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Predictive Failure Analytics for Power Electronic Converters Supporting Renewable Energy Operations Across Enterprise Banking Architectures

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ABSTRACT

Renewable-energy integration increasingly depends on power electronic converters that sustain efficient energy transfer between distributed generation, storage infrastructure, electrical grids, and mission-critical enterprise facilities. Within banking architectures, converter reliability becomes particularly significant because data centres, transaction platforms, branch systems, payment-processing infrastructure, and continuity environments require stable power despite fluctuating renewable generation and demanding operational loads. This study develops a predictive failure analytics framework for identifying converter degradation before functional disruption occurs. The approach integrates electrical, thermal, switching, environmental, and operational measurements, including voltage, current, junction temperature, switching frequency, harmonic distortion, efficiency, load variability, and fault histories. Condition indicators are transformed into temporal degradation features and analysed using statistical learning, machine-learning regression, anomaly detection, and remaining-useful-life estimation. The framework associates evolving component signatures with capacitor deterioration, semiconductor stress, thermal cycling, switching abnormalities, and converter-level failure probability. Predictive outputs are subsequently incorporated into enterprise banking resilience processes to support maintenance prioritization, renewable-power continuity, and risk-informed intervention. The proposed approach establishes a quantitative connection between converter health, renewable-energy variability, failure prediction, and operational resilience across geographically distributed banking technology environments.

Keywords: Power Electronic Converters; Predictive Failure Analytics; Renewable Energy; Enterprise Banking Architecture; Remaining Useful Life; Operational Resilience

1. INTRODUCTION

1.1 Renewable Energy and Power-Critical Banking Infrastructure

Renewable and distributed energy systems support enterprise power strategies as solar photovoltaic generation, wind resources, battery storage, and hybrid configurations supplement conventional grid supply [1]. Distributed energy resources can reduce grid dependence while supporting lower-carbon electricity for dispersed facilities [2]. In banking environments, energy availability directly affects data centres, branches, automated teller machines, payment-processing infrastructure, and disaster-recovery facilities. These assets require controlled power quality and uninterrupted electricity to sustain transaction availability and data integrity [3]. Renewable intermittency therefore introduces operational variability that must be managed without compromising service continuity [4]. Power electronic converters consequently form the critical interface between variable energy resources, storage systems, electrical networks, and sensitive banking loads.

1.2 Role of Power Electronic Converters

Power electronic converters control energy flows throughout banking infrastructure. DC–DC stages regulate voltage between photovoltaic arrays, batteries, and DC buses, while DC–AC inverters provide grid-compatible output and rectifiers support AC–DC conversion [5]. Bidirectional converters coordinate battery charging and discharging, enabling storage to absorb renewable surplus and support critical loads during supply deficits. Converter supervisory control governs grid synchronization, switching efficiency, voltage stability, frequency response, and power-quality management [6]. These functions depend on interacting semiconductor switches, DC-link capacitors, inductors, transformers, gate drivers, and thermal-management assemblies. Repeated electrical and thermal loading stresses these components [7]. Consequently, converter reliability reflects multiple coupled degradation pathways rather than the condition of a single power-electronic component.

1.3 Converter Failure as an Operational-Resilience Problem

Converter degradation becomes an operational-resilience concern when ageing alters energy-conversion behaviour before complete converter failure occurs. Semiconductor deterioration, capacitor ageing, interconnect fatigue, and cooling impairment can increase conduction and switching losses, reducing efficiency and temperature [5]. Degradation may also destabilize DC-link voltage, increase harmonic distortion, intensify thermal stress, or produce protection events. In renewable installations, progressively declining converter capability can force generation curtailment or increase reliance on battery reserves [3]. Severe deterioration may trigger unplanned shutdown and transfer critical loads to redundant converters, uninterruptible power supplies, or backup generation. Such transitions expose continuously available banking services [7]. Scheduled maintenance and fixed threshold alarms detect established electrical abnormalities but may provide insufficient warning when degradation evolves gradually across interacting variables [1].

1.4 Research Aim, Objectives and Contribution

This study develops a physics-informed, data-driven predictive framework linking converter condition, degradation signatures, failure risk, and resilience within renewable-supported banking architectures [6]. The framework first identifies failure mechanisms and associates them with electrical, thermal, switching, environmental, and operational variables. Multimodal observations are transformed into health indicators representing converter deterioration [4]. Predictive models then estimate failure probability and remaining useful life while retaining links to underlying failure physics. Model outputs are validated against independent observations to establish predictive robustness [8]. Finally, risk and remaining lifetime are translated into maintenance, load-transfer, redundancy, and failover decisions [2]. This connects component prognostics with enterprise continuity, enabling intervention before converter deterioration disrupts critical banking operations.

