



Data-Driven Reliability Optimization of Renewable Energy Power Converters Through Predictive Fault Detection and Adaptive Control

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ABSTRACT

Increasing penetration of renewable energy is shifting power systems toward converter-dominated architectures in which operational reliability depends strongly on the condition and control of power electronic interfaces. Variable generation, switching stress, thermal cycling, environmental exposure, and fluctuating loading progressively degrade semiconductor devices, DC-link capacitors, gate drivers, and cooling assemblies, creating failure mechanisms that conventional threshold-based protection may identify too late. This study develops a data-driven reliability optimization framework integrating multimodal condition monitoring, predictive fault detection, degradation estimation, and adaptive converter control. Electrical, thermal, switching, environmental, and operational measurements are transformed into condition indicators capturing resistance growth, voltage ripple, switching-loss variation, thermal stress, efficiency deterioration, and temporal degradation trajectories. Machine-learning models estimate anomaly states, fault probability, and remaining useful life, while uncertainty and feature attribution establish prediction confidence and physical interpretability. These outputs subsequently inform adaptive control actions including switching adjustment, thermal-stress reduction, power derating, load redistribution, and operating-point reconfiguration. By closing the loop between degradation prediction and control response, the framework shifts converter reliability management from reactive fault handling toward condition-aware operation that suppresses accumulated stress, extends component lifetime, reduces unexpected outages, and improves renewable-energy availability.

Keywords: Renewable Energy Power Converters; Predictive Fault Detection; Adaptive Control; Reliability Optimization; Remaining Useful Life; Condition Monitoring

1. INTRODUCTION

1.1 Converter-Dominated Renewable Energy Systems

Global electricity systems are increasingly incorporating photovoltaic generation, wind power, battery energy storage, microgrids, and hybrid renewable configurations to reduce dependence on conventional generation and improve energy flexibility [1]. Unlike synchronous generation, many renewable resources interface with electrical networks predominantly through power electronic converters [2]. Photovoltaic arrays require DC–DC conversion and inversion, while variable-speed wind systems employ converter stages to regulate generated power. Battery installations additionally depend on bidirectional converters for controlled charging and discharge [3]. Consequently, higher renewable penetration increases converter responsibility for voltage regulation, frequency support, grid synchronization, and controlled power transfer. Within microgrids, converters coordinate distributed resources and maintain power quality under changing generation and demand [4]. Converter performance therefore increasingly determines renewable-system stability, controllability, efficiency, and availability.

1.2 Reliability Challenges in Renewable Energy Power Converters

Renewable-energy converters operate under dynamic conditions that continuously alter electrical and thermal stress. Solar irradiance fluctuations, wind variability, storage cycling, and changing demand produce repeated load transitions that modify converter current, switching losses, and junction temperature [5]. Semiconductor devices consequently experience thermal cycling and switching stress, promoting package fatigue, bond-wire deterioration, solder degradation, and changing conduction characteristics [2]. DC-link capacitors undergo ripple-current and temperature-dependent ageing, causing capacitance reduction and increasing equivalent series resistance. Gate-driver deterioration can modify switching behaviour, while repeated stress affects magnetic components and electrical interconnects [6]. Environmental temperature, humidity, contamination, and vibration further influence insulation, corrosion, and cooling performance. Deteriorating fans, heat sinks, or thermal interfaces increase operating temperatures and can accelerate temperature-sensitive ageing mechanisms [7]. Reliability therefore emerges from interacting degradation processes rather than isolated component failures.

1.3 Limitations of Reactive Fault Protection and Scheduled Maintenance

Conventional converter protection is primarily designed to respond when electrical variables exceed predefined safe operating limits. Overcurrent, overvoltage, overtemperature, and short-circuit protection can rapidly isolate equipment, but such mechanisms indicate abnormal operation rather than quantify progressive degradation [5]. Fixed alarm thresholds similarly provide limited information when resistance, ripple, temperature, or switching losses deteriorate gradually while remaining within permissible ranges. Periodic inspection and time-based component replacement introduce another limitation because converters experiencing different loading and environmental histories rarely age identically [8]. Premature replacement increases maintenance expenditure, whereas delayed intervention can permit degradation to progress toward forced shutdown. Predictive reliability management instead evaluates condition trajectories and precursor behaviour, providing an opportunity to identify developing deterioration and estimate future failure before conventional protective thresholds are reached [9].

1.4 Research Aim, Objectives and Contribution

This study develops a data-driven reliability framework integrating multimodal condition monitoring, degradation characterization, predictive fault detection, remaining useful life estimation, and adaptive converter control [3]. Electrical, thermal, switching, environmental, and operational measurements are transformed into health indicators representing progressive component deterioration. Predictive models subsequently estimate abnormal states, future fault probability, and RUL while preserving relationships with identifiable degradation mechanisms [9]. These predictions become control inputs rather than maintenance information alone. Adaptive responses can modify switching conditions, redistribute loading, constrain thermal excursions, or temporarily derate vulnerable converters when deterioration accelerates [6]. The principal contribution is therefore a closed-loop connection between predicted equipment health and converter operation. By actively reducing degradation-producing stress before critical failure develops, the framework targets longer component lifetime, fewer unexpected outages, and improved renewable-energy availability [2].

