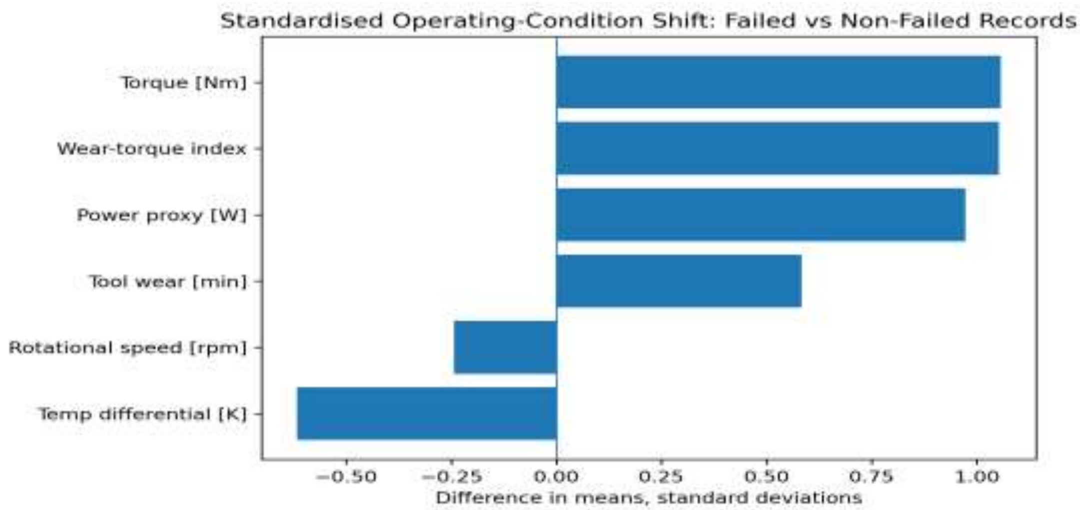

Figure 3. Standardised operating-condition shift between failed and non-failed records.

5.4 Heat-map analysis

Heat maps are useful because they convert operating regimes into visual priority zones for maintenance planning. In a live facility, a heat map may combine load, temperature, vibration, alarm frequency, starts/stops, electrical current, voltage sag, cabinet temperature, communication latency or maintenance backlog. In the AI4I benchmark, the torque-speed heat map shows how failure intensity concentrates in operating regimes that would otherwise be hidden by aggregate failure rates.