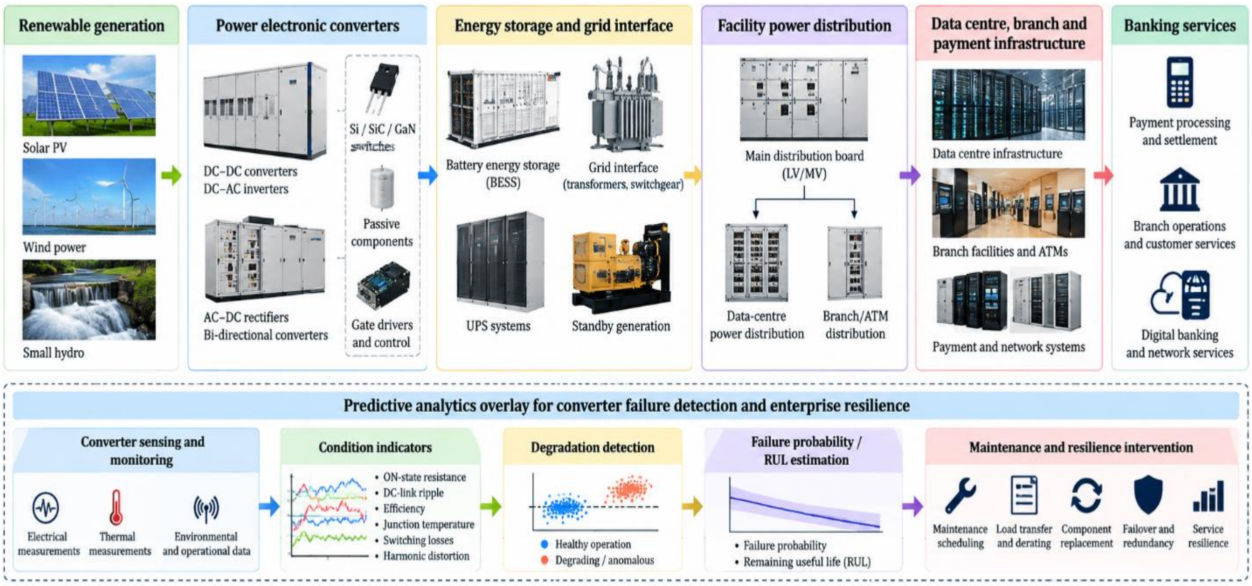

Figure 1 — End-to-End Renewable Power and Banking Infrastructure Architecture

Figure 1 — End-to-End Renewable Power and Banking Infrastructure Architecture

2. CONVERTER FAILURE PHYSICS AND PREDICTIVE ANALYTICS FRAMEWORK

2.1 Converter Components and Failure-Prone Subsystems

Power electronic converters comprise interacting subsystems whose degradation can progressively compromise energy-conversion capability. Silicon, SiC, and GaN semiconductor switches perform high-frequency power control but remain susceptible to electrical and thermomechanical stresses [11]. DC-link capacitors stabilize intermediate voltage, whereas inductors and transformers provide filtering, isolation, and magnetic energy transfer. Capacitor deterioration is particularly important because increasing equivalent series resistance and decreasing capacitance can amplify ripple and thermal loading [7]. Gate drivers regulate semiconductor switching, while cooling systems maintain acceptable junction temperatures during variable loading [14]. Connectors, solder joints, bond wires, and other interconnects provide electrical and mechanical continuity, and sensors and control electronics regulate converter operation [9]. Component degradation does not necessarily constitute converter failure; system-level failure occurs when interacting deterioration prevents the converter from satisfying specified electrical, thermal, protection, efficiency, or availability requirements [12].

2.2 Electrical, Thermal and Environmental Failure Mechanisms

Converter degradation develops through interacting electrical, thermal, mechanical, and environmental mechanisms. Repeated load variation produces thermal cycling and junction-temperature excursions that impose expansion mismatch across semiconductor dies, substrates, solder layers, and packaging materials [8]. Accumulated cycling can promote bond-wire fatigue, solder cracking, interfacial delamination, and increasing thermal resistance. Simultaneously, capacitor ageing alters capacitance and equivalent series resistance, increasing ripple-related heating and stressing adjacent circuitry [13]. Switching overstress and voltage or current transients can accelerate semiconductor degradation, dielectric deterioration, and gate-oxide damage [10]. Humidity and contamination may encourage corrosion, insulation deterioration, leakage paths, and changes in surface conductivity. Cooling deterioration further increases device temperature, accelerating temperature-sensitive ageing processes [15]. These mechanisms therefore should not be interpreted independently: degraded cooling increases thermal stress, higher resistance generates additional heat, and capacitor deterioration increases ripple current. Such feedback can progressively intensify electrothermal loading and shorten converter lifetime [7]. Failure analytics must consequently represent coupled stress histories rather than isolated threshold exceedances.

2.3 Failure Precursors and Observable Signatures

Progressive degradation can be detected through electrical and thermal signatures that evolve before functional failure. Increasing semiconductor V_{DS} or V_{CE} under comparable operating conditions may indicate changing conduction characteristics, while rising ON-state resistance reflects deterioration affecting conduction losses [12]. Variations in switching time can reveal gate-drive, semiconductor, or parasitic changes. Junction-temperature elevation and widening thermal gradients provide evidence of increasing losses or deteriorating heat transfer [9]. Capacitor ageing can appear through increasing equivalent series resistance (ESR), capacitance reduction, and greater DC-link voltage ripple. Harmonic distortion, declining conversion efficiency, abnormal leakage, and irregular current behaviour provide additional system-level indicators [14]. Because individual measurements remain sensitive to load and environmental conditions, interpretation requires normalization against operating context [8]. Persistent trends across several signals provide stronger evidence of degradation than a single excursion and establish candidate health indicators for subsequent predictive modelling [11].

