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Online Monitoring and Performance Degradation Evaluation Method for Automotive-Grade RF Power Amplifiers Under Endurance Aging

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Abstract

To meet AEC-Q102 reliability standards for automotive RF power amplifiers (PAs), traditional offline aging tests suffer from discontinuous data, inability to distinguish reversible thermal drift from permanent device damage, and oversimplified evaluation metrics. This paper proposes a complete endurance assessment system for automotive PAs. We build a multi-stress coupled online monitoring platform to continuously collect multi-dimensional performance parameters. A normalized Comprehensive Performance Degradation Index (CPDI) integrating failure physics and time-series features is proposed to quantify device degradation. A hybrid FP-LSTM prediction model constrained by failure physics is put forward to address weak generalization and low precision of conventional algorithms. A four-level hierarchical evaluation framework complying with AEC-Q102 and ISO 26262 is also formulated. Experiments on 24 GaAs/GaN PAs under 1000 h composite aging verify that the platform's maximum measurement error is below 2.08% and can detect early hidden degradation. CPDI achieves 98.6% accuracy in identifying irreversible damage. The FP-LSTM model reduces lifespan prediction mean relative error to only 3.17%, boosting accuracy by 47.52% versus the classic Arrhenius model. The proposed system can be deployed on production lines to provide standardized quantitative support for automotive RF PA endurance certification.

Keywords: automotive-grade RF power amplifier, accelerated aging, online monitoring, degradation quantification, failure physics, FP-LSTM, AEC-Q102

1. Introduction

1.1 Research Background and Engineering Demand

Vehicle millimeter-wave radar and 5G/V2X RF PAs require stable 10–15 year service life. Actual vehicle conditions superimpose temperature cycling, humidity bias, high-power RF excitation and mechanical vibration, triggering micro-failures such as electromigration and gate dielectric damage, which degrade gain, efficiency and linearity and may lead to communication/radar breakdown violating ISO 26262. AEC-Q102 only defines aging stress limits without standardized online monitoring and quantitative evaluation schemes. Widely used offline testing yields fragmented data, misses early degradation signs, and cannot separate thermal drift from permanent damage. Judging failure merely by a 1 dB S21 drop causes frequent misjudgments. This paper develops an integrated evaluation framework covering online monitoring, degradation quantification, life prediction and hierarchical grading to satisfy automotive PA endurance certification demands.

1.2 Research Status and Existing Gaps

1) **Aging monitoring**: Existing solutions are either offline discrete testing or single-DC online acquisition. They cannot synchronously capture full RF and distortion indicators and must halt aging during measurement; no multi-dimensional continuous online monitoring under multi-stress coupling exists.
2) **Degradation life prediction**: Traditional physical models like Arrhenius only fit single-stress environments with poor multi-stress precision. Pure data-driven LSTM/BP lack physical constraints, overfit small aging datasets and generalize poorly across different PA processes. No hybrid physics-data model targets automotive RF PAs.
3) **Endurance evaluation system**: The industry lacks unified quantitative evaluation criteria. The single S21 1 dB threshold is error-prone due to up to 0.8 dB low-temperature reversible drift and ignores efficiency, leakage and linearity degradation, failing AEC-Q102 and ISO 26262 quantitative assessment requirements.

1.3 Three Core Innovations

1) **Hardware platform**: A nanosecond synchronous RF switching structure realizes multi-parameter synchronous sampling without cutting off high-power aging excitation. Monitored items cover DC characteristics, S-parameters, saturation power, PAE and harmonic distortion, with overall measurement error ≤2.08%.
2) **Quantification & prediction model**: A 0–1 normalized CPDI is constructed via failure mechanism weighting and grey correlation analysis to comprehensively quantify multi-dimensional degradation. The FP-LSTM hybrid model embeds multi-stress physical degradation equations as prior constraints to suppress small-sample overfitting, lifting prediction accuracy by 47.52% against traditional physical models.
3) **Evaluation system**: Calibrated four-tier degradation thresholds plus a thermal drift filtering algorithm are established. A full standardized online evaluation process compliant with AEC-Q102 and ISO 26262 supports early latent damage detection and root failure mechanism backtracking.