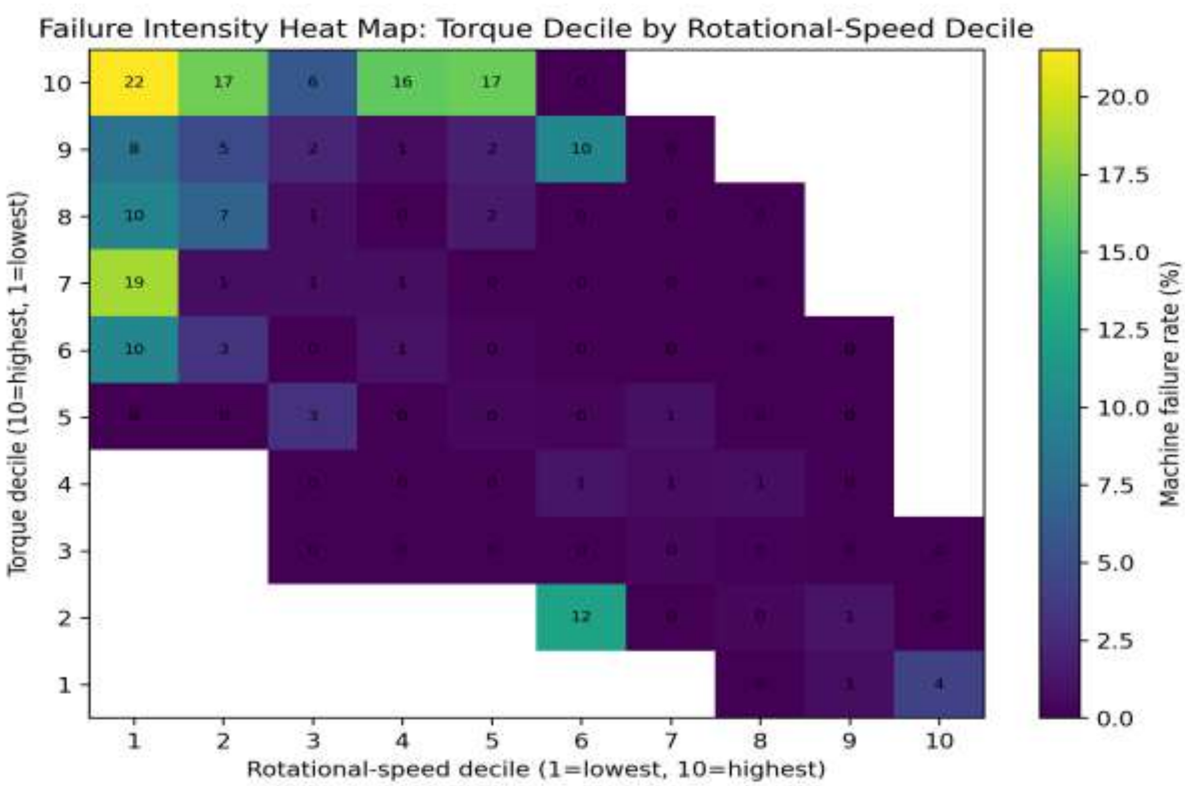

Figure 4. Failure intensity heat map by torque decile and rotational-speed decile. Values represent failure rate percentages in each operating bin.

The most important lesson from the heat map is not the exact value in any one cell; it is the commissioning logic. Functional testing should include normal load, peak load, low-speed/high-load states, high-speed states and transition states. Preventive maintenance should be triggered by risk regimes, not only by calendar intervals. Where torque-like load indicators and speed-like operational indicators jointly move into high-risk zones, the facility should escalate inspection, thermal checking, electrical testing, spares review and corrective-action verification.