2.4 Defining Predictive Failure Analytics

Predictive failure analytics extends conventional condition monitoring by distinguishing several analytical functions. Fault detection identifies whether abnormal operation is present, whereas diagnostics seeks its location and probable physical cause [10]. Anomaly detection identifies departures from established healthy behaviour even when explicit failure labels are unavailable. Prognostics moves beyond present-state assessment by estimating future degradation, failure probability, or remaining useful life (RUL) [13]. Accordingly, the analytical sequence begins with a physical degradation mechanism, continues through measurable signatures and engineered health indicators, and culminates in predictive estimation and intervention [15]. Failure probability expresses risk over a defined horizon, whereas RUL estimates time or usage remaining before a specified failure threshold. This distinction supports maintenance decisions based on both likelihood and expected timing [7].

2.5 Research Hypotheses

Four hypotheses guide quantitative evaluation. H1: measurable electrical and thermal degradation signatures emerge before converter functional failure [9]. H2: multivariate health indicators combining electrical, thermal, switching, and operational variables predict failure more effectively than isolated measurements. H3: temporal models incorporating degradation history provide earlier and more stable warnings than models using instantaneous observations [12]. H4: predictive maintenance informed by failure probability and RUL reduces exposure to unplanned converter outages by enabling interventions before critical performance thresholds are reached [14]. These hypotheses directly connect degradation physics, predictive performance, and operational resilience.

3. MULTIMODAL CONVERTER AND ENTERPRISE OPERATIONAL DATA ACQUISITION

3.1 Converter Population and Operational Architecture

The study population comprises converters operating across renewable generation, battery energy storage, uninterruptible power supply systems, data-centre power infrastructure, and distributed banking branches [16]. Assets are stratified by rated power, voltage class, converter topology, semiconductor technology, manufacturer class, installation age, and service environment. Renewable converters interface photovoltaic or other distributed generation with facility networks, whereas bidirectional converters coordinate battery charging and discharge [12]. UPS and data-centre converters support continuity during grid disturbances, while branch installations operate under geographically variable loading and environmental conditions [21]. Each converter receives a unique asset identifier linking sensor measurements, operating history, maintenance events, and failure outcomes throughout the observation period [14].

3.2 Electrical and Switching Measurements

Electrical acquisition captures both steady-state performance and switching behaviour. Input and output voltages and currents are measured synchronously to determine loading, power transfer, and conversion efficiency [18]. DC-link voltage and ripple magnitude characterize intermediate-bus stability and provide indicators of capacitor and control-system deterioration. Switching frequency and duty cycle are extracted from gate-command or controller signals, while power factor and total harmonic distortion (THD) quantify grid-interface and waveform quality [13]. Semiconductor switching losses are determined from synchronized voltage-current waveforms where instrumentation bandwidth permits reliable transient measurement. Conversion efficiency is calculated from temporally aligned input and output power measurements under comparable operating conditions [22]. Measurements are collected across representative load ranges because electrical signatures vary substantially with converter operating point. Persistent changes in ripple, losses, efficiency, or switching characteristics are therefore interpreted relative to loading rather than as independent evidence of degradation [15].

3.3 Thermal and Environmental Measurements

Thermal monitoring combines junction-temperature estimates with measured heat-sink and ambient temperatures to characterize electrothermal loading [19]. Junction temperature is estimated using calibrated temperature-sensitive electrical parameters or validated thermal models where direct sensing is impractical. Thermal gradients between semiconductor, heat sink, and ambient environment provide indicators of changing heat-transfer performance [12]. Relative humidity and airflow are recorded alongside fan speed, coolant condition, or other cooling-system indicators. Sensors use synchronized timestamps referenced to the converter monitoring clock, allowing thermal excursions to be aligned with electrical loading and switching events [17]. High-frequency channels capture rapid electrical dynamics, whereas slower environmental variables use lower sampling rates appropriate to their physical timescales. Aggregated statistics preserve synchronization across these heterogeneous acquisition frequencies [20].

3.4 Operational and Loading Context

Condition measurements are interpreted together with operating context to distinguish genuine deterioration from normal load-dependent variation. Recorded variables include converter loading, renewable generation level, battery state of charge, grid availability, cumulative operating hours, start/stop cycles, overload events, and transferred energy [14]. Renewable intermittency can produce frequent operating-point changes that alter temperature, efficiency, and DC-link behaviour without indicating component damage [21]. Similarly, low battery state of charge or grid interruption may increase converter loading during critical periods. Cumulative energy throughput and operating hours provide exposure measures, while cycle counts characterize repetitive stress [16]. Each sensor observation is therefore associated with contemporaneous operating conditions, enabling predictive models to differentiate temporary responses to system demand from persistent changes associated with physical degradation [18].