2. CONVERTER DEGRADATION PHYSICS AND RELIABILITY FRAMEWORK

2.1 Reliability-Critical Converter Components

Power electronic converter reliability depends on several electrically and thermally coupled subsystems. Semiconductor switches, including IGBTs, MOSFETs, and wide-bandgap devices, execute high-frequency power conversion and experience substantial electrical and thermal loading [11]. DC-link capacitors stabilize intermediate voltage and absorb ripple energy, making capacitance and equivalent series resistance important ageing parameters. Gate drivers determine switching transitions and device protection [8]. Inductors and transformers provide filtering, isolation, and energy transfer but remain vulnerable to insulation and thermal deterioration. Solder joints, bond wires, terminals, and busbar interconnects maintain electrical continuity [14]. Cooling assemblies regulate device temperature, while voltage, current, and temperature sensors supply feedback to control electronics responsible for modulation, protection, synchronization, and converter supervision [9].

2.2 Electrical and Switching Degradation Mechanisms

Electrical degradation originates when semiconductor and passive components repeatedly experience operating stresses approaching or exceeding their design conditions. Switching overstress, transient overcurrent, and overvoltage can damage semiconductor junctions, gate structures, and insulation systems [13]. Progressive gate-oxide deterioration can alter threshold behaviour, while increasing ON-state resistance raises conduction losses and produces additional heating. Changes in switching transitions similarly increase switching losses and device temperature [7]. In DC-link capacitors, sustained ripple current and elevated temperature accelerate electrolyte or dielectric degradation, increasing equivalent series resistance while reducing effective capacitance [15]. These changes weaken DC-bus stabilization and can increase voltage ripple. Semiconductor deterioration, gate-drive abnormalities, and capacitor ageing can subsequently distort converter voltage and current waveforms, increase harmonic content, reduce conversion efficiency, and impose additional electrical stress on neighbouring components [10].

2.3 Thermal, Mechanical and Environmental Stress

Thermal loading translates electrical losses into mechanical and material degradation. Repeated junction-temperature excursions create differential expansion among semiconductor dies, substrates, solder layers, bond wires, and packaging materials [12]. Accumulated cycling promotes solder fatigue, bond-wire lift-off, cracking, and interfacial delamination, progressively increasing electrical or thermal resistance. Degradation of thermal-interface materials further restricts heat transfer from semiconductor junctions to heat sinks [8]. Environmental humidity can promote moisture ingress, insulation deterioration, and electrochemical corrosion, while contamination creates conductive or thermally insulating deposits on converter assemblies. Mechanical vibration can loosen connections and accelerate fatigue in interconnects and mounted components [14]. Cooling deterioration caused by fan wear, blocked airflow, pump degradation, or heat-sink fouling elevates operating temperature. Higher temperature then accelerates temperature-dependent ageing, reinforcing interaction between cooling degradation and component deterioration [11].

2.4 From Component Degradation to Converter Failure

Converter failure develops through a progressive chain rather than appearing exclusively as an instantaneous event. Repeated electrical, thermal, mechanical, or environmental stress first alters component materials and interfaces [15]. Such degradation produces measurable precursors including increasing ON-state resistance, capacitor ESR growth, rising voltage ripple, abnormal switching losses, or changing thermal response. Continued deterioration subsequently reduces efficiency, voltage regulation, waveform quality, and thermal margins [9]. Functional deterioration may then activate alarms or protection systems before culminating in converter-level failure. These stages are strongly coupled: increasing resistance generates additional heat, elevated temperature accelerates material ageing, and deteriorating capacitors increase ripple stress on semiconductor devices [13]. Consequently, predictive analysis should evaluate interacting precursor trajectories rather than interpreting individual measurements as independent indicators of impending failure [10].

