Small-Sample Prediction Validation Testing: Uncertainty-Aware Design and Robust Maintenance Strategy for Power Electronic Converters

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***Abstract*—Reliable degradation prediction is paramount for ensuring operational stability and minimizing failure risks in power electronic converters (PECs). Effective maintenance strategies, and thus system longevity and safety, depend on the accuracy of these predictions. However, verifying prediction accuracy with limited data and test durations presents a persistent challenge. This article introduces a test design methodology for degradation prediction verification in PECs, coupled with a preventive maintenance strategy that explicitly incorporates prediction uncertainties. Our approach provides a systematic means of determining the minimum test duration and a principled basis for selecting small sample sizes, enabling the derivation of robust maintenance plans that account for all potential prediction error scenarios. The methodology is validated through a case study of a three-phase inverter, demonstrating its efficacy with sample sizes of fewer than ten. The results highlight the practicality and effectiveness of the proposed methodology in assessing degradation prediction accuracy and, critically, illustrate the superior performance of the uncertainty-aware maintenance strategy in mitigating the risk of catastrophic failures.**

***Index Terms*—Circuit reliability, maintenance, reliability engineering, reliability theory maintenance.**

I. Introduction

THE reliability issues of power electronic converters (PECs) encompass both sudden failure and degraded failure. Sudden failure may arise from design defects, manufacturing issues, single-event effects, overstress, or misuse, whereas degraded failure results from prolonged degradation over time [1]. With the optimization of design and advancements in manufacturing processes, early failures and random faults have gradually been mitigated, leading to improved reliability of PECs [2], [3]. Consequently, a growing focus is on performance degradation resulting from long-term usage. The reliability prediction of PECs typically involves the development of component degradation and lifetime models, as well as electrical and thermal modeling of the converters [2]. The component degradation and lifetime models serve as the foundation for the reliability analysis of PECs. These models are typically developed for specific degradation and failure mechanisms or may consist of mathematical or statistical formulations that do not incorporate physical information [4], [5]. The electrical model calculates the power loss of components, assesses the electrical stress associated with component degradation, and correlates this degradation with the degradation of PECs [6], [7]. The thermal stress can be derived from the component's power loss as input for the thermal model, enabling the calculation of component degradation [8], [9]. Ultimately, the PECs degradation can be determined through the electrical model [10]. While reliability analysis methods have become relatively well-established, validating reliability prediction results continues to present significant challenges. Experimental verification in related research primarily concentrates on verifying the accuracy of components, electrical, and thermal models [11].

The challenges associated with verifying the reliability prediction accuracy at the converter level stem from multiple factors. Firstly, design and manufacturing technology advancements have significantly extended the lifetime of power electronic components and converters. Even with heightened stress levels, lifetime value remains on an annual basis, resulting in verification testing costs that can be exceedingly high. Unlike highly accelerated life test, designed to induce failure of converters under extreme conditions [12], [13], obtaining lifetime data through accelerated life test—utilized to predict lifetime under normal operating conditions—presents significant challenges. This difficulty ultimately impedes the attainment of the desired prediction accuracy. On the other hand, performance degradation has become increasingly prevalent. Degradation prediction accuracy verification encounters specific challenges, including the design of stress levels, test duration, and sample size. In accelerated degradation test design research, the primary focus is

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establishing accurate degradation models or verifying whether a product meets specified reliability requirements through experimentation. Related studies have explored methods such as determining degradation test termination times based on mean time to failure and reducing failure thresholds to shorten test durations and obtain more lifetime data [14], as well as accelerated degradation test duration designs aimed at accurately estimating modeling parameters [15]. Minimizing the asymptotic variance of decision variables in reliability verification by optimizing the sample size as one of the key factors [16]. While established standards primarily aim to evaluate the reliability of products such as IEC 61649 [17], focusing on Weibull analysis, acknowledge the necessity of incorporating prior information when sample sizes are less than ten, and GB 2689.1-81 [18] mandates a minimum of ten samples per stress level (or five for specialized products). MIL-STD-810 [19] further emphasizes the need for sample size determination to be tailored to the specific product's mission risk and cost constraints, discouraging the rigid application of uniform quantity requirements. A persistent challenge in engineering practice is determining the necessary sample size for accurately assessing prediction accuracy and what impact the quantity of samples has on the resulting assessment of predictive accuracy. With a sufficient sample size, degradation prediction verification involves comparing the mean or distribution of predicted and actual degradation amounts at a specific time or comparing the times corresponding to the same degradation value [20]. However, obtaining reliable degradation prediction accuracy results remains challenging under small sample size constraints due to random fluctuations and sample bias.

Maintenance can be categorized into two primary types: preventive and corrective maintenance. Preventive maintenance actions are conducted prior to the failure, while corrective maintenance actions are implemented following a failure [21], [22]. Degradation-based maintenance is a preventive maintenance that relies on the monitoring and analysis of degradation, making it particularly suitable for PECs [23], [24]. Preventive maintenance strategies can be effectively implemented based on degradation predictions. However, model inaccuracies, uncertainties stemming from manufacturing variability, and other contributing factors inevitably lead to discrepancies between predicted and actual degradation. This inherent uncertainty in the discrepancy between predicted and real-world degradation poses a substantial challenge to developing robust and reliable maintenance strategies.

This article tackles these challenges by presenting a degradation prediction verification methodology for small samples. A key aspect of the proposed methodology is its broad applicability; it can be utilized with any existing degradation prediction model for a PEC, irrespective of the specific converter parameters or the methods used to predict them. The focus is on empirically validating the predictive capability and integrating this validated understanding, including its uncertainties, into maintenance planning.

The rest of this article is organized as follows. Section II details the proposed methodology, encompassing: degradation prediction; verification test design (stress level, test duration, and sample size); and assessment of prediction accuracy. Section III then leverages the degradation prediction results to develop a preventive maintenance strategy that explicitly incorporates prediction error. Section IV presents a comprehensive case study validating the methodology using a three-phase inverter. Finally, Section V concludes the article.