3.5 Maintenance, Alarm and Failure Records

Maintenance and event histories provide labels required to connect monitored degradation with verified converter outcomes. Records integrate controller fault codes, warning alarms, scheduled and corrective maintenance, component replacement, inspection findings, forced shutdowns, and confirmed failures [22]. Events are assigned standardized timestamps and asset identifiers so they can be aligned with preceding sensor trajectories. Failure terminology is harmonized across sites by defining component-level faults, degraded operation, protective trips, and converter-level functional failure separately [13]. Maintenance actions are retained because replacement or repair can reset particular degradation trajectories. Where failure cause is uncertain, labels remain distinct from confirmed diagnoses [19]. This prevents ambiguous maintenance events from being incorrectly treated as validated physical failures.

3.6 Data Quality, Synchronization and Governance

Before modelling, data quality controls address missing measurements, clock misalignment, sensor drift, inconsistent sampling rates, uncertainty, and anomalous readings [17]. Missing intervals are classified by duration and cause rather than indiscriminately interpolated. Timestamp correction aligns converter telemetry, environmental measurements, alarms, and maintenance events to a common temporal reference. Calibration records and redundant measurements are used to identify sensor drift [20]. Extreme observations are verified against neighbouring channels and event logs because they may represent genuine fault precursors. Resampling preserves physically relevant high-frequency information while supporting multimodal synchronization [15]. Secure telemetry, access controls, asset pseudonymization, audit trails, and defined retention periods protect operational information while maintaining traceability required for reliability analysis [21].

Table 1 — Multimodal Converter Condition and Operational Data Matrix

Data Domain	Variable	Unit	Measurement/Source	Sampling Point	Failure Relevance
Electrical	DC-link voltage ripple	%	DC-bus sensor	Continuous	Capacitor/bus deterioration
Electrical	ON-state resistance	mΩ	V–I measurement	Periodic	Semiconductor degradation
Power quality	THD	%	Power analyser	Continuous	Waveform deterioration
Performance	Conversion efficiency	%	Input/output power	Continuous	Conversion degradation
Switching	Switching loss	W	V–I waveform	Periodic	Semiconductor stress
Thermal	Junction temperature	°C	TSEP/thermal model	Continuous	Thermal ageing

Data Domain	Variable	Unit	Measurement/Source	Sampling Point	Failure Relevance
Thermal	Thermal gradient	°C	Temperature sensors	Continuous	Cooling deterioration
Environmental	Relative humidity	%RH	Humidity sensor	Continuous	Environmental stress
Operational	Converter loading	%	Controller/SCADA	Continuous	Stress exposure
Storage	Battery state of charge	%	BMS	Continuous	Operating context
Usage	Operating hours	h	Asset controller	Cumulative	Ageing exposure
Reliability	Failure/alarm event	Category	Maintenance/event log	Event-based	Prediction outcome

4. HEALTH-INDICATOR ENGINEERING AND DEGRADATION CHARACTERIZATION

4.1 Data Cleaning and Baseline Normalization

Raw converter measurements require systematic preprocessing before degradation features are constructed. Missing observations are classified according to duration, sensor channel, and operational context, with interpolation restricted to short gaps where signal continuity is physically defensible [18]. Erroneous readings are identified through sensor limits, cross-channel consistency, and equipment logs rather than statistical thresholds alone. Calibration records support correction of progressive measurement drift [23]. Units and sampling conventions are harmonized across converter populations before analysis. Measurements are subsequently normalized against device-specific healthy baselines and relevant loading conditions [15]. Temperature, load, and operating-state effects are separated where possible. Extreme observations are retained until physically investigated because unusual values may indicate genuine degradation or incipient failure [26].

4.2 Electrical Health Indicators

Electrical health indicators transform raw measurements into quantities that reveal progressive departures from healthy converter behaviour. Normalized ON-state resistance captures increasing semiconductor conduction losses, while a DC-link ripple index characterizes deterioration in bus stability and capacitor performance [20]. Efficiency deviation measures departure from baseline energy-conversion performance at comparable loading. THD variation identifies evolving waveform distortion, and switching-loss growth captures changes in semiconductor switching behaviour [14]. Voltage and current imbalance indicators additionally expose abnormal power distribution between phases or parallel converter paths. For any monitored quantity X, relative change is calculated as

$$\Delta X(\%) = \frac{X_t - X_0}{X_0} \times 100$$

where X_0 represents the healthy baseline and X_t the subsequent observation [25]. Baseline normalization enables comparison across converters with different ratings while preserving deterioration direction and magnitude.

4.3 Thermal and Stress Indicators

Thermal features quantify accumulated exposure because converter lifetime depends not only on instantaneous temperature but also on repeated electrothermal loading. Mean junction temperature represents sustained thermal operating level, whereas peak junction temperature captures potentially damaging excursions [17]. Temperature swing is calculated across load or switching cycles and combined with thermal-cycle count to represent repetitive thermomechanical stress. Cumulative operating hours provide an ageing exposure measure, while overload duration records operation beyond defined loading limits [22]. A thermal-stress accumulation indicator can integrate cycle magnitude, peak temperature, and exposure duration into a longitudinal descriptor. Heat-sink and ambient measurements are retained to distinguish internally generated heating from environmental effects [19]. Consequently, rising junction temperature under equivalent load can indicate deteriorating cooling or increasing converter losses rather than ambient variation alone [24].