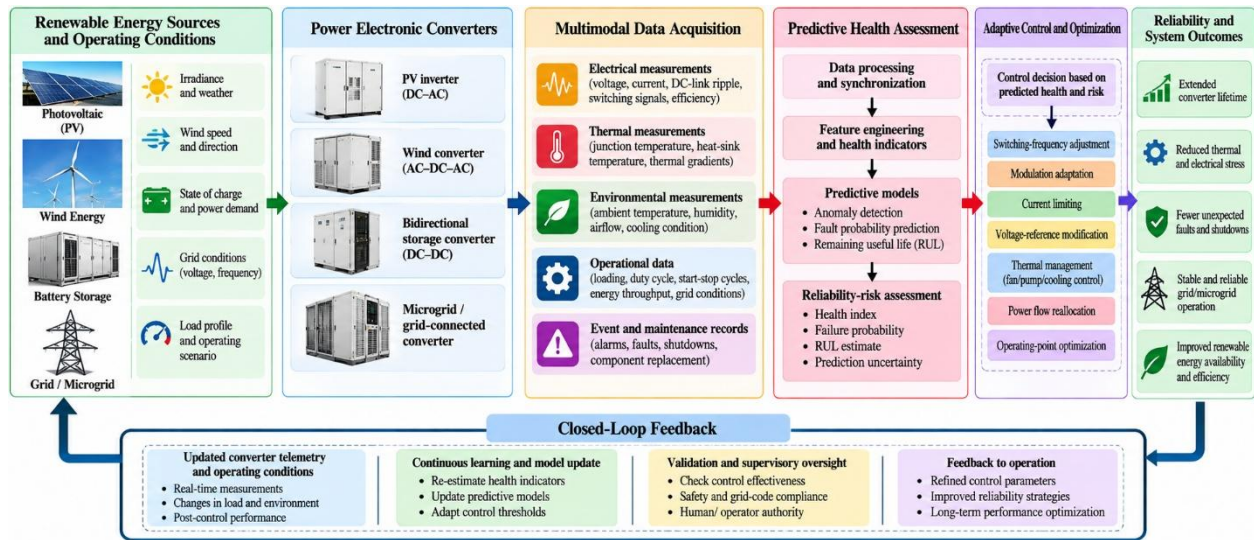


Figure 1 — Integrated Predictive Reliability and Adaptive Converter-Control Architecture

2.5 Reliability Optimization as a Closed-Loop Problem

Reliability optimization requires moving beyond passive condition observation toward closed-loop intervention. Monitored electrical, thermal, switching, and operational variables are converted into health indicators, degradation trajectories, failure probabilities, and remaining useful life estimates [12]. Predicted deterioration then becomes feedback for adaptive control rather than solely triggering maintenance notifications. Depending on degradation severity, control actions can adjust switching behaviour, redistribute power, limit current, modify thermal loading, or temporarily derate the converter [7]. Subsequent measurements determine whether intervention reduces damaging stress and stabilizes health indicators. This feedback structure enables converter operation to respond dynamically to evolving condition, directly linking predictive analytics with lifetime preservation and reliability improvement [14].

3. MULTIMODAL CONVERTER DATA ACQUISITION AND CONDITION MONITORING

3.1 Converter Population and Operating Profiles

The converter population should represent the principal power-electronic interfaces used across renewable-energy systems. Photovoltaic inverters regulate DC generation and grid injection, while wind converters accommodate variable generator speed and grid requirements [17]. Bidirectional storage converters manage battery charging, discharge, and DC-bus support, whereas microgrid and grid-connected converters coordinate distributed generation and loads [13]. Each asset is characterized by rated power and voltage, conversion topology, semiconductor technology, installation age, and operating duty cycle. Switching architecture and cooling configuration are additionally recorded because converters with similar ratings may experience different degradation rates [21]. This asset-level characterization provides the context required for meaningful cross-converter reliability comparisons.

3.2 Electrical and Switching Measurements

Electrical acquisition captures converter loading, energy-conversion quality, and emerging component deterioration. Synchronized input and output voltage and current measurements quantify instantaneous power transfer and expose abnormal regulation behaviour [19]. DC-link voltage ripple provides a degradation-sensitive measure of capacitor and bus stability, while switching frequency and duty cycle characterize semiconductor operating conditions. Power factor and total harmonic distortion quantify grid-interface performance and waveform deterioration [14]. ON-state voltage or

resistance is measured under comparable current and temperature conditions because progressive increases can indicate semiconductor or interconnect degradation. Where instrumentation bandwidth permits, synchronized device voltage and current waveforms are used to estimate switching energy and cumulative switching losses [22]. Conversion efficiency is calculated from aligned input and output power measurements. Measurements are interpreted relative to operating point because load variation can change losses, ripple, harmonics, and switching behaviour without necessarily indicating deterioration [16].

3.3 Thermal and Environmental Measurements

Thermal acquisition determines whether electrical operation is producing abnormal heat accumulation or progressive cooling deterioration. Semiconductor junction temperature is measured indirectly through calibrated temperature-sensitive electrical parameters or estimated using validated electrothermal models where direct sensing is impractical [20]. Heat-sink and ambient temperatures provide reference conditions for calculating thermal gradients across the heat-removal path. Increasing junction-to-heat-sink gradients under comparable loading can indicate deteriorating thermal interfaces or cooling effectiveness [15]. Relative humidity is recorded to characterize moisture exposure, while airflow measurements identify restrictions affecting forced-air cooling. Fan speed, coolant flow, pump condition, or equivalent cooling-system indicators are incorporated according to converter design [18]. Combining environmental and internal thermal measurements distinguishes externally driven temperature variation from heat generated by emerging electrical or thermal degradation.

3.4 Loading and Renewable Operating Context

Condition signals require operating context because renewable converters rarely experience stationary loading. Converter load is recorded alongside photovoltaic or wind generation to identify stress associated with fluctuating renewable input [13]. For storage converters, battery state of charge establishes whether charging or discharging conditions influence current and temperature behaviour. Grid voltage, frequency, availability, and disturbance events characterize external operating conditions [21]. Start-stop cycles capture repetitive energization stress, whereas overload duration measures exposure above normal loading limits. Cumulative operating hours represent chronological usage, and cumulative energy throughput provides a load-sensitive measure of lifetime utilization [17]. Linking these variables with condition measurements allows models to separate normal operating variation from persistent degradation-related change.