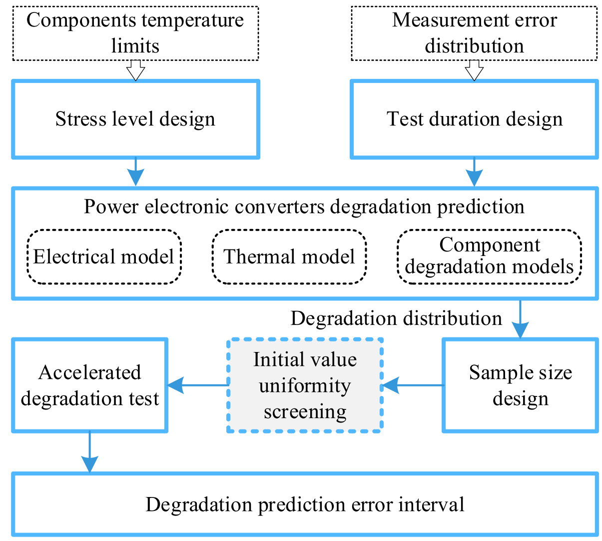

Fig. 1. Framework for degradation prediction verification.

II. Degradation Prediction and Verification

To provide a clear overview of the proposed methodology and to facilitate an understanding of the relationships between its key parts, a flowchart is presented in Fig. 1. Stress level design is conducted with consideration for various temperature limits within the converter to maximize the degradation rate, and the minimum required test duration is determined by accounting for inherent measurement error fluctuations. The predicted degradation distribution informs the sample size design, balancing the need for statistical rigor with the practical constraints of limited data. Finally, the accelerated degradation test is performed, and the proposed methodology is applied to obtain a prediction error interval. The critical parts of the method will be elaborated upon in subsequent subsections.

A. Degradation Prediction

Predicting PEC degradation usually establishes electrical and thermal models. The electrical model calculates component power loss P_{loss} and electrical stress, fundamentally linking component degradation to overall PEC degradation. The thermal model then uses this P_{loss} and ambient temperature to determine component temperatures, vital inputs for calculating component degradation. Integrating these component-level degradation results back into the electrical model, while accounting for inherent parameter distributions, enables the derivation of the converter's overall degradation distribution. The degradation prediction of PECs has been extensively researched, and more details can be seen [1], [2]. It is important to note that the specific nature or origin of these component degradation models (e.g., physics-based, data-driven, or empirical) is not a limitation for the subsequent verification and maintenance strategy proposed in this article. The core requirement is the existence of a model that yields a prediction of PEC degradation.

B. Verification Test Design

This part details the design of the degradation prediction verification test (DPVT). The key elements of this design include (1) determining the appropriate stress levels to accelerate degradation, (2) establishing the minimum test duration required for meaningful data collection, and (3) selecting a statistically sound sample size to ensure reliable results, particularly when constrained by small sample sizes.

1) Stress Level Design: To attain a high degradation rate, it is necessary to elevate the stress level. However, it must be relatively high, as this may lead to converter failure due to overstress or introduce degradation mechanisms that differ from those encountered in normal operating conditions.

Without loss of generality, under constant-load conditions, the electrical stresses associated with component degradation in PECs—such as capacitor voltages, MOSFET turn-ON/OFF voltages, and IC supply voltage—are generally treated as constant and nonaccelerating. Consequently, our stress-level design focuses on thermal stress for PECs operating under constant loads. In variable-load scenarios, components may experience complex fluctuations in coupled electrothermal stresses, which introduces new challenges for accelerated stress design. These challenges fall outside the scope of this article and are therefore not addressed here. Determining the appropriate thermal stress level for the DPVT requires careful consideration of two key factors: the maximum operating temperature of each component and the maximum allowable temperature for the component degradation model. The maximum operating temperature defines the upper limit at which a component can function reliably and within its specified performance parameters; exceeding this limit can lead to immediate failure. The manufacturer typically specifies these maximum operating temperatures in the component datasheets. During the DPVT, it is crucial to ensure that the temperature of all components remains below their respective maximum operating temperatures to avoid introducing failure modes that differ from those expected under normal operating conditions and to prevent unexpected converter faults. Additionally, the component temperatures must not exceed the maximum allowable temperature of the degradation model itself, as exceeding this limit can invalidate the model's assumptions or introduce degradation mechanisms not accounted for within the model's scope.

2) Test Duration Design: The design of the test duration must account for the presence of measurement errors. As PECs become increasingly reliable, their degradation rates tend to decrease significantly. Therefore, to ensure the validity of the DPVT, the minimum test duration must be sufficient to ensure that the observed changes in degradation increment (i.e., the change relative to the initial value) are significantly larger than the inherent measurement fluctuations within the testing process. Otherwise, measurement errors could mask the actual degradation, compromising the accuracy of the verification. To address this, it is essential to quantify the measurement error first. This can be achieved by repeatedly measuring the parameters before initiating the formal DPVT. Critically, this preliminary measurement process should replicate all steps involved in the formal DPVT, including the connection of test leads and equipment, to accurately capture the full spectrum of measurement fluctuations present during the actual test. Subsequent statistical analysis of this data allows for a reliable determination of the measurement error. To achieve that, for each unit, the mean measurement value is calculated and then subtracted from each individual measurement to obtain a set of measurement errors

$$\varepsilon_{i,j} = y_{i,j} - \bar{y}_i \tag{1}$$

where $\varepsilon_{i,j}$ is the measurement error for the *i*th unit and *j*th measurement, $y_{i,j}$ is the *j*th measurement on the *i*th unit, and $\overline{y}_i$ is the mean measurement value for the *i*th unit. These individual measurement errors are then pooled across all units, and a statistical analysis is performed to determine the distribution characteristics. In many cases, the measurement error can be reasonably approximated by a normal distribution with a mean of zero. In such cases, the standard deviation σ of the measurement error can be estimated, and a range of $\pm 3\sigma$, encompassing approximately 99.7% of the measurement errors, can be determined. Subsequently, the minimum test duration is determined based on the degradation prediction results, such that the predicted degradation increment (ΔD_{pred})—defined as the difference between the degradation and initial value—exceeds the measurement error range

$$|\Delta D_{\text{pred}}| > 3\sigma. \tag{2}$$

3) Sample Size Design: In DPVT, a sample size exceeding 30 is generally preferred to improve the statistical power and accuracy of degradation characterization. When assessing populations characterized by high levels of inherent variability, a larger sample size may be required to achieve sufficient statistical power for reliable inference. This is because increased dispersion necessitates a greater number of observations to estimate population parameters accurately. However, the practical challenges associated with large-scale experimentation, including budgetary constraints and time limitations, often preclude this approach. As the sample size dictates the allocation of essential resources, its careful estimation is paramount prior to DPVT. Consequently, the a priori determination of a defensible sample size becomes critical in justifying research funding requests. This article directly addresses the statistically complex problem of obtaining credible prediction accuracy results despite the inherent limitations of small sample sizes ($n \leq 10$).