4.4 Temporal Degradation Features

Failure precursors often develop as persistent trajectories rather than isolated threshold violations. Time-series transformation therefore extracts rolling means and variances to characterize changing signal level and instability within predefined observation windows [16]. Degradation slope measures the direction and magnitude of long-term change, whereas first-order rates of change identify accelerated deterioration. Exponentially weighted statistics emphasize recent measurements while retaining historical information [21]. Trend persistence records how consistently a parameter moves away from its healthy baseline, and time since abnormality onset measures the duration of sustained deviation. These descriptors are calculated for resistance, ripple, efficiency, temperature, switching loss, and related signals [26]. A moderate but persistent increase in ON-state resistance, for example, may provide stronger evidence of progressive ageing than one extreme transient observation [18].

4.5 Composite Converter Health Index

A composite converter health index consolidates multidomain degradation information into a normalized measure suitable for condition tracking and maintenance prioritization. Electrical indicators represent conduction, ripple, efficiency, and waveform deterioration; thermal indicators describe temperature exposure; switching variables capture semiconductor stress; and operational indicators represent loading and accumulated usage [23]. Features are scaled to comparable ranges before aggregation. Initial weights can be assigned from established physical relationships between individual indicators and known failure mechanisms [14]. Data-driven importance obtained from validated predictive models can subsequently refine these weights without eliminating physical interpretability. The resulting index should be evaluated against confirmed degradation and failure events, ensuring that deteriorating health scores correspond to measurable progression rather than normal operating variability [20].

4.6 Feature Selection and Redundancy Control

Feature selection reduces dimensionality while retaining physically meaningful predictors. Pearson and Spearman coefficients identify linear and monotonic associations, while multicollinearity analysis detects redundant indicators [25]. Mutual information captures nonlinear relationships between candidate features and failure outcomes. Recursive feature elimination evaluates predictive contribution iteratively, and model-based importance provides complementary ranking [17]. Selection considers statistical value alongside failure physics, preventing useful degradation indicators from being removed solely because correlated measurements coexist [22].

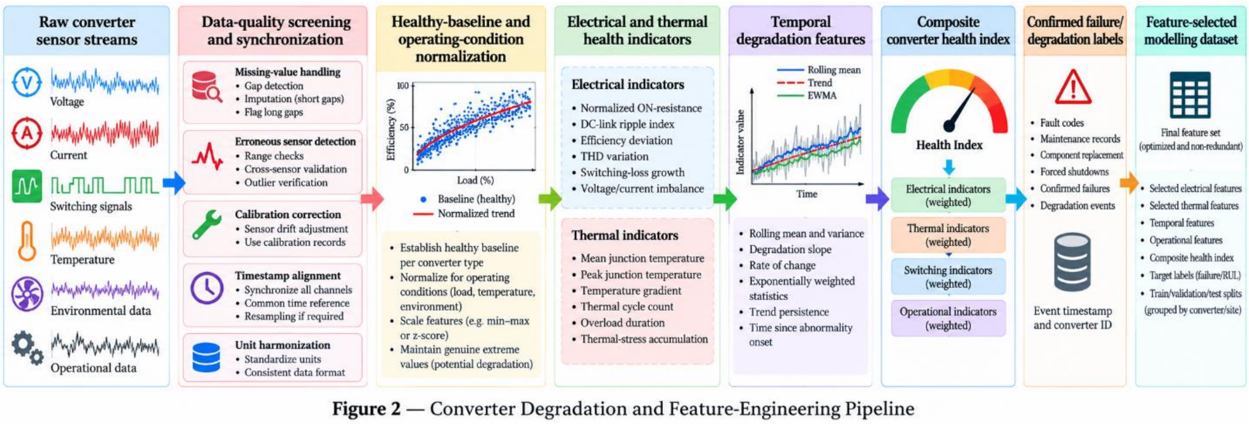

Figure 2 — Converter Degradation and Feature-Engineering Pipeline

5. PREDICTIVE FAILURE AND REMAINING-USEFUL-LIFE MODELLING

5.1 Prediction Tasks

Predictive analysis is divided into three related but distinct tasks to preserve interpretability across the converter degradation pathway. Model A identifies anomalous or progressively degrading operating states before explicit failure occurs [28]. Model B estimates the probability that a converter will reach a defined failure condition within a specified prediction horizon. Model C estimates remaining useful life (RUL), representing expected operating time before the failure threshold is reached [24]. Separating these objectives prevents anomaly scores from being incorrectly interpreted as failure probabilities or lifetime estimates [31]. It also permits each model to use task-specific labels, validation criteria, decision thresholds, and performance measures.