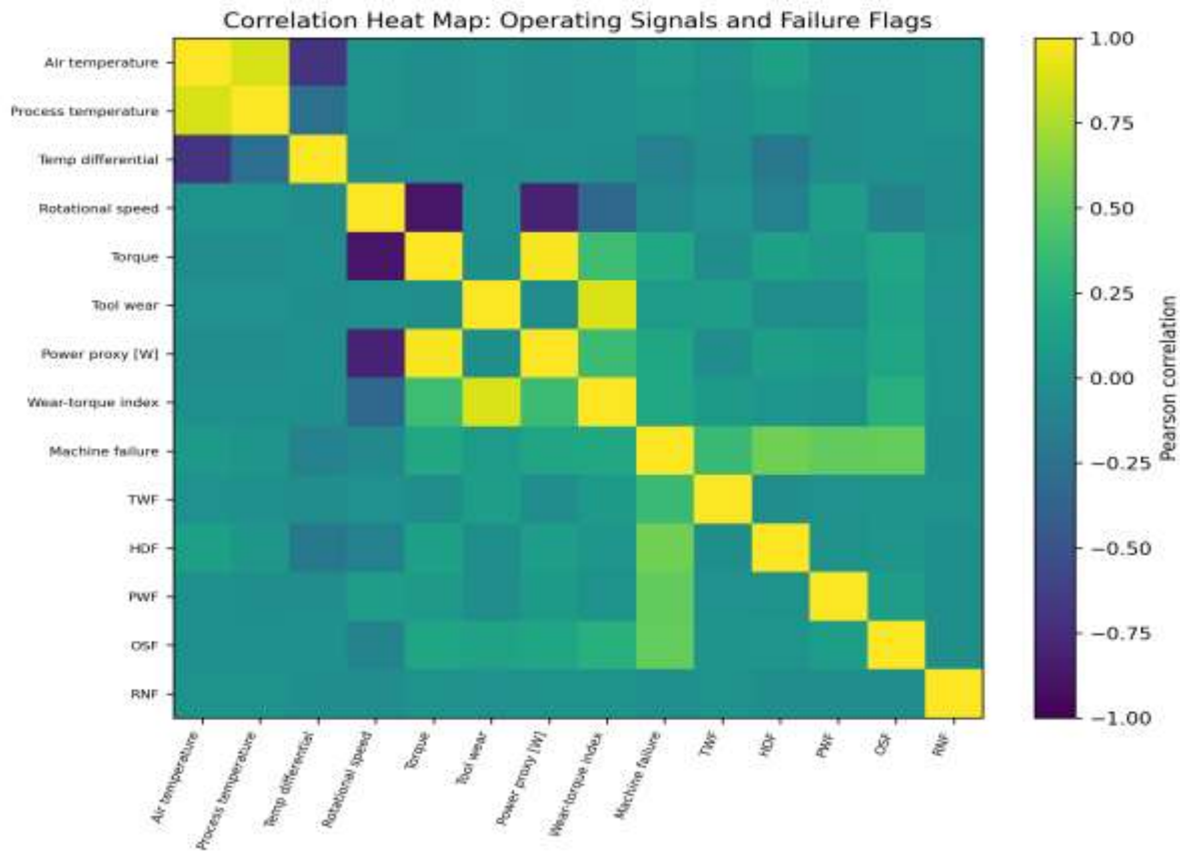

Figure 5. Correlation heat map for operating signals and failure flags.

Table 6. Model performance on stratified hold-out

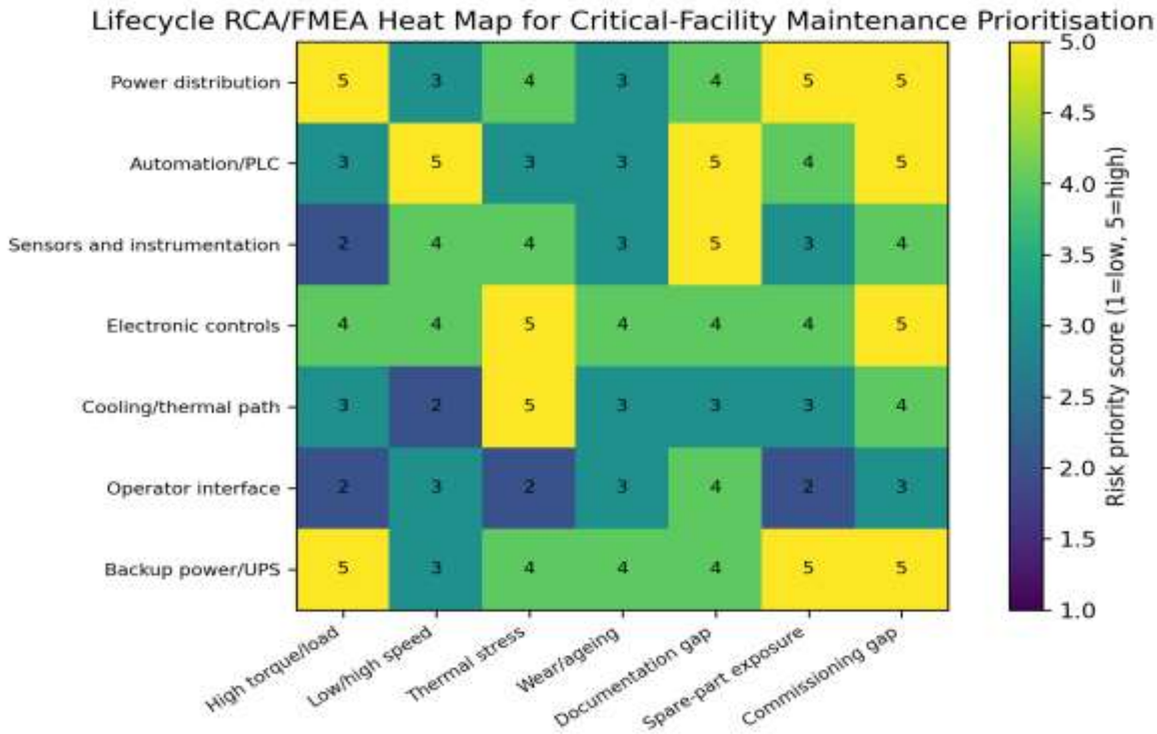

Figure 6. Lifecycle RCA/FMEA heat map for critical-facility maintenance prioritisation.