3.5 Fault, Maintenance and Component-Replacement Records

Historical event records connect measured precursor behaviour with confirmed reliability outcomes. Controller alarms and protection events are timestamped alongside forced shutdowns, diagnosed faults, inspections, and corrective maintenance [22]. Component-replacement records identify whether semiconductors, capacitors, gate drivers, cooling equipment, or interconnects were repaired or renewed. Maintenance interventions are retained because they can interrupt or reset degradation trajectories [16]. Where post-failure inspection establishes a physical cause, that diagnosis provides a higher-confidence label than an alarm code alone. Separating confirmed failures from unverified anomalies reduces label noise during predictive-model development [19].

3.6 Data Quality, Synchronization and Governance

Multimodal data require quality controls before reliability indicators are constructed. Missing intervals are classified by duration and cause, while erroneous readings are evaluated against physical limits, neighbouring channels, and event histories [18]. Calibration records support identification and correction of sensor drift. Common timestamps align electrical waveforms, thermal measurements, operating states, alarms, and maintenance events despite heterogeneous sampling frequencies [14]. Resampling preserves degradation-relevant information without unnecessarily discarding high-frequency switching behaviour. Each observation retains converter identity, sensor provenance, calibration status, and processing history to ensure traceability [20]. Secure access controls, audit records, and defined retention policies protect operational telemetry while preserving the longitudinal histories required for reliability analysis.

Table 1 — Multimodal Converter Reliability Data Matrix

Data Domain	Representative Variable	Unit	Acquisition Source	Reliability Significance
Electrical	DC-link voltage ripple	%	DC-bus sensor	Capacitor/bus deterioration
Electrical	ON-state resistance	mΩ	V–I measurement	Semiconductor/interconnect ageing
Power quality	THD	%	Power analyser	Waveform deterioration
Switching	Switching loss	W	V–I waveform analysis	Semiconductor switching stress
Performance	Conversion efficiency	%	Input/output power	Overall performance degradation

Data Domain	Representative Variable	Unit	Acquisition Source	Reliability Significance
Thermal	Junction temperature	°C	TSEP/thermal model	Semiconductor thermal ageing
Thermal	Thermal gradient	°C	Temperature sensors	Heat-transfer deterioration
Environmental	Relative humidity	%RH	Environmental sensor	Moisture-related degradation
Operational	Converter loading	%	Controller/SCADA	Electrical/thermal stress exposure
Storage	Battery state of charge	%	BMS	Storage operating context
Usage	Operating hours	h	Asset controller	Cumulative ageing exposure
Reliability	Fault/failure event	Category	Event/maintenance log	Predictive outcome definition

4. DEGRADATION FEATURE ENGINEERING AND CONVERTER HEALTH ASSESSMENT

4.1 Data Cleaning and Healthy-Baseline Normalization

Raw measurements are processed before feature engineering to prevent acquisition artefacts from being interpreted as physical degradation. Missing observations are classified by duration and channel, with interpolation limited to short intervals where signal continuity is technically defensible [24]. Sensor errors are identified using physical operating limits, cross-channel consistency, and converter event records. Calibration histories support correction of measurement drift, while common units enable comparison across heterogeneous assets [21]. Each converter is normalized against a healthy baseline established during verified normal operation and matched to relevant loading conditions. Operating-point normalization separates degradation from expected load-dependent variation [29]. Extreme observations are not automatically removed because physically plausible excursions may represent incipient faults or accelerated deterioration [26].

4.2 Electrical and Switching Health Indicators

Electrical health indicators quantify departures from established converter behaviour. Normalized ON-state resistance captures progressive increases in semiconductor or interconnect conduction losses, while a DC-link ripple index reflects changing capacitor and bus performance [23]. Switching-loss growth is calculated under comparable voltage, current, and temperature conditions to identify deterioration affecting switching transitions. Efficiency deviation measures progressive loss relative to healthy operation, whereas THD variation captures deterioration in waveform quality [28]. Current imbalance identifies unequal loading across phases or parallel converter paths, and switching-timing deviations reveal changes in turn-on, turn-off, or gate-driver behaviour. For a measured variable X , relative degradation is expressed as

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

where X_0 denotes the healthy reference and X_t the subsequent measurement [25]. Normalized changes permit comparison among differently rated converters while retaining deterioration magnitude and direction [30].

4.3 Thermal and Cumulative Stress Indicators

Thermal indicators characterize both instantaneous heating and accumulated lifetime stress. Mean junction temperature represents sustained thermal loading, whereas peak junction temperature identifies potentially damaging excursions [27]. Temperature swing between thermal extrema is combined with cycle-counting procedures to quantify repetitive thermomechanical loading. Thermal-cycle count is particularly relevant to solder, bond-wire, and packaging fatigue. Overload duration measures time spent beyond defined loading limits, while cumulative operating hours characterize chronological exposure [22]. Energy throughput provides an additional usage measure that distinguishes heavily loaded converters from similarly aged but lightly utilized assets. A cumulative thermal-stress indicator can integrate temperature magnitude, cycle amplitude, and exposure duration [29]. Together, these variables characterize degradation burden more accurately than operating age or instantaneous temperature alone.