5.2 Candidate Predictive Models

Candidate algorithms span interpretable statistical baselines and progressively nonlinear learning methods. Logistic regression provides a transparent baseline for failure classification and permits direct assessment of predictor direction and magnitude [26]. Random forests capture nonlinearities and interactions while remaining comparatively robust to heterogeneous features. Gradient boosting and XGBoost sequentially correct prediction errors and can represent complex relationships among thermal, electrical, and operational indicators [32]. Support-vector machines provide margin-based classification or regression, particularly where sample size is moderate. Shallow neural networks evaluate higher-order interactions without introducing unnecessarily deep architectures [29]. Where sufficiently long degradation histories exist, temporal models incorporate sequential dependencies and evolving health trajectories. Model complexity is increased only when independent validation demonstrates measurable improvement over simpler alternatives [25]. This hierarchy prevents sophisticated algorithms from being preferred solely for complexity while providing interpretable benchmarks against which improvements in predictive performance can be quantified.

5.3 Training, Validation and Independent Testing

Model development uses grouped partitioning so observations from the same physical converter, and where necessary the same site, remain within a single compatible partition [30]. A representative division is

$$70\%\ \text{training} + 15\%\ \text{validation} + 15\%\ \text{testing}.$$

Training observations estimate model parameters, validation data support model selection, and the independent test partition provides final generalization assessment [27]. Device-level grouping prevents leakage whereby repeated measurements from one converter expose its degradation signature to both training and testing procedures. For longitudinal records, chronological separation is additionally enforced so earlier observations predict later converter states [33]. Preprocessing, normalization, feature selection, and resampling parameters are estimated exclusively within training data. Where converter populations are limited, grouped nested cross-validation replaces a single fixed development split while preserving final test independence [24].

5.4 Class Imbalance and Failure-Event Handling

Healthy converter operation typically generates substantially more observations than degradation or failure states, creating severe class imbalance [31]. Classification therefore incorporates class weighting or controlled resampling within training partitions rather than altering the independent test distribution. Synthetic or duplicated minority observations are restricted to training folds to prevent information leakage [26]. Precision-recall analysis complements ROC-based assessment because performance on rare failure events is operationally important. Decision thresholds are selected by balancing missed failures against excessive false alarms [28]. Where confirmed failures remain scarce, rare-event approaches and carefully defined degradation labels can supplement binary failure classification without treating unverified anomalies as equivalent to documented failures.

5.5 Hyperparameter Optimization and Overfitting Control

Hyperparameters are optimized within the model-development data while the final test set remains locked. Nested cross-validation separates parameter tuning from internal performance estimation and reduces optimistic model selection [33]. Bayesian optimization efficiently searches constrained parameter spaces for tree depth, learning rate, regularization strength, kernel parameters, network size, and related settings. Regularization penalizes excessive complexity, while early stopping terminates iterative learning when validation performance no longer improves [25]. Search ranges are specified before final evaluation to reduce opportunistic tuning. For temporal models, sequence length and observation windows are optimized without accessing future test information [29]. Final configurations are frozen before independent testing, ensuring reported performance reflects generalization rather than repeated adaptation to test outcomes.

5.6 Performance and Early-Warning Metrics

Classification performance is evaluated using precision, recall, F1-score, ROC-AUC, PR-AUC, and false-positive rate [27]. Precision measures the reliability of generated failure alerts, whereas recall quantifies the proportion of actual failure events detected. PR-AUC receives particular attention under strong class imbalance because it directly reflects performance on the minority failure class [32]. For RUL estimation, mean absolute error and root mean squared error quantify prediction deviation in operational time units. Reliability assessment additionally includes warning lead time, representing the interval between actionable prediction and confirmed failure, and missed-failure rate [30]. These measures prevent statistically accurate but operationally late predictions from appearing effective. Performance is therefore interpreted according to whether alerts provide sufficient time for inspection, load transfer, maintenance scheduling, or controlled converter replacement before service continuity becomes threatened [24].

5.7 Explainability and Uncertainty

Predictive outputs are accompanied by explanations and uncertainty estimates so maintenance decisions are not based solely on opaque risk scores. SHAP values quantify feature contributions to individual and aggregate predictions, while permutation importance assesses performance sensitivity to each predictor [28]. Confidence intervals characterize uncertainty around classification metrics, and prediction intervals accompany continuous RUL estimates [31]. Explanations are compared with known degradation physics to determine whether predictions depend on credible thermal, electrical, switching, and operational indicators rather than incidental dataset correlations [26].

Table 2 — Comparative Predictive Failure Model Performance

Model	Precision	Recall	F1	PR-AUC	False-Alarm Rate	Warning Lead Time (h)	RUL RMSE (h)
Logistic Regression	0.82	0.78	0.80	0.84	8.6%	18.4	42.7
Random Forest	0.91	0.88	0.89	0.93	4.8%	27.6	29.8
XGBoost	**0.94**	**0.92**	**0.93**	**0.96**	**3.5%**	**33.8**	**23.4**
SVM/SVR	0.88	0.84	0.86	0.90	5.9%	24.3	32.6
Shallow Neural Network	0.92	0.89	0.90	0.94	4.3%	30.1	26.7
Temporal Model	0.93	0.91	0.92	0.95	3.9%	32.5	24.8