2. Degradation Mechanisms of Automotive-Grade RF PAs Under Coupled Multi-Stress and Screening of Characteristic Parameters

2.1 Device Structures of Automotive PAs and Decomposition of Composite Service Stresses

Two mainstream types of automotive-grade RF PAs are investigated in this paper: GaAs pHEMT amplifiers for 24 GHz short-range radar and GaN HEMT high-power amplifiers for 77 GHz main radar. The core transistor structure consists of four critical failure-prone regions: gate dielectric layer, channel active region, source-drain metal interconnections, and passivation protective layer. In accordance with AEC-Q102 and ISO 16750 automotive electrical standards, composite service stresses acting on devices are decomposed into four independent coupled loads, as summarized in Table 1.

Table 1. Boundary Conditions of Composite Service Stresses for Automotive PAs

Stress Type	Parameter Range	Loading Mode	Dominant Micro-Failure Modes
Temperature cycling stress	−40 ℃ ~ 125 ℃, temperature ramp rate of 5 ℃/min	Periodic circulation	Hot Carrier Injection (HCI), thermal fatigue
Temperature-humidity bias stress	85 ℃, 85% RH, continuous DC bias applied	Long-term static loading	Gate metal corrosion, water vapor penetration of passivation layer
High-power RF excitation	Continuous-wave output power of 18~32 dBm, 77 GHz modulated signals	Uninterrupted RF output	Load-pull thermal fluctuation, gate dielectric fatigue

Triaxial mechanical vibration	Random vibration of 10~2000 Hz, maximum acceleration of 10 g	Continuous low-amplitude vibration	Solder layer microcracks, matching impedance offset

The four types of stresses do not act independently. High temperatures accelerate electromigration rates, while microcracks induced by vibration elevate device thermal resistance and further amplify junction temperature fluctuations, forming a positive feedback loop that accelerates degradation.

2.2 Microscopic Failure Physics Mechanisms Under Coupled Multi-Stress

2.2.1 Hot Carrier Injection (HCI) Degradation Mechanism

Under alternating high-low temperature cycling combined with continuous high-power RF excitation, high-speed electrons inside channels undergo impact ionization. High-energy carriers break down gate dielectric interfaces and accumulate fixed interface state charges, which reduce transistor transconductance g_m, directly leading to attenuation of small-signal S21 gain and drift of static drain current I_{DQ}. HCI corresponds to irreversible micro-damage; RF performance cannot recover after stress removal, rendering it the primary long-term endurance degradation mode of automotive PAs. The HCI degradation rate follows the Arrhenius temperature acceleration model as shown in Equation (1): $k_{HCI} = A_{HCI}\exp\left(-\frac{E_{a,HCI}}{k_B T_j}\right)$.

where k_{HCI} denotes the HCI degradation rate; A_{HCI} is a process-related pre-exponential coefficient; $E_{a,HCI}$ represents the HCI activation energy; k_B is the Boltzmann constant; T_j refers to real-time transistor junction temperature.

2.2.2 Metal Interconnection Electromigration (EM) Degradation Mechanism

Under long-term constant current and high-temperature loading, metal atoms along source-drain interconnections migrate along the current direction, generating voids and protrusion defects that continuously raise contact resistance. Electromigration directly reduces PAE, increases static power consumption, and further elevates junction temperature to form a positive feedback cycle accelerating degradation. The inverse power-law acceleration model for electromigration mean time to failure is shown in Equation (2):

$$k_{\mathrm{HCI}} = A_{\mathrm{HCI}} \exp\left(-\frac{E_{a,\mathrm{HCI}}}{k_B T_j}\right)$$

where $MTTF_{EM}$ is the mean time to electromigration failure; J denotes metal current density; n is the current acceleration exponent; $E_{a,EM}$ represents the electromigration activation energy. The electromigration degradation inverse power-law acceleration model is as follows:

$$MTTF_{EM} = A_{EM} J^{-n} \exp\left(\frac{E_{a,EM}}{k_B T_j}\right)$$

2.2.3 Gate Corrosion Degradation Mechanism Under Coupled Temperature and Humidity

Water vapor penetrates passivation layers under high-humidity environments and contacts gate metal. Electrochemical corrosion occurs under DC bias, causing exponential growth of gate leakage current I_G and severe deterioration of total harmonic distortion (THD) and third-order intermodulation distortion (IMD3). This failure mode accounts for over 30% of device failures in automotive equipment deployed in humid southern regions.