Assuming that the predicted and actual degradation distributions have a similar level of dispersion, this suggests they follow the same distributional form (e.g., normal, Weibull) and have comparable standard deviations, with differences primarily in their mean values. This assumption posits that, given the accurate quantification of component parameter variability and a high-fidelity electrical model, the calculated PEC parameters can be validated against and calibrated with the actual parameters of PEC prior to the DPVT. The closer the agreement between these calculated and actual parameters, the more reliable the error assessment will be. This validation and calibration process is a

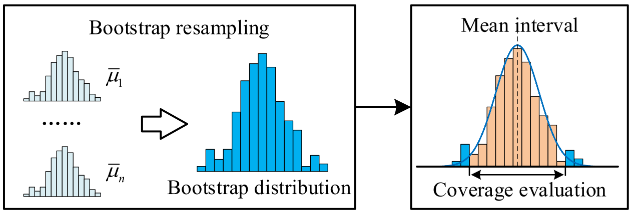

Fig. 2. Determination of degradation mean interval.

critical prerequisite for achieving accurate degradation predictions. This allows us to leverage the predicted distribution to inform sample size selection for verification testing. The bootstrap method, a nonparametric resampling technique, provides a powerful approach for estimating the sampling distribution of a statistic by repeatedly drawing samples with replacement from the observed data. This technique allows statistical inference without relying on restrictive parametric assumptions, rendering it particularly well-suited for scenarios involving small sample sizes or nonnormal distributions. As illustrated in Fig. 2, the distributional characteristics of degradation can be obtained from the prediction results. Subsequently, a range of sample sizes can be evaluated using bootstrap resampling to derive the corresponding resampled mean distributions. In this context, the bias-corrected and accelerated (BCa) bootstrap is recommended due to its superior performance in achieving accurate and reliable interval estimation with limited data [25], [26]. The construction of the interval then proceeds as follows:

$$[D_L, D_U] = \left[\hat{\theta}_j^*, \hat{\theta}_k^*\right] \tag{3}$$

where θ represents a parameter of interest. $\hat{\theta}$ is an estimator of θ. $\hat{\theta}_j^*$ denotes the jth quantile (lower limit), and $\hat{\theta}_k^*$ denotes the kth quantile (upper limit). Subtracting the initial value, the degradation increment interval is [ΔD_L, ΔD_U]. The j, k is calculated as

$$j = \Phi\left\{\hat{z}_0 + \frac{\hat{z}_0 + z^{\alpha/2}}{1 - \hat{a}\cdot(\hat{z}_0 + z^{\alpha/2})}\right\}\cdot B \tag{4}$$

$$k = \Phi\left\{\hat{z}_0 + \frac{\hat{z}_0 + z^{1-\alpha/2}}{1 - \hat{a}\cdot(\hat{z}_0 + z^{1-\alpha/2})}\right\}\cdot B \tag{5}$$

where Φ is the standard normal cumulative distribution function, α is the significance level, $z^{(\alpha/2)}$ is the $100\times(\alpha/2)$th percentile point of a standard normal distribution, and B is the number of bootstrap samples.

The quality of a mean confidence interval is evaluated based on several key criteria, balancing the desire for a reliable and precise estimate of the population mean. A primary consideration is the coverage probability, defined as the proportion of times the interval, if repeatedly constructed from independent samples, would contain the true population mean; ideally, this should closely match the stated confidence level (e.g., 95%). Beyond coverage, a "good" confidence interval also exhibits a narrow width, reflecting a more precise estimate. A simulation study or repeated sampling approach is typically employed to estimate the coverage probability empirically. The process involves the following steps:

1) *Define the Population:* Specify the characteristics of the population from which samples will be drawn. For example, when focusing on the prediction accuracy at the end of the verification test, the distribution type and parameters of the degradation at that specific time need to be determined.
2) *Generate Repeated Samples:* Generate N independent random samples from the defined population, each of size n.
3) *Construct Confidence Intervals:* For each of the N samples, construct a confidence interval for the population mean using the BCa bootstrap method.
4) *Determine Coverage:* For each confidence interval, determine whether it contains the true population mean μ. This can be represented as a binary indicator variable I_i

$$I_i = \begin{cases} 1, & \text{if} \mu \in \text{CI}_i \\ 0, & \text{if} \mu \notin \text{CI}_i \end{cases} \tag{6}$$

where CI_i represents the ith confidence interval.

5) *Calculate Coverage Probability:* Estimate the coverage probability as the proportion of confidence intervals that contain the true population mean

$$\text{Coverage} = \frac{1}{N}\cdot\sum_{i=1}^{N} I_i. \tag{7}$$

It is important to note that the accuracy of the estimated coverage probability depends on the number of simulations (N). A larger value of N will generally yield a more precise estimate of the true coverage probability. As the significance level α decreases, the confidence interval bounds extend toward more extreme quantiles of the distribution, increasing interval width. This expansion reflects the higher confidence level; for example, increasing the confidence level from 95% to 99% widens the interval to encompass a larger portion of the data distribution in the tails, thereby increasing the probability that the interval covers the actual mean value. The average interval length $\bar{W}$ can also be calculated to determine whether the uncertainty range of error assessment meets expectations

$$\bar{W} = \frac{1}{N}\sum_{i=1}^{N}\left(D_U^i - D_L^i\right) \tag{8}$$

where D_U^i is the upper bound of CI_i, D_L^i is the lower bound of CI_i, both obtained using (3).