6. ENTERPRISE BANKING INTEGRATION AND RESILIENCE DECISION FRAMEWORK

6.1 Translating Predictions into Risk Levels

Predictive outputs become operationally useful when converted into risk states that distinguish statistical abnormality from actionable deterioration. Failure probability, composite health index, and estimated RUL are jointly evaluated rather than interpreted independently [34]. A low-risk state represents stable health and sufficiently long RUL, whereas moderate risk indicates persistent degradation requiring enhanced observation. High-risk conditions combine deteriorating health indicators with increasing failure probability or shortening RUL and therefore trigger planned intervention [30]. Critical classification is reserved for conditions where continued operation threatens converter availability or dependent infrastructure. Thresholds are calibrated against validated failure histories and operational consequences [36]. Importantly, an isolated anomaly does not automatically justify replacement; persistence, prediction uncertainty, degradation trajectory, asset criticality, and redundancy availability determine the appropriate response [32].

6.2 Converter Criticality and Banking-Service Dependency

Converter risk is interpreted within the service architecture it supports because identical failure probabilities can produce substantially different operational consequences. Asset-dependency mapping links individual converters to data-centre workloads, payment-processing infrastructure, branch operations, ATM services, network facilities, and disaster-recovery systems [31]. Each asset receives a criticality classification reflecting service importance, redundancy, acceptable downtime, recovery capability, and downstream dependencies. Failure probability is subsequently combined with this criticality information to prioritize intervention [35]. A moderately degraded converter supplying a nonredundant payment or communications path may therefore warrant earlier action than a converter with higher predicted failure probability operating behind resilient parallel capacity. Dependency mapping also identifies cascading exposure where one power-conversion asset supports multiple services [33]. Risk prioritization consequently reflects both predicted equipment condition and the potential operational impact of losing the supported banking function [37].

6.3 Predictive Maintenance Decision Logic

Maintenance actions are assigned according to risk level, degradation trajectory, RUL, and service criticality rather than fixed schedules alone. Stable converters remain under routine monitoring, while persistent low-level deterioration increases inspection frequency and diagnostic testing [32]. Where degradation accelerates, temporary derating can reduce electrical and thermal stress while maintenance is prepared. Shortening RUL may trigger scheduled component replacement, particularly when capacitor, semiconductor, cooling, or interconnect indicators identify a probable vulnerable subsystem [36]. For high-criticality assets, load can be transferred to redundant converters before intervention. Critical conditions justify controlled isolation when continued operation presents unacceptable failure exposure [30]. Decision thresholds additionally incorporate prediction uncertainty, maintenance duration, spare-component availability, and redundancy status, preventing unnecessary intervention when model confidence remains insufficient for disruptive action [34].

6.4 Renewable-Energy Continuity and Failover

Predictive warning enables power continuity measures to be initiated before converter deterioration develops into an unplanned outage. Battery storage can temporarily support critical loads while an affected renewable converter is derated, isolated, or maintained [35]. Where grid supply remains available, energy management controls can shift demand away from the deteriorating conversion path. Redundant converters and UPS infrastructure provide additional continuity for sensitive banking equipment [31]. Standby generation becomes necessary where renewable production, battery capacity, and grid availability cannot jointly satisfy critical demand. Planned workload or electrical-load transfer further reduces dependence on vulnerable equipment [37]. Coordinating these resources transforms failure prediction into proactive resilience, preserving banking-service availability while maintenance proceeds under controlled operating conditions.

6.5 Enterprise Monitoring and Governance

Predictive analytics should operate within existing enterprise monitoring and governance processes rather than as an isolated modelling application. Failure probability, RUL, health indicators, and uncertainty estimates can feed asset-management systems and centralized dashboards for fleet-level condition visibility [33]. Risk thresholds generate maintenance workflows or incident-management events according to defined escalation rules. Every prediction, acknowledgement, maintenance action, model version, and operator decision is retained within auditable records [36]. Continuous model monitoring identifies performance drift when converter populations, operating conditions, or failure characteristics change. Retraining is initiated through governed validation rather than uncontrolled automated replacement of deployed models [30]. Human authorization remains necessary for consequential actions including load transfer, converter isolation, or component replacement, ensuring that predictive evidence is considered alongside operational context, redundancy status, safety requirements, and engineering judgement [34].