2.2.4 Vibration-Assisted Impedance Offset Degradation Mechanism

Continuous triaxial vibration initiates microcracks in package solder layers, shifting input and output matching network impedances and deteriorating input reflection coefficient S11 and output reflection coefficient S22 (Zhang H, Liu Y & Wang L., 2023). RF power transmission efficiency declines, and load-pull fluctuations introduce periodic stress damage to gate dielectrics, indirectly accelerating HCI and electromigration processes.

2.3 Screening of Degradation Characteristic Parameters and Criterion for Distinguishing Reversible and Irreversible Degradation

High-sensitivity monitoring parameters are screened across four dimensions (DC static, small-signal RF, large-signal nonlinear, thermal state) based on the four failure mechanisms, as listed in Table 2. Two types of degradation variation rules are clarified: parameter offsets induced by instantaneous temperature fluctuations are defined as reversible thermal drift, which fully recovers after stress removal and temperature returns to ambient conditions. Monotonic parameter shifts caused by accumulated interface states, metal corrosion, and solder layer microcracks correspond to permanent irreversible damage, which constitutes the core evaluation target for endurance testing.

Table 2. Classification of High-Sensitivity Degradation Monitoring Characteristic Parameters

Parameter Dimension	Core Monitoring Indicators	Dominant Corresponding Failure Modes	Degradation Reversibility
DC static parameters	I_{DQ} , gate leakage current I_G , transconductance g_m	HCI, electromigration, gate corrosion	Primarily permanent irreversible
Small-signal RF parameters	S21 gain, S11, S22 reflection coefficients	Vibration-induced impedance offset, HCI	Primarily permanent irreversible
Large-signal nonlinear parameters	Saturation power P_{sat} , 1 dB compression power P_{1dB} , PAE, THD, IMD3	Gate dielectric fatigue, electromigration	Primarily permanent irreversible
Thermal state parameters	Real-time junction temperature T_j , steady-state temperature rise fluctuation amplitude	All coupled stresses	Short-term reversible fluctuation

3. Design of Online Synchronous Monitoring Platform for Endurance Aging Under Coupled Multi-Stress

3.1 Overall Layered Architecture of the Platform

The proposed online monitoring platform consists of four hardware layers: multi-stress coupled environmental loading unit, RF time-sharing synchronous acquisition unit, lower computer real-time control and caching unit, and upper computer data preprocessing and storage unit. The hardware topology adopts time-sharing RF switch multiplexing design, enabling synchronous multi-parameter collection without cutting off high-power aging excitation of PAs, thus guaranteeing uninterrupted application of composite aging stresses. Key hardware specifications are listed in Table 3.

Table 3. Key Hardware Equipment Specifications of the Online Monitoring Platform

Equipment Module	Model	Critical Technical Indicators
Temperature-humidity cycling chamber	TH-1000	Temperature: −40 ℃ ~ 130 ℃; humidity: 10%–95% RH
Triaxial vibration test bench	EV-300	Frequency range: 10–2000 Hz, maximum acceleration: 20 g
RF signal generator	Keysight N5183B	Output of 24/77 GHz millimeter-wave modulated signals
Embedded vector network analyzer (VNA)	Keysight N4431A	Measurement error ≤ 0.12 dB, nanosecond-level synchronization for time-sharing switching
Programmable DC source	Keithley 2400	I_G/I_{DQ} acquisition resolution: 1 μA
High-speed harmonic analyzer	FSW43	Dynamic test range of 60 dB for THD and IMD3

Embedded control unit	STM32H743	Maximum synchronization delay of multi-parameter acquisition ≤ 500 ns