In evaluating the accuracy of the predicted degradation, a high coverage probability and a narrow confidence interval for the actual degradation mean are essential. A high coverage probability enhances the reliability of conclusions regarding predicted accuracy, ensuring that observed errors in comparison to the interval accurately reflect the true prediction error. Additionally, a narrower confidence interval facilitates a more precise assessment of the prediction's accuracy. When the predicted mean is compared to a narrow interval encompassing the true mean, it allows for more decisive conclusions regarding the proximity of the prediction to the true value. Conversely, a wider interval increases uncertainty in the accuracy assessment.'

C. Prediction Accuracy Assessment

Conventional methods for assessing prediction accuracy, such as relative error (RE) calculation, can be misleading in the context of degradation prediction for highly reliable PECs. In such cases, the numerator in the RE formula approaches zero, resulting in understated error percentages, despite a potentially significant absolute difference between predicted and actual degradation

$$\mathrm{RE} = |(D_{\mathrm{pred}} - D_{\mathrm{true}})/\, D_{\mathrm{true}}| \times 100\% \tag{9}$$

where D_{pred} is the predicted degradation and D_{true} is the actual degradation. To address this, a more comprehensive approach is proposed to consider both the degradation increment and the uncertainty in the experimental data. The RE of the degradation increment $\mathrm{RE}_{\mathrm{incr}}$ is used as a key metric

$$\mathrm{RE}_{\mathrm{incr}} = \frac{\Delta D_{\mathrm{true}} - \Delta D_{\mathrm{pred}}}{\Delta D_{\mathrm{pred}}} \times 100\% \tag{10}$$

where $\Delta D_{\mathrm{pred}} = D_{\mathrm{pred}}$ - D_{initial} and $\Delta D_{\mathrm{true}} = D_{\mathrm{true}}$ - D_{initial} . Note that this formulation allows for both positive and negative error values, indicating the direction of the prediction error. The utilization of the BCa bootstrap for constructing the confidence interval around the true degradation mean leads to an error assessment that is also interval-valued

$$\left[\mathrm{RE}_{\mathrm{incr}}^{\min}, \mathrm{RE}_{\mathrm{incr}}^{\max}\right] = \left[\min\left(\mathrm{RE}_{\mathrm{incr}}\right), \max\left(\mathrm{RE}_{\mathrm{incr}}\right)\right] \tag{11}$$

where $\Delta D_{\mathrm{true}} \in [\Delta D_L,\ \Delta D_U]$. This error interval provides a more complete and nuanced assessment of the prediction's accuracy. It captures not only the magnitude of the potential error but also its direction, while acknowledging the range of plausible values for the true degradation increment. The RE assessed during the DPVT is used as a general estimate of the prediction accuracy across all operating conditions. Specifically, if the error associated with the predicted value D_{pred} under DPVT conditions is estimated to lie within the interval [$\mathrm{RE}_{\mathrm{incr}}^{\min}$, $\mathrm{RE}_{\mathrm{incr}}^{\max}$], it is hypothesized that the same error bounds [$\mathrm{RE}_{\mathrm{incr}}^{\min}$, $\mathrm{RE}_{\mathrm{incr}}^{\max}$] remain applicable for D_{pred} under any other stress conditions.

The stress level design presented in this article primarily focuses on accelerating thermal stress for PECs operating under constant stress conditions. Degradation under dynamic stress may exhibit complex phenomena, such as path dependency, thereby limiting the direct applicability when considering the interaction of dynamic stress levels in the degradation path [27], [28]. Addressing these complexities and extending the verification framework to dynamic stress scenarios represents a key direction for future research. However, the proposed sample size design and error assessment methodologies are not constrained by this, as they are fundamentally rooted in mathematical and statistical principles.

III. Preventive Maintenance Strategy Incorporating Prediction Error

Regular maintenance is essential to ensure the long-term stable operation of PECs, and maintenance strategies can be formulated based on degradation prediction. The degradation

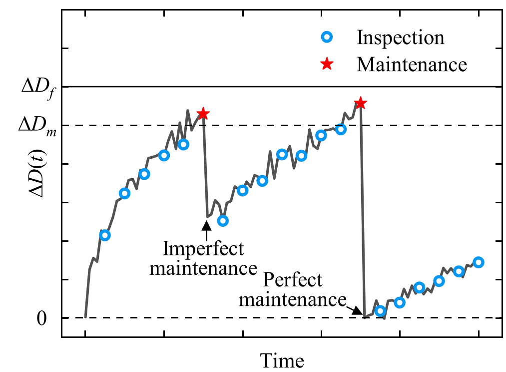

Fig. 3. Inspection and maintenance.

increment of the parameter in the PEC at time t is defined as $\Delta D(t)$, with $\Delta D(t) = 0$ when $t = 0$. The value of $\Delta D(t)$ can be obtained through inspection conducted at intervals of Δt. Maintenance is performed when $\Delta D(t)$ exceeds a predetermined threshold ΔD_m ($\Delta D(t) \geq \Delta D_m$). As shown in Fig. 3, maintenance may be perfect or imperfect, depending on the specific options for component replacement. Perfect maintenance is the most typical maintenance, which reducing the ΔD to 0. Each inspection and maintenance action incurs associated costs. To prevent malfunctions, it is essential to ensure that $\Delta D(t)$ does not exceed the fault threshold ΔD_f ($\Delta D(t) \geq \Delta D_f$) at any time. The fault threshold ΔD_f is typically defined based on specific constraints, such as ensuring that the motor does not exceed a fixed speed or that the voltage remains below a specified value. Consequently, the objective is to identify the optimal values of Δt and ΔD_m while ensuring no malfunctions occur. An optimal maintenance strategy aims to minimize costs while ensuring uninterrupted operation. However, the uncertainty in degradation prediction error complicates the design of robust maintenance strategies. Maintenance costs include the expenses associated with inspections and the replacement of components. The cumulative maintenance cost at time t is represented as C_t