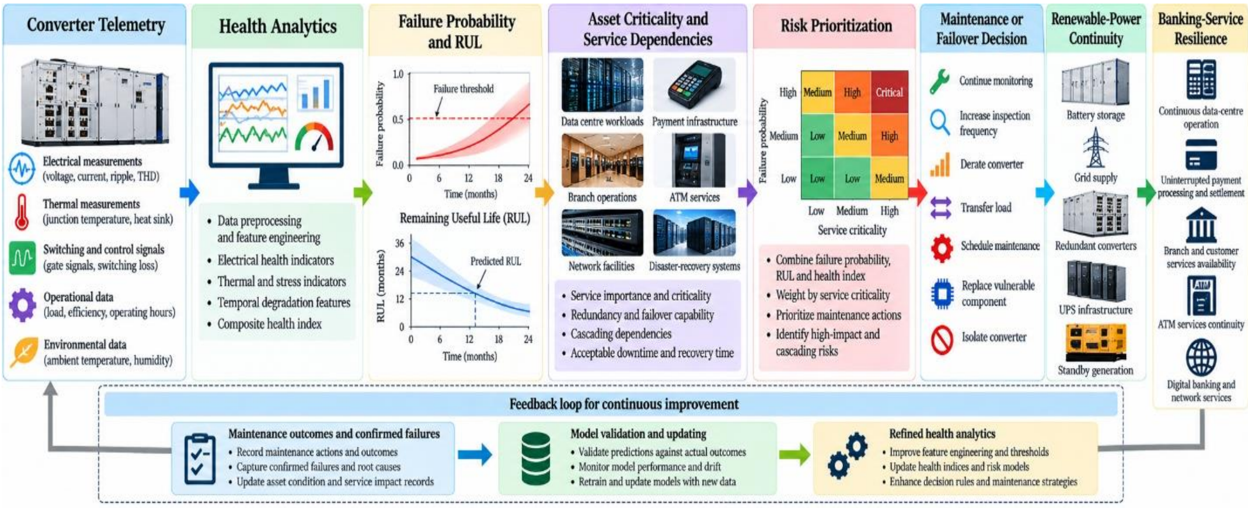

Figure 3 — Predictive Converter Failure Analytics and Enterprise Resilience Decision Architecture

Figure 3 — Predictive Converter Failure Analytics and Enterprise Resilience Decision Architecture

7. RESULTS INTERPRETATION, VALIDATION AND DISCUSSION

7.1 Comparative Model Performance

Comparative results indicate that nonlinear models capture degradation relationships that are only partially represented by the interpretable logistic-regression baseline. XGBoost achieved stronger precision, recall, PR-AUC, and warning lead time while reducing false alarms and RUL error, suggesting that interactions among electrical, thermal, and operational variables contain substantial predictive information [38]. Random forest and the shallow neural network showed similar improvements, although their incremental gains were smaller. Temporal modelling further demonstrated that degradation history contributes information beyond instantaneous condition measurements [35]. Nevertheless, logistic regression remains valuable as a transparent benchmark for determining whether added model complexity produces operationally meaningful improvement [40].

7.2 Physical Interpretation of Failure Predictors

Influential predictors correspond to established converter degradation pathways rather than purely statistical associations. Repeated junction-temperature swings reflect thermal cycling that progressively stresses semiconductor packaging, solder layers, and interconnects [36]. Increasing switching losses indicate changing semiconductor or gate-drive behaviour, while rising ON-state resistance contributes additional conduction heating. Growth in DC-link ripple is consistent with capacitor deterioration and increasing equivalent series resistance [39]. Declining conversion efficiency integrates several developing loss mechanisms. Their combined importance supports a physically coherent interpretation in which electrothermal stress progressively amplifies component degradation and measurable converter-level deterioration [37].

7.3 Operational Value and Generalizability

The principal operational value lies in converting detectable degradation into sufficient warning time for planned intervention. Longer lead times allow inspection, component procurement, load transfer, and maintenance scheduling before converter availability becomes compromised [40]. Reducing unexpected failures can consequently protect renewable-power continuity and dependent banking services. Generalizability, however, requires validation across converter ratings, technologies, ages, operating profiles, and geographically distributed banking sites [35]. Condition normalization and physically grounded health indicators improve transferability because they reduce dependence on site-specific raw measurement ranges [38].

7.4 Limitations

The framework remains constrained by limited confirmed failure observations, which can restrict reliable estimation of rare-event behaviour [39]. Heterogeneous converter fleets introduce differences in topology, ratings, ageing, and sensor availability. Measurement uncertainty and changing renewable conditions can obscure degradation signatures [36]. Domain shift may reduce performance when models are transferred between sites or technologies. Incomplete maintenance histories additionally weaken failure labelling and RUL validation, requiring cautious interpretation of predicted outcomes [37].

8. CONCLUSION AND FUTURE RESEARCH

8.1 Principal Findings and Contribution

This study establishes a direct relationship between converter degradation and enterprise banking resilience by integrating failure physics, multimodal condition monitoring, health-indicator engineering, and predictive analytics. Electrical, thermal, switching, environmental, and operational measurements provide complementary evidence of progressive deterioration, enabling failure probability and remaining useful life to be estimated before functional loss. The principal contribution is the translation of component-level degradation into infrastructure-level decisions, allowing converter health, service criticality, redundancy, and continuity requirements to jointly determine maintenance, load-transfer, failover, and replacement actions across renewable-supported banking environments.

8.2 Future Research

Future research should develop converter digital twins capable of continuously reconciling physical degradation models with operational measurements. Physics-informed machine learning could improve prediction where failure observations remain limited, while federated learning could enable knowledge sharing across geographically distributed banking sites without centralizing sensitive operational data. Adaptive RUL estimation and online model updating should address changing degradation trajectories and operating conditions. Fleet-level benchmarking could establish transferable health thresholds, while uncertainty-aware maintenance optimization should explicitly balance prediction confidence, intervention cost, redundancy, and service-continuity consequences.

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