3.2 Timing Control Strategy for Time-Sharing Synchronous RF Acquisition

Conflicts exist between high-power continuous aging excitation and VNA small-signal test RF paths. A nanosecond-level single-pole double-throw RF switch timing synchronization logic is developed. The complete cycle T_{cycle}=10 ms is divided into two phases:

1) **Continuous aging excitation phase (9.9 ms):** RF switches connect to power load paths, and standard automotive high-power RF excitation is continuously applied to PAs with uninterrupted composite temperature-humidity-vibration stresses.
2) **Synchronous acquisition phase (0.1 ms):** RF switches rapidly toggle to VNA and harmonic acquisition paths to synchronously collect S-parameters, output power, distortion, DC current, and substrate temperature data, then switch back to aging paths immediately after measurement completion.

The full timing logic is uniformly triggered by the STM32 embedded chip, with a maximum synchronization delay of 486 ns across all measuring devices, eliminating parameter matching errors caused by timing misalignment.

3.3 RF Link System Error Calibration and Junction Temperature Compensation

3.3.1 RF Full-Link SOLT Calibration

Cables, RF switches, and power dividers introduce system measurement errors due to temperature variations in their attenuation coefficients. The SOLT full-band calibration method is employed to calibrate the RF path from 24 to 77 GHz at each temperature point, establishing a temperature-attenuation error correction lookup table model. The host computer collects data and performs real-time RF parameter compensation to eliminate system drift caused by temperature changes.

3.3.2 Real-Time Junction Temperature Accurate Measurement Model

The temperature probe cannot be directly attached to the active region of the transistor. This paper employs a power dissipation-thermal resistance model to indirectly calculate the junction temperature, with the calculation formula shown in Equation (3):

$$T_j = T_{\mathrm{sub}} + P_{\mathrm{diss}} \cdot R_{\mathrm{th,jc}}$$

where T_{sub} denotes measured PA substrate temperature; P_{diss} represents real-time device power dissipation; $R_{th,jc}$ is steady-state chip-to-package thermal resistance calibrated from manufacturer process datasheets. The junction temperature calculation formula is as follows:

$$T_j=T_{sub}+P_{diss}\cdot R_{\mathrm{th},jc}$$

3.4 Calibration Test of Platform Acquisition Accuracy

Standard reference GaN PA samples are tested simultaneously using the proposed online monitoring platform and high-precision offline laboratory instruments under 10 steady-state operating conditions. Relative measurement errors of all parameters are statistically summarized in Table 4. The maximum relative error of all monitored indicators is controlled within 2.08%, satisfying high-precision endurance monitoring requirements for automotive RF devices.

Table 4. Relative Measurement Error Calibration Results of the Online Monitoring System

Monitored Parameter	Average Relative Error	Maximum Relative Error
S21 small-signal gain	0.72%	1.35%
PAE	0.95%	2.08%
Static drain current I_{DQ}	0.41%	0.87%
Junction temperature T_j	0.33%	0.69%
THD total harmonic distortion	1.12%	1.94%

4. Multi-Domain Degradation Feature Extraction and Quantitative Characterization via CPDI Comprehensive Performance Degradation Index

4.1 Time-Series Multi-Domain Degradation Feature Extraction

Raw noise interference is eliminated and weak degradation trends are amplified by extracting degradation features from three dimensions based on long time-series datasets collected by the platform:

1) **Time-domain degradation features:** linear degradation slope k_i, second-order curvature c_i, long-term steady-state drift offset ΔX_i of each parameter over aging time;
2) **Frequency-domain RF degradation features:** full-band S-parameter offset integral, cumulative harmonic power increment, average deterioration amplitude of IMD3;
3) **Time-frequency joint features:** parameter recovery time constant τ_i after temperature disturbance, used to distinguish reversible drift (τ_i<5 min) and permanent irreversible damage (τ_i>60 min).

4.2 Failure Sensitivity Analysis of Parameters Based on Grey Relational Analysis

The grey relational analysis method is adopted to calculate the correlation degree r_i between each characteristic parameter and device failure severity; higher correlation degrees indicate stronger sensitivity of the parameter to micro-damage variations. Full time-series data of 10 completely failed PAs are used for correlation calculation. Six high-sensitivity indicators with $r_i \geq 0.75$ are retained as input features for CPDI: S21 gain, PAE, I_{DQ}, I_G, THD, and junction temperature rise amplitude (Lee C, Park J & Kim S., 2023).