5.5 Predictive-maintenance model performance

Table 6. Model performance on stratified hold-out test data.

Model	Accuracy	Balanced accuracy	Precision	Recall	F1-score	ROC-AUC	PR-AUC
Logistic regression	0.861	0.849	0.176	0.835	0.290	0.922	0.421
Random forest	0.987	0.897	0.810	0.800	0.805	0.984	0.837
Gradient boosting	0.994	0.906	1.000	0.812	0.896	0.974	0.910

The gradient-boosting model delivers the highest F1-score in this run, while the random-forest model provides a strong balance between recall, precision and interpretability through feature importance. Logistic regression produces high recall but at the cost of low precision, which would generate too many false alarms in a live maintenance environment unless used as a broad screening layer. For critical facilities, the appropriate operating point depends on consequence of failure. A hospital emergency-power system may tolerate more false positives than a low-criticality convenience subsystem; a border-control automation system may require high recall during peak operations but tighter precision during routine shifts.

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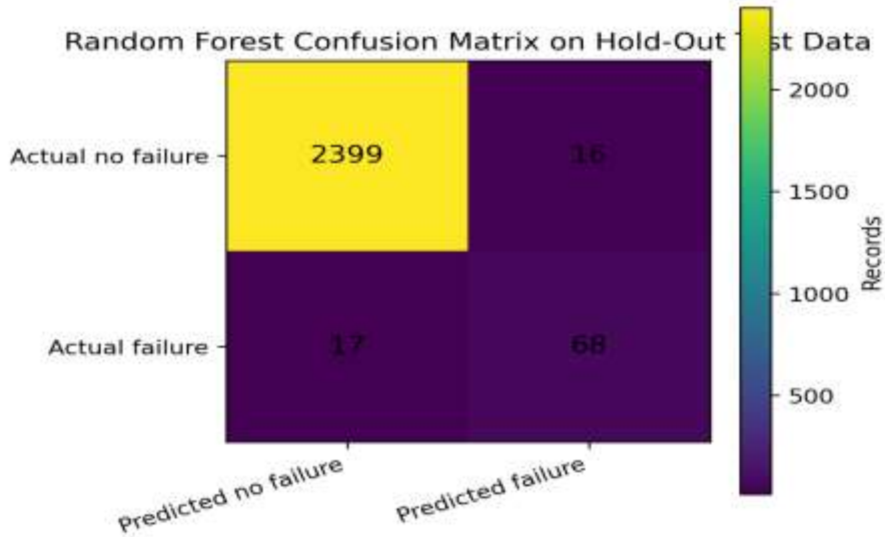

Figure 7. Random-forest confusion matrix on hold-out test data.

Table 7. Random-forest feature importance ranking.

Feature	Relative importance
Rotational speed [rpm]	0.192
Power proxy [W]	0.174
Torque [Nm]	0.165
Tool wear [min]	0.128
Wear-torque index	0.118
Temp differential [K]	0.087
Thermal load index	0.074
Air temperature [K]	0.037
Process temperature [K]	0.018
Type_L	0.004