$$C_t\left(\Delta t, D_m\right) = N_i\left(t\right) C_i + N_r(t) C_r \tag{12}$$

where C_i and C_r represent the costs associated with each inspection and maintenance. $N_i(t)$ and $N_r(t)$ denote the number of inspections and maintenance performed, respectively. The development of preventive maintenance strategies incorporating prediction error can be considered as a robust optimization framework to minimize the worst-case cost C_t under parametric uncertainty $\mathrm{RE}_{\mathrm{incr}} \in [\mathrm{RE}_{\mathrm{incr}}^{\min}, \mathrm{RE}_{\mathrm{incr}}^{\max}]$, where both the objective and constraint are deterministic but lack analytical expressions. The objective is to minimize the worst-case cost

$$\min\nolimits_{\Delta t, D_m} \max\nolimits_{\mathrm{RE}_{\mathrm{incr}} \in \left[\mathrm{RE}_{\mathrm{incr}}^{\min}, \mathrm{RE}_{\mathrm{incr}}^{\max}\right]} C_t. \tag{13}$$

To achieve cost minimization, $\mathrm{RE}_{\mathrm{incr}}$ can be discretized into N scenarios using Latin Hypercube Sampling or quasi-Monte Carlo methods to capture the uncertainty spectrum. Then, the

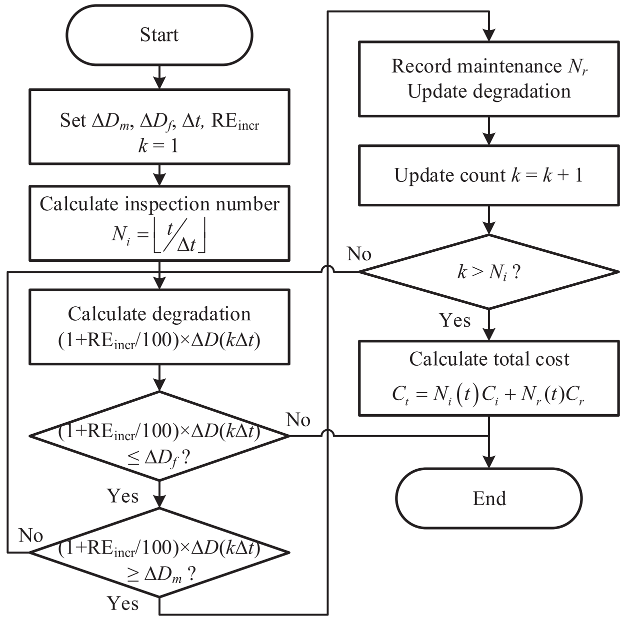

Fig. 4. Maintenance cost computation process.

discretized problem becomes

$$\min_{\Delta t, D_f} h$$
$$\text{s.t. } C_t\left(\Delta t, D_f, e^{(i)}\right) \le h, \qquad \forall i = 1, \ldots, N$$
$$\text{s.t.} D(t) \le D_f \qquad \forall i = 1, \ldots, N, \forall t. \tag{14}$$

Black box optimization algorithms, such as genetic algorithms, can be used to solve this problem. The maintenance cost computation process is shown in Fig. 4. A key criterion in the cost calculation process is to ensure that all samples do not exceed the ΔD_f. Additionally, the proportion of samples exceeding the ΔD_m during each inspection is determined to calculate the cost of component replacement.

The preventive maintenance strategy here is fundamentally prediction-driven, with maintenance schedules (defined by inspection interval Δt and maintenance threshold ΔD_m) being proactively determined solely based on the predicted future degradation. When considering the prediction uncertainty, it allows for the formulation of robust maintenance strategies, aiming to mitigate risks even when faced with imperfect predictions. It does not involve online condition monitoring data to dynamically update the prediction model or adjust maintenance thresholds during operation. The focus is on establishing a robust *preventive* plan based on the best available (though potentially uncertain) foresight.

IV. Case Study: Three-Phase Inverter

The proposed method is demonstrated through a three-phase inverter, as shown in Figs. 5 and 6. The dc–dc converters supply power to driver chips, current sensors, and operational amplifiers. The inverter operates in constant current effective value mode using the sine pulsewidth modulation control. Output phase current feedback is obtained through current sensors and operational amplifiers and regulated via proportional-integral control. This case focuses on the phase current root mean square value I_{RMS} degradation. The degradation impact analysis indicates that the feedback resistors of the 5 V dc–dc converter and current sensors significantly influence closed-loop control and the I_{RMS}. Consequently, their degradation models are used to predict the degradation of I_{RMS}.

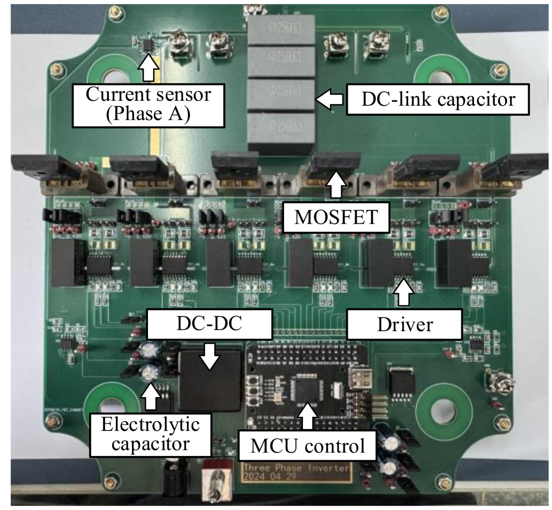

Fig. 5. Three-phase inverter printed circuit board.