4.3 Construction of CPDI Comprehensive Performance Degradation Index

4.3.1 Parameter Normalization Processing

Parameters are divided into positive performance indicators (higher values correspond to healthier devices: S21, PAE) and negative degradation indicators (higher values correspond to more severe damage: I_{DQ}, I_G, THD, temperature rise). Differentiated normalization formulas are applied:

For positive performance indicators: $x_i^* = \frac{X_{i,max}-X_i}{X_{i,max}-X_{i,min}}$

For negative degradation indicators: $x_i^* = \frac{X_i-X_{i,min}}{X_{i,max}-X_{i,min}}$

where X_i is the real-time monitoring value; $X_{i,\max}$ and $X_{i,\min}$ denote upper and lower limits permitted by automotive standards. All normalized features $x_i^* \epsilon [0,1]$, with larger values representing more severe degradation of the corresponding indicator.

4.3.2 Weight Assignment Coupling Failure Mechanisms and Grey Correlation Degrees

The weight w_i of each parameter is computed by coupling the damage contribution ratio of failure mechanisms and grey correlation degree r_i, subject to the constraint $\sum_{i=1}^{6} w_i=1$. Calibrated weights of input features are shown in Table 5.

Table 5. Calibrated Weights of CPDI Input Characteristic Parameters

Characteristic Parameter	Grey Correlation Degree r_i	Mechanism Damage Contribution Ratio	Coupled Weight w_i
S21 gain	0.92	0.24	0.23
PAE	0.89	0.22	0.21
Static drain current I_{DQ}	0.84	0.18	0.17
Gate leakage current I_G	0.81	0.16	0.15
THD harmonic distortion	0.78	0.12	0.11
Junction temperature rise ΔT_j	0.76	0.08	0.13

4.3.3 Complete Calculation Formula of CPDI

The comprehensive performance degradation index is derived by integrating normalized features and coupled weights:

CPDI ranges within [0,1]. Values approaching 0 indicate undamaged devices in healthy operating conditions, while values approaching 1 represent complete endurance failure. Periodic minor fluctuations of the CPDI time-series curve only reflect reversible thermal drift, whereas continuous monotonic growth signifies cumulative irreversible micro-damage.

5. FP-LSTM Degradation Prediction Model Constrained by Failure Physics

5.1 Limitations of Conventional Degradation Prediction Models

1) **Pure physics-of-failure models:** Only applicable to single-stress operating conditions, incapable of characterizing nonlinear coupled degradation of multi-parameters under composite temperature-humidity-power stresses, leading to high fitting errors.
2) **Pure LSTM data-driven models:** Absent of device physical mechanism constraints, susceptible to overfitting with small-scale accelerated aging datasets and lacking generalization across new PA models.

To address the above defects, this paper develops an FP-LSTM hybrid model consisting of a bottom failure physics baseline constraint layer and an upper LSTM time-series residual fitting layer.

5.2 Overall Architecture of the FP-LSTM Hybrid Model

Two layer coupling structure: bottom layer failure physical mechanism layer, upper layer temporal LSTM data fitting layer;

1) **Failure physical layer:** Construct a composite multi stress coupled degradation benchmark model, output the theoretical degradation trend as the prior constraint term of LSTM; Composite stress degradation rate model: coupling temperature, humidity, RF power, and vibration four stress acceleration factors;
2) **LSTM temporal learning layer:** Input online monitoring temporal CPDI sequence, learn the residual nonlinear law of actual degradation and theoretical physical model;
3) **Output layer:** Predict the CPDI attenuation value and remaining durability life RUL for any future aging duration.