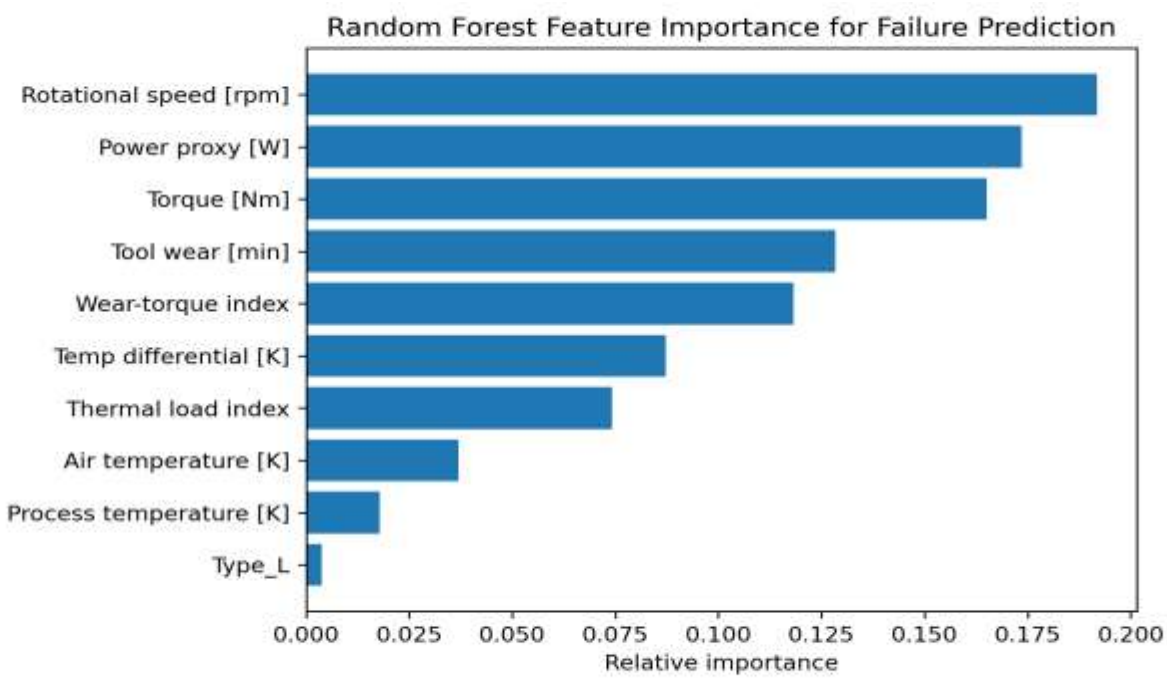

Figure 8. Random-forest feature importance for failure prediction.

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VI. THE COMMISSIONING RELIABILITY AND PREVENTIVE-MAINTENANCE MODEL (CR-PMM)

The empirical analysis supports a practical CR-PMM built around eight linked functions. The model is designed for automation, power-distribution and electronic infrastructure, but it is adaptable to PV, BESS, UPS, generator, transfer-switch, BMS, SCADA, network, sensor, access-control, electronic-ticketing, AV and mission-support systems.

Table 8. CR-PMM lifecycle functions and deliverables.

CR-PMM function	Purpose	Key deliverables
1. Asset criticality classification	Classify systems by safety, service continuity, regulatory, customer, revenue and recovery-time impact.	Criticality register; RTO/RPO target; failure consequence rating.
2. Commissioning readiness baseline	Validate installation, configuration, functional tests, alarms, interlocks, user acceptance, documentation and safety requirements before handover.	Commissioning checklist; functional test script; punch-list closure evidence.
3. Issue-backlog triage	Prioritise defects by impact, recurrence, safety, system dependency and operational timing.	Risk-ranked issue log; SLA by class; open/close ageing report.
4. Root-cause taxonomy	Tag each incident using standard cause categories: thermal, power, mechanical, control logic, sensor, network, human-process, documentation or spares.	RCA coding dictionary; five-why form; cause-consequence map.
5. Preventive-maintenance trigger design	Create calendar, usage, condition, risk-zone and event-based triggers.	PM matrix; condition thresholds; inspection intervals; test requirements.
6. Spares and readiness planning	Map high-risk failure modes to critical spares, supplier lead times, substitutions and on-site storage requirements.	Critical spares list; minimum stock levels; lead-time risk register.
7. Performance validation after intervention	Verify that corrective action removed the root cause, not only the symptom.	Post-maintenance test record; repeat-fault rate; re-commissioning evidence.
8. Stakeholder risk communication	Translate technical risk into operational decisions for owners, operators, vendors, safety teams and management.	Reliability dashboard; exception report; escalation protocol; lessons-learned log.