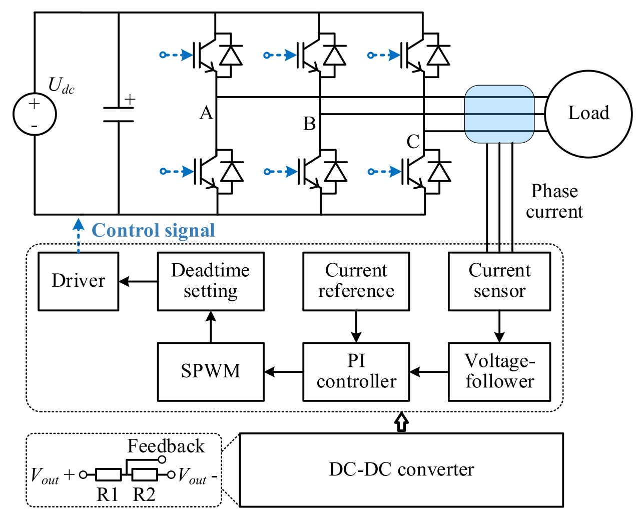

Fig. 6. Three-phase inverter circuit diagram.

A. Degradation Prediction Verification Test Design

1) Stress Level Design: In the three-phase inverter, the maximum operating temperature for the operational amplifier in the feedback circuit is the lowest among the components, set at 85 °C. This constraint limits the allowable increase in DPVT temperature. At an ambient temperature of 80 °C, the operational amplifier's temperature, calculated by the thermal model, reaches 82.5 °C. A DPVT temperature of 80 °C is selected to maintain a safety margin.

TABLE I
COMPONENT DEGRADATION MODELS

Component	Parameter	Initial value	Degradation model
Current sensor	Sensitivity	$\mu = 0.0444$ V/A $\sigma = 4.4\times10^{-4}$ V/A	$\Delta V = a_1 \cdot \exp(-b_1/T)\cdot t$
	Zero-current output voltage	$\mu = 2.5$ V $\sigma = 0.01$ V	——
Feedback resistor 1 (R1)	Resistance	$\mu = 3$ KΩ $\sigma = 10$ Ω	$\Delta R = a_2 \cdot \exp(-b_2/T)\cdot t^m$
Feedback resistor 2 (R2)	Resistance	$\mu = 1$ KΩ $\sigma = 3.3$ Ω	$\Delta R = a_3 \cdot \exp(-b_3/T)\cdot t$

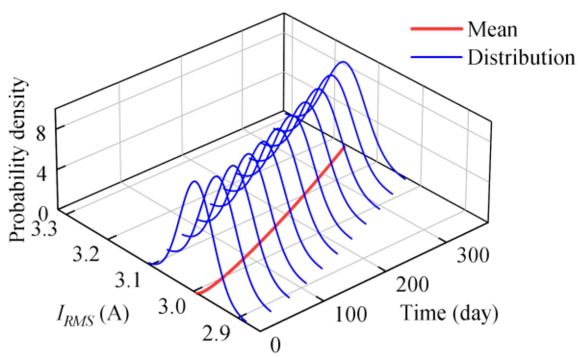

Fig. 7. I_{RMS} degradation prediction.

The degradation model of components, with temperature T and time t as inputs, is given in Table I. The I_{RMS} is closely associated with the degradation of current sensors and feedback resistors. The current sensor sensitivity degradation directly affects the modulation depth. The 5V dc–dc provides the power supply for the current sensor, while its feedback resistor regulates the output voltage. Degradation of the resistance can lead to variations in the voltage, subsequently impacting the current sensor's zero-current output voltage and sensitivity. The a, b, m are coefficients. The degradation models are formulated in terms of changes in parameters. Additionally, the initial value is assumed to follow a normal distribution. Although capacitors and MOSFETs are critical components in PECs, their parameter degradation does not affect the performance indicator of interest in this case study, namely the phase current RMS I_{RMS}. Therefore, they are not considered in the degradation prediction herein. Under 80 °C, utilizing the distribution of component parameters, the degradation of I_{RMS} can be predicted, as illustrated in Fig. 7. The dispersion of the degradation distribution increases over time.

2) Test Duration Design: A total of 30 repeated I_{RMS} measurements are conducted on ten individual inverters before the DPVT, and the results are presented in Fig. 8. Measurement errors can be considered to follow a normal distribution with a mean of 0. The range of $\pm 3\sigma$ standard deviations, encompassing approximately 99.7% of the measurement errors, is approximately 0.05. This indicates that the test duration for DPVT must result in an I_{RMS} degradation of at least 0.05 A for the prediction accuracy results to be meaningful. This duration can be initially estimated based on the degradation prediction results. Specifically, according to the prediction results, it corresponds to 3232 h. Therefore, DPVT is initially designed for 4000 h. The test duration can be further refined based on the actual degradation test results. It is important to note that the test duration established through the statistical characteristics of measurement errors represents only the minimum requirement.

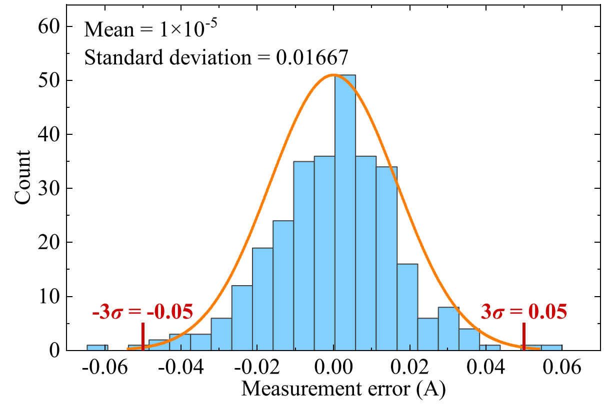

Fig. 8. Measurement error distribution.