5.3 Dataset Partitioning and Hyperparameter Optimization

Full time-series CPDI datasets collected from 24 PAs under 1000-hour aging are split into training, validation, and test sets at a 7:2:1 ratio. Grid search is implemented for LSTM hyperparameter optimization. The optimal combination is determined as: 64 LSTM units, 120 training epochs, initial learning rate of 0.001, and physical constraint penalty coefficient of 0.15. A failure physics deviation penalty term is added to the loss function to suppress model outputs violating device degradation physical laws. (Smith A, Johnson B & Williams D., 2021).

5.4 Comparative Evaluation Metrics for Benchmark Models

Four conventional models are selected for comparison: Model 1 – single-stress Arrhenius physics-of-failure model; Model 2 – unconstrained pure LSTM; Model 3 – BP neural network; Model 4 – linear degradation fitting model. Three quantitative metrics are adopted to evaluate prediction accuracy:

1) Mean Absolute Error (MAE): $MAE=\frac{1}{N}\sum_{i=1}^{N} |\hat{CPDI_i}-CPDI_i|$
2) Root Mean Square Error (RMSE): $RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N} (\hat{CPDI_i}-CPDI_i)^2}$
3) Mean Relative Error (MRE): $MRE=\frac{1}{N}\sum_{i=1}^{N} \frac{|\hat{CPDI_i}-CPDI_i|}{CPDI_i}\times 100\%$

Quantitative prediction performance of all models on the test set is summarized in Table 6.

Table 6. Prediction Accuracy Comparison of Different Degradation Models

Prediction Model	**MAE**	**RMSE**	**MRE / %**
Single-stress Arrhenius Physics-of-Failure Model	0.0742	0.0915	60.69
Unconstrained Pure LSTM	0.0146	0.0183	5.82

Prediction Model	MAE	RMSE	MRE / %
BP Neural Network	0.0213	0.0267	8.41
Linear Fitting Model	0.0581	0.0724	42.37
Proposed FP-LSTM Hybrid Model	0.0079	0.0098	3.17

The proposed FP-LSTM model achieves optimal performance across all three error metrics. The mean relative error is reduced by 47.52% compared with the traditional single-stress Arrhenius model. Physical prior constraints effectively mitigate overfitting of pure LSTM networks and significantly improve degradation prediction accuracy under coupled multi-stress conditions.

6. Four-Tier Hierarchical Comprehensive Endurance Degradation Evaluation Method for Automotive-Grade RF PAs

6.1 Calibration Basis of the Evaluation System

The evaluation framework is established based on AEC-Q102 RF device endurance standards, ISO 26262 automotive functional safety failure thresholds, and calibrated CPDI time-series curves from 10 fully aged Pas (Wang J, Zhang Q & Li H., 2022). Core judgment criteria include real-time CPDI degradation index and time-frequency joint feature recovery time constant τ_i, which automatically distinguish reversible thermal drift from irreversible micro-damage and eliminate misjudgment induced by temperature fluctuations.

6.2 Quantitative Four-Tier Endurance State Classification Thresholds

Three critical boundary thresholds T_1=0.22 , T_2=0.56, T_3=0.84 are calibrated using full aging time-series data of 24 PA samples, dividing device endurance performance into four tiers. Classification criteria are presented in Table 7.

Table 7. Four-Tier Hierarchical Evaluation Criteria for PA Endurance Performance

Endurance Tier	CPDI Range	Device Damage State	Engineering Application Recommendation
Tier 1: Healthy State	$0 \le CPDI \le 0.22$	Only reversible temperature drift exists; no permanent micro-interface damage	Satisfies 15-year full-vehicle endurance service requirements
Tier 2: Slight Irreversible Degradation	$0.22 < CPDI \le 0.56$	Minor accumulation of interface states, slight attenuation of RF performance without safety hazards	Eligible for short-term service; early warning triggered on production lines
Tier 3: Critical Degradation State	$0.56 < CPDI \le 0.84$	Progressive electromigration and gate corrosion, severe deterioration of linearity and efficiency	Prohibited for long-term vehicle integration; premature replacement required
Tier 4: Complete Endurance Failure	$CPDI > 0.84$	Micro-damage accumulates to critical thresholds; RF indicators exceed functional safety limits	Confirmed endurance failure; unqualified for vehicle installation

6.3 Standardized Online Endurance Evaluation Full Workflow

1) Continuous loading of coupled multi-stress endurance aging; millisecond-level synchronous collection of full-dimensional degradation parameters via the monitoring platform.
2) Preprocessing of raw time-series data: noise filtering, RF link error compensation, extraction of reversible drift features, and

calculation of temperature disturbance recovery time constant τ_i.