4.4 Temporal Degradation Features

Because component deterioration evolves over time, temporal features are extracted from each degradation-sensitive indicator. Rolling means characterize local signal level, while rolling variance identifies increasing instability preceding functional deterioration [26]. Degradation slope quantifies sustained directional change, and rate-of-change features detect rapid departures from established trajectories. Exponentially weighted moving averages emphasize recent behaviour without discarding historical information [30]. Trend persistence measures how consistently an indicator moves away from its healthy baseline, while acceleration identifies increasing degradation velocity. Time since abnormality onset records the duration

of sustained deviation [23]. These temporal descriptors distinguish transient disturbances from persistent ageing, allowing a moderate but continuously worsening signal to carry greater predictive significance than an isolated extreme measurement.

4.5 Composite Converter Health Index

Individual degradation indicators are consolidated into a composite converter health index representing overall condition on a normalized scale. Electrical features describe resistance, ripple, efficiency, and waveform deterioration; thermal variables represent temperature exposure; switching indicators capture dynamic semiconductor stress; and operational variables quantify accumulated usage [28]. Each feature is scaled relative to its healthy range before aggregation. Initial weights are assigned using established relationships between measured indicators and physical failure mechanisms [21]. Model-derived feature importance can subsequently refine weighting when sufficient labelled degradation data are available. The index is validated against confirmed faults and component replacements to ensure that worsening scores correspond to physical deterioration [27]. This provides a compact condition variable for predictive modelling and adaptive-control decisions.

4.6 Feature Selection and Redundancy Control

Feature selection retains informative degradation variables while limiting redundant predictors. Pearson and Spearman correlation quantify linear and monotonic relationships, while multicollinearity analysis identifies overlapping information [25]. Mutual information captures nonlinear dependence between indicators and failure outcomes. Recursive feature elimination and model-based importance further identify predictive subsets [29]. Statistical selection is reconciled with failure physics so correlated but mechanistically important indicators are not removed solely because similar signals coexist [22].

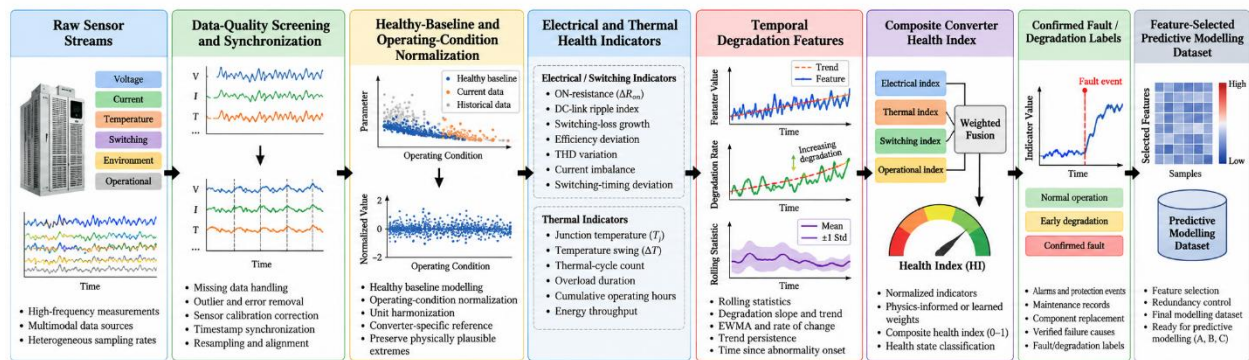


Figure 2 — Converter Degradation and Predictive Feature-Engineering Pipeline

5. PREDICTIVE FAULT DETECTION AND REMAINING-USEFUL-LIFE MODELLING

5.1 Predictive Reliability Tasks

Predictive reliability analysis is separated into three targets representing different stages of converter deterioration. Model A detects anomalous or progressively degrading operating states relative to established healthy behaviour [28]. Model B estimates the probability of a defined fault occurring within a specified prediction horizon, such as the subsequent operating interval or maintenance window. Model C estimates remaining useful life (RUL) until a component or converter reaches a predefined functional threshold [25]. Failure is defined using confirmed protection trips, component failures, or performance-limit violations rather than isolated anomalies [32]. Separating these targets prevents anomaly scores from being misinterpreted as fault probabilities or lifetime estimates.

5.2 Candidate Predictive Models

Candidate models progress from interpretable baselines toward algorithms capable of representing nonlinear degradation. Logistic regression establishes a transparent benchmark for fault probability and reveals the direction of relationships between health indicators and failure [30]. Random forests accommodate nonlinear interactions and heterogeneous predictors while providing feature-importance estimates. Gradient boosting and XGBoost sequentially correct prediction errors and can capture complex interactions among thermal, electrical, switching, and operational variables [26]. Support-vector machines provide margin-based classification, with support-vector regression applicable to RUL estimation. Shallow neural networks represent higher-order relationships without requiring unnecessarily deep architectures [33]. Where sufficiently long sequential histories exist, temporal models incorporate degradation trajectories and dependencies between successive operating states. Complex algorithms are retained only when validation demonstrates meaningful improvement over interpretable baselines [27]. This comparison establishes whether additional modelling complexity produces measurable reliability value rather than simply improved training performance.