6.1 Root-cause taxonomy for critical-facility systems

A useful RCA taxonomy must be simple enough for technicians to use but detailed enough to support analytics. Table 9 proposes a practical taxonomy that can be embedded into a CMMS, ticketing system, commissioning punch list or reliability dashboard.

Table 9. Root-cause taxonomy for automation, power and electronic infrastructure.

Cause family	Typical symptoms	Required evidence	Preventive / corrective action
Thermal	Cabinet overheating; inverter derating; blocked ventilation; high room temperature; cooling fan failure.	Temperature trend; thermal image; alarm log; environmental reading; airflow check.	Improve ventilation, clean filters, recalibrate derating thresholds, replace fans, verify heat path.
Power quality / distribution	Voltage sag; overload; breaker trip; poor coordination; loose	Power-quality meter; trip log; load profile; infrared	Torque terminal, balance load, test breaker/relay, update

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	termination; abnormal transfer sequence.	scan; maintenance test report.	sequence, review coordination study.
Control logic / automation	PLC logic conflict; configuration drift; failed interlock; software update mismatch.	Version log; ladder logic review; simulation result; event history; operator report.	Restore baseline, version-control logic, test interlocks, approve changes, re-commission sequence.
Sensor / instrumentation	Drifted reading; dead sensor; calibration lapse; communication noise.	Calibration certificate; sensor reading comparison; loop test; network packet loss.	Calibrate/replace sensor, improve shielding, verify I/O mapping, update calibration schedule.
Mechanical / duty cycle	High cycling; actuator wear; fan bearing degradation; pump stress; vibration.	Runtime hours; start count; vibration trend; current signature; work-order history.	Adjust duty cycle, replace wear parts, lubricate, align, rebalance, revise PM interval.
Human-process / documentation	Incomplete SOP; undocumented change; weak handover; incorrect setpoint.	SOP review; training record; change ticket; commissioning checklist gap.	Revise SOP, retrain operators, implement change control, update systems manual.
Spares / vendor exposure	No critical spare; long lead time; obsolete component; vendor dependency.	Inventory record; supplier quote; lead-time log; substitution analysis.	Set minimum stock, approve alternate parts, negotiate SLA, build critical spares kit.

6.2 Preventive-maintenance control matrix

Table 10. Preventive-maintenance control matrix for critical facilities.

Subsystem	Maintenance routine	Trigger conditions	Evidence required	Reliability benefit
Power distribution	Monthly visual inspection; quarterly thermal scan; annual maintenance testing; event-based inspection after trip.	Abnormal heat, nuisance trips, voltage deviation, load growth, harmonics, loose terminations.	NFPA 70B maintenance basis; NETA MTS field-testing logic; power-quality trend.	Reduced forced outage, safer equipment operation, improved serviceability.
Automation / PLC / control panels	Quarterly logic backup; six-month interlock test; annual simulation and change-control review.	Configuration drift, failed interlock, repeated faults, unexplained alarms.	Version-control register; I/O checks; change tickets; functional test scripts.	Reduced repeat faults and faster fault isolation.
Sensors and instrumentation	Calibration by criticality; loop testing; sensor redundancy check; drift trending.	Out-of-range readings, inconsistent readings, dead bands, alarm mismatch.	Calibration certificate; BMS/SCADA trend; loop test result.	Improved alarm fidelity and more reliable decisions.
UPS and backup power	Battery impedance testing; transfer-test schedule; generator start tests; fuel and load-bank evidence.	Transfer delay, battery degradation, failed start, abnormal runtime, overload.	UPS report, ATS log, generator controller data, fuel quality record.	Improved emergency-power availability and recovery confidence.
Electronic devices and	Firmware inventory; power-cycle resilience	Packet loss, device hang, intermittent	Network log, firmware baseline,	Reduced hidden downtime and

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communications	test; network monitoring; environmental checks.	failure, update mismatch, overheating.	uptime records, environmental trend.	improved operator interface reliability.
CMMS/ticketing and documentation	Weekly backlog review; monthly RCA trend review; quarterly spares review; annual systems-manual update.	Repeated issues, stale tickets, missing closeout evidence, missing spares.	Issue log, RCA codes, closeout photos, spares inventory, training records.	Converted maintenance history into reliability intelligence.