TABLE II
INTERVAL COVERAGE PROBABILITY

Sample size	Significance level				
	0.01	0.02	0.03	0.04	0.05
2	48.6 %	51.3 %	48.4 %	49.5 %	49.7 %
3	75.7 %	75.1 %	74.0 %	73.2 %	73.3 %
4	84.8 %	84.7 %	81.6 %	80.9 %	79.7 %
5	90.1 %	86.7 %	85.9 %	84.4 %	83.6 %
6	91.6 %	89.5 %	88.1 %	87.9 %	85.8 %
7	92.5 %	91.6 %	90.2 %	89.6 %	87.8 %
8	94.7 %	93.0 %	91.8 %	90.4 %	89.3 %
9	94.8 %	93.6 %	92.4 %	90.2 %	88.7 %
10	95.8 %	93.1 %	91.9 %	91.2 %	90.2 %

3) Sample Size Design: Based on the prediction results, the I_{rms} at 4000 h is considered to follow a normal distribution with a mean of 3.052 and a standard deviation of 0.043. Subsequently, the sample size is set, and random samples are generated based on prediction degradation distribution characteristics. The BCa bootstrap is employed for resampling to calculate the mean distribution. Finally, a significance level is set to determine the interval for the mean. Here, sample sizes range from 2 to 10, with significance levels varying from 0.01 to 0.05 are analyzed. The proportion of intervals that include the true mean of 3.052, as illustrated in Table II. Specifically, $\alpha = 0.05$ (corresponding to a 95% confidence level) is a standard benchmark widely adopted in scientific research, ensuring comparability with existing literature. Adopting $\alpha = 0.01$ (corresponding to a 99% confidence level) signifies a more stringent evaluation, illustrating the inherent tradeoff in small-sample scenarios where higher confidence levels typically necessitate wider confidence intervals. Furthermore, the inclusion of intermediate significance levels

(0.02, 0.03, 0.04) facilitates a more nuanced observation of the dynamic evolution of confidence interval width and actual coverage probability in response to varying confidence levels. By examining outcomes across this spectrum of α values, rather than relying on a singular α, we endeavor to more comprehensively portray the characteristics of our findings and deepen the understanding of the trade-off between confidence and precision inherent in small-sample contexts. It is important to recognize that practical engineering applications are not limited to these α values; indeed, broader exploration may be warranted to determine intervals that best suit specific needs.

Taking the results from five samples at $\alpha = 0.01$ as an example, the obtained mean interval corresponding to a coverage of 90.1%. This implies that by randomly selecting five three-phase inverters for DPVT, the probability that the actual degradation mean falls within the degradation mean interval calculated for 4000 h with $\alpha = 0.01$ is 90.1%. The presented results demonstrate a clear positive correlation between sample size and coverage probability at a constant significance level, thereby providing a valuable basis for informing sample size design in DPVT. Specifically, these findings suggest that achieving a coverage probability exceeding 90% for the mean credible interval in DPVT may require a minimum sample size of only five units. By explicitly considering the trade-off between coverage probability and sample size, the proposed methodology facilitates a more flexible and resource-efficient approach to sample size design, allowing researchers to tailor the experimental effort to meet specific accuracy requirements and budgetary constraints. Besides, sample characteristics that fail to yield credible intervals encompassing the true population mean can also be leveraged to prescreen candidate samples prior to commencing DPVT. Our results suggest that samples lacking coverage are often characterized by skewness, indicating a nonuniform distribution of converter parameters around the true mean. These findings underscore the importance of selecting DPVT samples that exhibit a balanced representation of parameter values. In practical terms, this implies that for a sample size of six converters, an optimal selection strategy would aim to include approximately three converters with initial I_{RMS} values exceeding the population mean of 3 A, and three with values below this mean, thereby mitigating potential bias in the subsequent verification process.

B. Prediction Accuracy Assessment

The degradation of A-phase I_{RMS} is shown in Fig. 9. The I_{RMS} is tested at intervals of a week (approximately 166 h) following temperature stabilization at 25 °C. At the end of DPVT, the degradation mean interval obtained at $\alpha = 0.05$ is [3.0692, 3.1244]. By subtracting the initial value, the resulting degradation increment interval is [0.0765, 0.1321]. The predicted mean is 3.052, with a corresponding degradation increment of 0.062. The predicted error range can thus be calculated as [23.4%, 113.1%]. As the significance level decreases, there is a corresponding increase in the coverage probability; however, this relationship also expands the error interval. The error result is shown in Fig. 10. Compared to the results obtained from five samples at a significance level of 0.01 (approximately 90% coverage), the error interval in the small sample size is broader. This suggests that while larger samples at a given significance level are more reliable, the use of small sample sizes may be acceptable if the increased uncertainty in range is tolerable. The degradation prediction error assessment provides a robust foundation for subsequent PEC optimization. For instance, if a slower degradation rate is desired, this information can guide the selection of more stable components (e.g., lower-drift sensors) or implementing circuit-level mitigation techniques (e.g., parallel resistor configurations). A new degradation prediction can then be performed, enabling iterative design improvements.

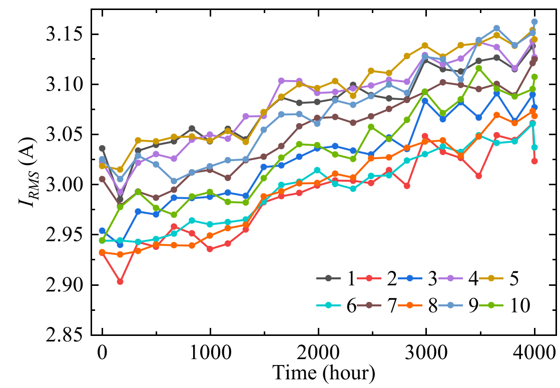

Fig. 9. I_{RMS} degradation in DPVT.

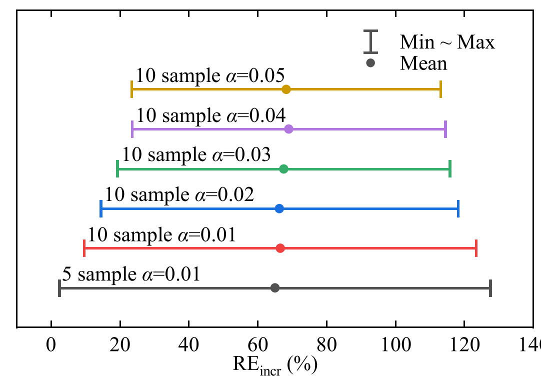

Fig. 10. Error interval comparison.