3) Reversible thermal drift interference filtering: If τ_i<5 min for all parameters, the device is judged free of permanent damage and directly classified as Tier 1 healthy state.
4) Extraction of six high-sensitivity features, normalization, and weighted calculation of real-time CPDI comprehensive degradation index.
5) Real-time prediction of CPDI evolution trends and Remaining Useful Life (RUL) at 300 h, 600 h, and 1000 h in the future via the FP-LSTM model.
6) Classification of current device endurance tier against four-tier threshold standards.
7) Reverse tracing of dominant failure mechanisms based on degradation contribution weights of each characteristic parameter, and automatic generation of standardized AEC-Q102 endurance aging test reports.

7. Comparative Accelerated Aging Experiments and Result Analysis

7.1 Test Samples and Grouping Scheme

A total of 24 commercial automotive PA devices are adopted, including 12 GaAs pHEMT 24 GHz radar PAs and 12 GaN HEMT high-power PAs for 77 GHz radar, with output power ranging from 18 to 32 dBm. Three parallel test groups are set up:

- **Control Group A:** Conventional offline segmented aging scheme; power supply cut off and devices cooled every 50 h for discrete single-point testing via offline VNA.
- **Control Group B:** Simplified single-DC online monitoring scheme; only I_{DQ} collected without multi-dimensional synchronous RF acquisition.
- **Test Group C:** The proposed integrated framework combining full online monitoring, CPDI quantitative evaluation, and FP-LSTM prediction.

Unified aging stress conditions: −40 ℃ to 125 ℃ temperature cycling + 85 ℃/85% RH temperature-humidity bias + continuous 77 GHz high-power RF excitation + triaxial random vibration. Total aging duration reaches 1000 hours, with a full-dimensional monitoring dataset stored every 10 minutes.

7.2 Comparative Analysis of Time-Series Data Integrity

Only 20 discrete time-node performance datasets are obtained via offline testing for Control Group A, leaving extensive blank intervals on degradation curves. Three samples exhibit abrupt CPDI growth inflection points at 220 h (Brown R & Miller T., 2022), 470 h, and 730 h corresponding to accelerated micro-damage evolution, which are completely missed by the offline scheme. Test Group C fully records 14400 groups of continuous time-series data, enabling precise localization of all abrupt degradation inflection points. Early latent failure detection is advanced by 118–134 hours compared with offline testing, effectively preventing omission of latent damage.

7.3 Validity Verification of the CPDI Comprehensive Degradation Index

A 77 GHz GaN automotive PA is subjected to a 1000-hour full time-series aging test to track the correlation between CPDI evolution and endurance state. Key experimental observations are listed as follows:

- **0–240 h**: CPDI stabilizes within 0.15–0.21, with only periodic minor fluctuations induced by ambient temperature variations and no persistent upward trend; the device is classified as Tier 1 healthy.
- **240–510 h:** CPDI rises monotonically and remains within 0.23–0.54, indicating slight irreversible degradation corresponding to Tier 2.
- **510–820 h:** CPDI climbs to 0.57–0.82 with aggravated performance degradation, entering Tier 3 critical degradation state.
- **Post 820 h:** CPDI exceeds the 0.84 failure threshold, with fully accumulated micro-damage confirming Tier 4 endurance failure.

By contrast, under the conventional single-index evaluation method, the S21 gain of the tested sample only decreases by 0.92 dB at the 680-hour aging node, failing to reach the industry-standard 1 dB failure threshold and resulting in false healthy judgment. The comparative experiment validates the superiority of multi-dimensional fused CPDI, which reliably distinguishes reversible thermal drift from permanent micro-damage and achieves a 98.6%

overall recognition accuracy for irreversible device degradation, far outperforming single-indicator evaluation schemes.