VII. DISCUSSION

The results support a practical proposition: commissioning reliability is strongest where operational signals, failure modes and maintenance actions are traceable across the asset lifecycle. In the AI4I benchmark, failure is rare, but failure probability rises sharply in particular operating regimes. This mirrors critical facilities, where most assets operate normally most of the time, yet risk concentrates during peak load, thermal stress, repeated cycling, abnormal transfer events, unresolved alarms and deferred maintenance.

The analysis also shows why root-cause discipline matters. A generic failure label does not tell a maintenance manager what to do. A heat dissipation failure points toward thermal paths, cabinet ventilation, cooling fans, enclosure temperature and derating logic. A power failure points toward load, transfer logic, under/over-power conditions, protective devices and power-quality analysis. An overstrain failure points toward duty-cycle limits, overload, actuation stress and design assumptions. A random failure flag reminds the engineer that not all faults are captured by the available variables, and that commissioning must preserve space for field judgement, inspection evidence and incident narrative.

For critical facilities, a predictive score should therefore become a work-order input rather than a standalone management dashboard. The score should generate questions: what asset is affected, what consequence follows, what failure mode is most plausible, what test will confirm it, what spare is needed, what operational window is available, what risk is created if action is deferred, and who needs to be informed? This is the difference between data visualisation and maintenance governance.

The CR-PMM also places documentation at the centre of reliability. Documentation is often treated as a closeout artifact; in reality, it is a control. Commissioning scripts, as-built drawings, functional tests, alarm matrices, firmware baselines, spares lists, SOPs, calibration certificates and maintenance reports are the memory of the facility. When these records are incomplete, repeated faults become more likely because the next technician must rediscover what the previous technician already learned.

VIII. IMPLEMENTATION BLUEPRINT FOR CRITICAL FACILITIES

A facility can implement CR-PMM in phases without waiting for a fully mature predictive-maintenance platform. The first phase is governance: classify asset criticality, build a systems manual, create a root-cause coding dictionary and standardise issue prioritisation. The second phase is data quality: ensure that CMMS, SCADA, BMS, generator, UPS, PV inverter, access-control, network and ticketing data are timestamped, linked to asset IDs and capable of supporting trend analysis. The third phase is analytics: build heat maps, exception rules, dashboards and simple supervised models. The fourth phase is operational integration: link risk scores to work orders, spares, inspection scripts and re-commissioning evidence. The fifth phase is continuous improvement: review repeat faults, false alarms, near misses, deferred maintenance, spares gaps and technician feedback.

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Table 11. CR-PMM implementation roadmap.

Timeframe	Priority actions	Expected output
0-30 days	Create asset criticality register; review commissioning documents; standardise issue taxonomy; define risk owner.	Criticality register; RCA code set; issue-priority matrix.
31-60 days	Map available data sources; clean asset IDs; identify missing sensors; review spares and maintenance intervals.	Data-source map; spares risk list; PM interval baseline.
61-90 days	Build first heat maps and reliability dashboard; train technicians on RCA coding; run backlog review.	Dashboard; technician guidance; repeat-fault report.
91-180 days	Pilot predictive or condition-based triggers on highest-criticality assets; validate with work-order results.	Pilot model; work-order integration; verification template.
181-365 days	Scale to additional subsystems; revise commissioning templates to include maintenance analytics; formalise annual re-commissioning.	CR-PMM standard; re-commissioning plan; annual reliability review.

IX. KEY PERFORMANCE INDICATORS

The model should be governed by metrics that matter to both engineering teams and facility leadership. Table 12 proposes KPIs that align commissioning, maintenance and operational risk communication.

Table 12. KPIs for commissioning reliability and preventive maintenance.