C. Maintenance Strategy Development

To illustrate the application of verified degradation predictions in optimizing preventive maintenance strategies, a cost model was developed and applied to the three-phase inverter case study. The inspection cost is defined as 20, while the maintenance cost is defined as 38. The expected total working time is set as 10 years, and the operational profile of the inverter is modeled using a Markov chain. This Markov chain, a common tool for representing stochastic systems, captures the probabilistic transitions between two distinct states: operational and nonoperational. The operating ambient temperature is 80 °C, while the nonoperating ambient temperature is 25 °C. At 25 °C, degradation is considered negligible. The transition probability

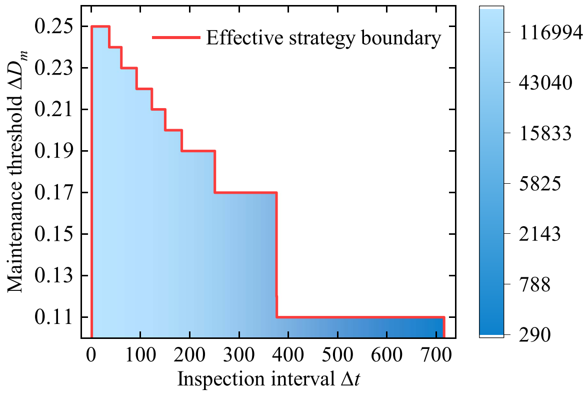

Fig. 11. Maintenance cost results without considering predicted errors.

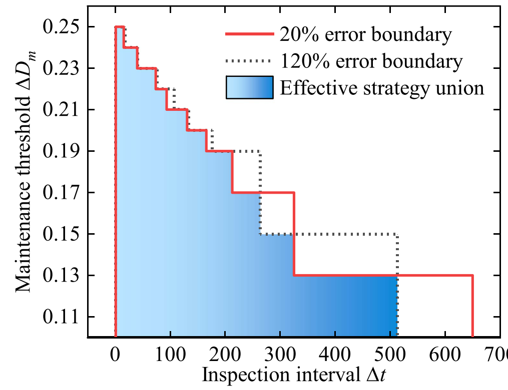

Fig. 12. Effective maintenance strategy determination.

matrix is defined as follows:

$$P = \begin{bmatrix} p_{11} & p_{10} \\ p_{01} & p_{00} \end{bmatrix} = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \end{bmatrix} \tag{15}$$

where p_{11} represents the probability of transitioning from operational to another operational state, p_{10} denotes the probability of transitioning from operational to nonoperational, p_{01} indicates the probability of transitioning from nonoperational to an operational state, and p_{00} signifies the probability of remaining in nonoperational. The matrix presented here serves as a simplified example for case study purposes. Matrix values can be determined from operational history data. For instance, if there are 80 operational days in the historical data, with 40 of those days followed by a nonoperational day, then p_{10} would be 0.5.

The selection of an appropriate maintenance threshold ΔD_m is critical. Setting ΔD_m too low may lead to excessive maintenance interventions, while setting it too high may increase the risk of catastrophic failure. To balance these considerations, ΔD_m was constrained to be greater than 0.1, ensuring that it exceeds the range of typical initial parameter variations in the population of three-phase inverters. Specifically, the 95% of the I_{RMS} initial value distribution was observed to be approximately 3.1 A, suggesting that a degradation maintenance threshold of 0.1 A or higher is necessary to ensure its practical significance. Therefore, this article explored the maintenance threshold ΔD_m within the range of 0.1 to 0.3 A to identify the optimal maintenance strategy, with a failure threshold ΔD_f set at 0.3 A. This implies that phase current I_{RMS} degradation should not exceed 3.3 A, beyond which the inverter is considered to have failed. The inspection interval Δt is measured in days, with a minimum duration of one day, reflecting practical constraints on inspection frequency.

Recognizing the inherent uncertainty in the degradation predictions, the analysis explicitly incorporates the predicted error range of [20%, 120%], derived from the DPVT. This range, while illustrative, is based on [23.4%, 113.1%]. To demonstrate the impact of prediction error on maintenance decisions, initial analyses were performed without accounting for prediction errors, as shown in Fig. 11. The results revealed a minimum maintenance cost at $\Delta D_m = 0.11$ and $\Delta t = [609, 716]$. Combinations of ΔD_m and Δt that fall within unfilled areas represent invalid strategies, as they lead to I_{RMS} exceeding the failure threshold ΔD_f. To develop a more robust maintenance strategy, the analysis was extended to incorporate the full range of predicted errors. While optimization algorithms could be directly applied based on Section III to obtain the optimal solutions, this section presents the results of the union of the effective strategy sets, as illustrated in Fig. 12. The influence of increased prediction error on the boundaries of feasible maintenance strategies is monotonic. All feasible strategies for error between 20% and 120% are contained within the union of the feasible strategy sets defined at the 20% and 120% error boundaries. The resulting minimum cost is achieved at $\Delta t = 513$ with $\Delta D_m = [0.11, 0.13]$. Notably, this inspection interval is significantly shorter than that obtained without accounting for prediction errors, highlighting the critical importance of explicitly incorporating prediction uncertainty into maintenance strategy development. This result suggests that maintenance strategies developed without considering predicted errors are likely to underestimate the required maintenance frequency, thereby increasing the risk of failure. The maximum overestimation is close to 40%. Therefore, the proposed methodology explicitly accounts for prediction uncertainty and offers a more robust and reliable approach to developing effective preventive maintenance strategies.

V. Conclusion

This article presents a verification test design methodology tailored for predicting degradation in PECs under small-sample conditions, demonstrating its efficacy alongside a preventive maintenance strategy that integrates prediction error uncertainty. To ensure the validity of the DPVT within the constraints of limited data, the test duration is designed to be sufficiently long to ensure that degradation increments significantly exceed inherent measurement fluctuations. Furthermore, a bootstrap-based approach is employed to construct a credible interval for the degradation, addressing the challenges of accuracy assessment with small sample sizes. By integrating these design considerations and employing the bootstrap method to evaluate prediction accuracy with limited samples, this article introduces novel tools and insights for PEC reliability analysis. A case study on a three-phase inverter validates the practicality of the proposed approach. Compared to traditional methods, the uncertainty-informed maintenance strategy markedly improves system stability and safety while reducing failure risks.

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