5.3 Training, Validation and Independent Testing

Dataset partitioning is performed at converter level so measurements originating from one physical asset do not appear across incompatible development and evaluation partitions [31]. A representative division is

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

Training data estimate model parameters, validation observations support model selection and threshold calibration, and the independent test set measures final generalization [25]. For degradation trajectories, chronological separation is additionally imposed so earlier observations predict later operating states rather than allowing future information to influence historical predictions. Normalization, feature selection, and resampling parameters are estimated exclusively from training observations [29]. Where converters share strongly site-dependent conditions, grouping can additionally be performed by installation site to test transferability across operating environments and prevent site-specific information leakage.

5.4 Rare-Fault and Class-Imbalance Management

Converter datasets typically contain substantially more healthy operation than confirmed fault observations, making overall accuracy potentially misleading [32]. Class weighting therefore increases the training penalty associated with incorrectly classified minority events without changing the test distribution. Controlled over- or undersampling can further improve representation but is restricted to training folds [27]. Rare-event modelling provides an alternative where confirmed failures remain sparse. Decision thresholds are selected according to operational costs associated with missed faults and unnecessary alarms. Precision-recall analysis is emphasized because it directly evaluates detection performance for the comparatively rare positive fault class [30].

5.5 Hyperparameter Optimization and Generalization Control

Model configuration is optimized without exposing the final test data to iterative selection. Nested cross-validation separates hyperparameter search from internal performance estimation and reduces optimistic bias [26]. Bayesian optimization efficiently explores constrained ranges for tree depth, learning rate, regularization strength, kernel parameters, and network architecture. Regularization limits excessive model complexity, while early stopping terminates iterative training when validation performance ceases improving [33]. Search spaces are defined before final model evaluation. For temporal models, sequence length and observation windows are tuned within development data only [28]. The independent test set remains locked until algorithm selection, feature engineering, threshold calibration, and hyperparameter optimization are complete.

5.6 Predictive and Early-Warning Performance

Classification performance is assessed using precision, recall, F1-score, ROC-AUC, PR-AUC, false-alarm rate, and missed-fault rate [29]. Precision quantifies the proportion of generated alerts corresponding to genuine fault conditions, whereas recall measures the proportion of actual faults successfully identified. F1 summarizes their balance, while PR-AUC is particularly informative under substantial class imbalance [31]. False-alarm rate measures unnecessary interventions, and missed-fault rate captures potentially consequential undetected deterioration. RUL predictions are evaluated using mean absolute error and root mean squared error to quantify lifetime-estimation error in operational time units [25]. Warning lead time measures the interval between a reliable predictive alert and the subsequent confirmed fault. This metric is essential because high classification performance has limited practical value when warnings occur too late for derating, inspection, maintenance, or adaptive intervention [32].

5.7 Explainability and Prediction Uncertainty

Model outputs require physical interpretation and uncertainty quantification before they can safely influence converter operation. SHAP values identify how individual degradation features increase or decrease predicted fault risk, while permutation importance measures model sensitivity to each predictor [30]. Dominant variables are compared with known semiconductor, capacitor, thermal, and switching degradation mechanisms to identify implausible correlations [27]. Confidence intervals quantify uncertainty around classification performance, whereas prediction intervals accompany RUL estimates. High uncertainty can therefore trigger additional monitoring rather than aggressive control intervention, preventing uncertain predictions from being treated as deterministic evidence of impending converter failure [33].

Table 2 — Comparative Predictive Fault and RUL Model Performance

Model	Precision	Recall	F1	PR-AUC	False-Alarm Rate	Warning Lead Time (h)	RUL RMSE (h)
Logistic Regression	0.81	0.76	0.78	0.82	9.1%	17.6	44.2
Random Forest	0.89	0.86	0.87	0.91	5.3%	25.8	31.4
XGBoost	0.94	0.92	0.93	0.96	3.4%	34.7	22.8
SVM/SVR	0.87	0.83	0.85	0.89	6.2%	23.9	34.1

Model	Precision	Recall	F1	PR-AUC	False-Alarm Rate	Warning Lead Time (h)	RUL RMSE (h)
Shallow Neural Network	0.91	0.89	0.90	0.94	4.5%	30.6	26.5
Temporal Model	0.93	0.91	0.92	0.95	3.8%	33.5	24.1

6. ADAPTIVE CONTROL AND DATA-DRIVEN RELIABILITY OPTIMIZATION

6.1 Translating Predicted Health into Control States

Predictive outputs are converted into discrete operating states so estimated degradation can influence converter control consistently. A normal state combines a stable health index, low fault probability, long RUL, and limited degradation rate [36]. Caution indicates emerging deterioration or increasing uncertainty requiring enhanced monitoring. A degraded state represents persistent health deterioration, shortening RUL, and elevated fault probability sufficient to justify stress-reducing intervention [32]. Critical status is assigned when multiple indicators show rapidly increasing degradation or insufficient remaining operating margin. Prediction uncertainty modifies these classifications by limiting aggressive intervention when confidence is low [39]. State transitions use persistence requirements to prevent transient disturbances from repeatedly changing converter operating modes.