7.4 Engineering Validation of FP-LSTM Lifespan Prediction

Six PA samples from the test set are selected for remaining lifespan prediction at early aging nodes of 200 h, 400 h, and 600 h. The proposed FP-LSTM model delivers a maximum prediction deviation of 32 hours for remaining useful life, while the traditional Arrhenius model exhibits a maximum early-stage prediction deviation of 168 hours. The results verify the superior reliability of the physics-constrained time-series network under small-sample early aging conditions, supporting advance prediction of device endurance lifespan on production lines and optimizing automotive device screening workflows.

7.5 Case Validation of the Four-Tier Hierarchical Evaluation System

Three typical failure samples are selected for mechanism tracing verification:

1) **Electromigration-dominated failure:** I_{DQ} and PAE contribute over 60% to total CPDI degradation weight; the evaluation system automatically traces metal interconnection degradation as the root cause.
2) **Gate corrosion under humid conditions:** I_G and THD occupy the highest degradation contribution weights, identifying gate electrochemical corrosion as the dominant failure mechanism.
3) **Pure reversible thermal drift:** Recovery time constant τ_i=2.1 min, directly classified as Tier 1 healthy without permanent damage.

Tier classification and failure mechanism tracing results for all three samples perfectly match post-test Scanning Electron Microscopy (SEM) micro-morphology observations of dissected devices, demonstrating robust engineering reliability of the complete evaluation framework.

8. Conclusions and Future Outlook

8.1 Core Quantitative Conclusions of This Work

1) A multi-stress coupled online synchronous monitoring platform for automotive RF PA endurance aging is constructed with a nanosecond-level time-sharing RF switching timing architecture. Multi-parameter synchronous acquisition of DC metrics, RF characteristics, distortion, and junction temperature is realized without interrupting high-power aging stresses. The maximum relative measurement error of all parameters is controlled within 2.08%. The platform fully captures early latent degradation inflection points missed by offline testing, advancing latent failure detection by an average of 126 hours.
2) The CPDI comprehensive performance degradation index is established via coupled weighting of grey correlation degrees and failure mechanisms, enabling quantitative degradation characterization normalized within the range of 0–1. The index automatically distinguishes reversible thermal drift from permanent micro-damage and achieves a 98.6% recognition accuracy for irreversible device degradation, resolving the risk of missed failure judgment induced by single RF indicator evaluation.
3) The FP-LSTM hybrid degradation prediction model embeds composite-stress failure physics models as prior constraints into LSTM time-series networks. Under composite accelerated aging conditions, the model delivers a mean relative error of 3.17% for lifespan prediction, representing a 47.52% accuracy improvement over the traditional single-stress Arrhenius model. Generalization performance under small-sample early aging scenarios is significantly enhanced.
4) Standardized four-tier endurance degradation thresholds are defined based on extensive accelerated aging calibration. A complete standardized workflow covering data acquisition, preprocessing, quantitative characterization, lifespan prediction, tiered judgment, and failure mechanism tracing is established, fully compliant with AEC-Q102 and ISO 26262 automotive device reliability qualification standards, and readily integrable into semiconductor production line aging test equipment.

8.2 Future Research Directions

1) Expand online monitoring methodologies for multi-channel System-in-Package (SiP) integrated RF front-end modules, incorporating channel electromagnetic coupling degradation correction models to adapt to endurance testing of integrated vehicle-mounted RF transceivers.

2) Optimize the FP-LSTM training pipeline via transfer learning: pre-train the model using aging datasets of mature PAs to drastically reduce sample quantities required for calibration of new PA models and shorten production line qualification cycles.

3) Integrate in-situ infrared thermal imaging and offline SEM micro-morphology observation data to construct a multi-scale coupled failure physics model linking micro-morphology and macroscopic electrical performance, further improving degradation prediction and failure mechanism tracing precision.

4) Conduct real-vehicle road endurance online monitoring experiments to establish a lifespan mapping model between laboratory accelerated aging and natural full-vehicle service aging, enabling direct conversion of laboratory test results to equivalent 15-year full-vehicle endurance performance assessments.

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