KPI	Definition	Target logic	Why it matters
Commissioning closure integrity	Closed commissioning issues with verified evidence / total closed issues.	>= 95% evidence-backed closure.	Prevents administrative closure without technical verification.
Repeat-fault rate	Repeated failures of same asset/cause within 30, 60 or 90 days.	Downward trend quarter-on-quarter.	Measures whether RCA removed the root cause.
Mean time to detect (MTTD)	Average time from abnormal condition to alarm/ticket creation.	Shorter for critical assets.	Measures monitoring and alarm fidelity.
Mean time to repair (MTTR)	Average time from ticket creation to verified restoration.	Segment by criticality.	Measures maintenance responsiveness and spares readiness.
Preventive-maintenance compliance	Completed PM tasks / scheduled PM tasks.	>= 95% for critical assets.	Measures discipline of scheduled maintenance.
Condition-trigger response	Triggered condition alerts reviewed within SLA.	>= 90% within SLA.	Measures usefulness of condition monitoring.
Critical spares coverage	Critical components with approved on-site spare or SLA / total critical components.	>= 90% for high-criticality assets.	Controls vendor and lead-time exposure.
Documentation freshness	Assets with current drawings, settings, firmware and SOPs / total critical assets.	>= 95%.	Protects organisational memory.
False-alarm burden	Non-actionable alerts / total alerts.	Reduce without lowering recall.	Controls alarm fatigue.
Re-commissioning coverage	Critical systems revalidated after change, event or annual cycle.	100% of qualifying changes/events.	Ensures changes do not erode baseline reliability.

X. LIMITATIONS AND FUTURE RESEARCH

The AI4I 2020 dataset is synthetic and represents an industrial process rather than a live critical facility. It is useful for method development because it contains labelled failure modes and interpretable operating variables, but it does not include the full complexity of facility operations: environmental changes, operator behaviour, maintenance history, vendor interventions, cyber events, spare-parts delays, power-quality waveforms, relay-test results, alarm floods, weather disruption, emergency scenarios or regulatory inspections. Accordingly, the empirical results should not be treated as direct performance claims about any real facility.

Future research should test CR-PMM against multi-source facility data. A stronger dataset would include time-stamped CMMS work orders, alarm logs, switchgear test records, UPS battery results, generator starts, ATS transfer tests, thermal images, PLC change logs, BMS trends, network downtime, parts inventory, technician narratives and post-maintenance verification results. Such a dataset would allow survival analysis, remaining-useful-life estimation, causal modelling, anomaly detection, natural-language processing of work orders, and cost-risk optimisation.

The second research frontier is explainability. Critical-facility engineers cannot rely on opaque recommendations when safety, public service and business continuity are at stake. Predictive models should show which signals drove the alert, what failure mode is plausible, what field test should be performed, what spare may be required, what operational risk exists if no action is taken, and what evidence will close the issue. This aligns with emerging research on explainable predictive maintenance and human-centred XAI (Pashami et al., 2023; Cummins et al., 2024).

XI. CONCLUSION

This paper developed a Commissioning Reliability and Preventive-Maintenance Model for automation, power distribution and electronic infrastructure in critical facilities. The model addresses a practical gap between commissioning documents, maintenance tickets, root-cause learning, spares readiness, condition monitoring and stakeholder risk communication. Using the public AI4I 2020 predictive-maintenance dataset, the empirical analysis showed that failure is rare but concentrated in identifiable operating regimes. Failed records display materially higher load, wear and power-proxy characteristics than non-failed records, while failure-mode patterns point to the importance of thermal, power, overstrain and wear-related causes.

The central contribution is not a single model score. It is an integrated engineering-management method that turns commissioning evidence into maintenance intelligence. Critical facilities should use commissioning not merely to declare readiness, but to establish the asset baseline, test abnormal operating regimes, validate alarm and control sequences, close issues with evidence, build root-cause libraries, define preventive-maintenance triggers, plan critical spares and communicate technical risk in operational terms. In this way, commissioning becomes the first layer of long-term reliability governance rather than the last step before handover.

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