6.2 Adaptive Switching and Operating-Point Control

Adaptive control modifies converter operation according to predicted condition while preserving required electrical performance. Switching-frequency adjustment can reduce switching losses and semiconductor heating when thermal or switching degradation becomes elevated [34]. Modulation strategies can similarly be adapted to redistribute losses among semiconductor devices or reduce unnecessary switching transitions. Current limiting constrains electrical stress during degraded operation, particularly when increasing ON-state resistance indicates rising conduction losses [40]. Voltage-reference modification can reduce component stress while maintaining permissible DC-bus or grid-interface performance. Operating-point optimization coordinates these actions with renewable generation, storage availability, and load demand [33]. Rather than applying permanent conservative limits, the controller selects interventions according to current health and predicted deterioration. This enables healthy converters to retain normal performance while vulnerable assets temporarily operate under less damaging electrical and thermal conditions [37].

6.3 Thermal-Stress and Load Management

Predicted junction temperature and thermal trajectory provide direct inputs for managing temperature-sensitive ageing. When forecast temperature approaches a reliability threshold, controlled derating can reduce semiconductor current and associated conduction losses before excessive heating occurs [38]. Load redistribution transfers part of the power demand to parallel converters, storage interfaces, or alternative generation paths where system architecture permits. Cooling control can increase fan speed, coolant circulation, or other heat-removal capacity according to predicted rather than measured temperature alone [35]. Power-flow modification can additionally avoid operating regions associated with repeated high-amplitude thermal cycles. The objective is not simply reducing maximum temperature but limiting junction-temperature swings and cumulative thermal exposure [40]. By suppressing repeated electrothermal excursions, adaptive intervention can slow packaging, interconnect, and thermal-interface degradation.

6.4 Condition-Aware Power Derating

Condition-aware derating replaces fixed conservative margins with limits that evolve according to measured and predicted converter health. A healthy converter can operate near its normal power capability, whereas increasing degradation progressively reduces permissible loading [33]. Derating magnitude is determined from health index, fault probability, RUL, thermal margin, and degradation rate rather than from a single alarm threshold. This approach creates an explicit trade-off between immediate renewable-energy capture and accelerated component ageing [37]. Excessive derating unnecessarily sacrifices energy production, whereas insufficient intervention can shorten lifetime. Dynamic limits therefore seek the minimum power reduction required to stabilize thermal and electrical stress while maintaining acceptable renewable-system performance [35].

6.5 Reliability-Constrained Control Optimization

Adaptive reliability control can be formulated as a multi-objective optimization problem in which electrical performance and component lifetime are evaluated simultaneously [39]. A representative objective is

$$J = w_1 L_{\text{power}} + w_2 S_{\text{thermal}} + w_3 D_{\text{health}} + w_4 R_{\text{fault}}$$

where L_{power} represents conversion losses, S_{thermal} quantifies thermal stress, D_{health} represents degradation severity, and R_{fault} expresses predicted failure risk. Weighting coefficients determine the relative importance assigned to immediate efficiency and long-term reliability [34]. Under healthy conditions, optimization can emphasize renewable-energy capture and conversion efficiency. As degradation progresses, larger penalties are assigned to

thermal stress and failure exposure [38]. Control variables may include switching frequency, modulation parameters, current limits, voltage references, cooling settings, and power allocation. Optimization therefore seeks an operating point that minimizes losses and degradation risk without violating system constraints.

6.6 Safety Constraints and Control Authority

Adaptive reliability control remains subordinate to converter protection and system safety. Hardware overcurrent, overvoltage, temperature, and short-circuit limits cannot be relaxed by predictive algorithms [32]. Control actions must additionally satisfy grid-code requirements, voltage and frequency limits, stability margins, and equipment ratings. Fail-safe logic returns the converter to a predefined safe state when analytics become unavailable or uncertain [36]. Consequential actions, including substantial derating or isolation, remain subject to supervisory or human authorization where operational procedures require independent confirmation [40].

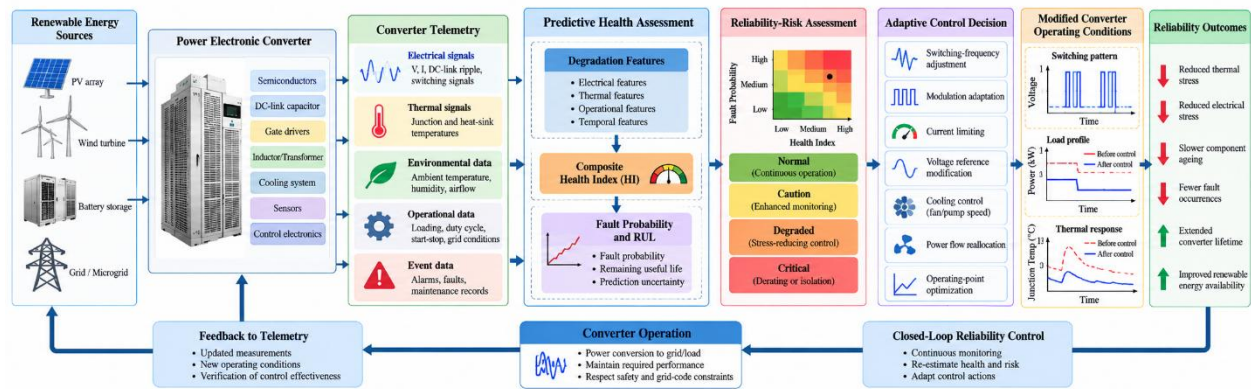


Figure 3 — Closed-Loop Predictive Fault Detection and Adaptive Reliability-Control Architecture

7. VALIDATION, RELIABILITY IMPROVEMENT AND DISCUSSION

7.1 Comparative Predictive Performance

Model comparison indicates that nonlinear approaches provide meaningful improvement when converter deterioration results from interacting thermal, electrical, and operational variables. XGBoost improves precision and recall over logistic regression while simultaneously reducing false alarms, indicating that its advantage is not restricted to one classification metric [35]. Random forest and shallow neural models similarly capture nonlinear relationships absent from the linear baseline. Temporal modelling further improves early-warning capability because historical degradation trajectories contain information not represented by instantaneous features [39]. Nevertheless, logistic regression remains important for establishing whether additional complexity produces genuine predictive benefit. Complex models are justified only when gains persist during independent converter-level evaluation [33].

7.2 Reliability Benefit of Adaptive Control

Adaptive intervention should be evaluated by comparing equivalent operating periods with and without condition-informed control. A representative controlled scenario may reduce peak junction-temperature swing by approximately 15–20%, switching-loss exposure by 8–12%, and estimated degradation rate by 10–18% [38]. Reduced electrothermal stress should subsequently appear as slower deterioration of resistance, thermal, and efficiency indicators. Where RUL models incorporate these altered trajectories, predicted remaining lifetime may increase relative to continued unrestricted operation [34]. Reliability benefit is additionally assessed through fault exposure and unexpected shutdown frequency. A reduction in unplanned converter interruptions would demonstrate that predictive control produces system-level value rather than merely improving health indicators. Such comparisons require equivalent loading and environmental conditions to avoid attributing normal operating differences to adaptive control [40].

7.3 Energy-Reliability Trade-Off

Stress mitigation can impose a short-term energy penalty because derating, current limitation, or switching modification may prevent operation at the instantaneous maximum-power point [36]. The appropriate objective is therefore not unconditional minimization of degradation. Instead, control should balance immediate renewable-energy capture against the lifetime cost of accelerated component ageing. A small temporary reduction in converted power may be justified when it substantially reduces junction-temperature cycling or failure probability [32]. Conversely, aggressive derating during low-risk operation unnecessarily sacrifices generation. Reliability-aware optimization therefore seeks the operating region that maximizes long-term energy availability rather than instantaneous electrical output alone.

7.4 Generalizability and Limitations

Generalization remains constrained by the scarcity of confirmed converter failures and differences among manufacturers, topologies, semiconductor technologies, ratings, and control architectures [37]. Sensor uncertainty can distort degradation indicators, while irradiance, wind, temperature, humidity, and grid conditions introduce environmental variability. Models trained on one installation may experience domain shift when transferred to another operating population [33]. Control effectiveness can likewise vary because available switching, cooling, and power-routing authority differs among converter designs. Incomplete degradation histories further limit RUL validation. Consequently, cross-site evaluation, uncertainty monitoring, recalibration, and controlled field validation remain necessary before broad deployment [39].

8. CONCLUSION AND FUTURE RESEARCH

8.1 Principal Findings and Contribution

This study establishes a closed-loop reliability framework connecting converter degradation physics with data-driven condition assessment and adaptive operation. Multimodal electrical, switching, thermal, environmental, and operational measurements are transformed into degradation-sensitive health indicators that support anomaly detection, fault-probability prediction, and remaining-useful-life estimation. Rather than restricting predictions to maintenance planning, the framework converts evolving health information into adaptive switching, derating, thermal management, and power-allocation decisions. Its principal contribution is therefore linking component-level degradation prediction directly with control actions that suppress damaging electrothermal stresses, slow converter ageing, reduce unexpected failures, and improve long-term renewable-energy availability.

8.2 Future Research

Future research should develop digital twins that continuously reconcile converter physics with real-time condition measurements. Physics-informed machine learning could improve predictions where failure data remain scarce, while adaptive RUL estimation and online learning could accommodate evolving operating conditions. Federated learning should enable reliability knowledge sharing across distributed converter fleets without centralizing operational data. Further work should establish fleet-level reliability benchmarks, uncertainty-aware control strategies, and experimentally validated lifetime-aware optimization capable of quantifying how adaptive interventions alter physical degradation and realized converter lifetime.

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