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Reliable Board-Level Degradation Prediction with Monotonic Segmented Regression under Noisy Measurement

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***Abstract*—The increasing complexity of electronic systems in autonomous electric vehicles necessitates robust methods for forecasting the degradation of critical components such as printed circuit boards (PCBs). Various time series forecasting methods have been investigated to predict in-situ resistance degradation under vibration loads. However, these methods failed to capture the degradation trend under strong measurement noise. This paper introduces Monotonic Segmented Linear Regression (MSLR), a novel approach designed to capture monotonic degradation trends in time series data under significant measurement noise. By incorporating monotonic constraints, MSLR effectively models the non-decreasing behavior characteristic of degradation processes. To further enhance reliability of the prediction, we integrate Adaptive Conformal Inference (ACI) with MSLR, enabling the estimation of statistically valid upper bounds for resistance degradation with high confidence. Extensive experiments demonstrate that MSLR outperforms state-of-the-art time series forecasting baselines on real-world PCB degradation datasets.**

***Index Terms*—Board-Level Reliability, Physical Health Monitoring, Prognostics, Physics of Degradation, N-BEATS, Segmented Regression**

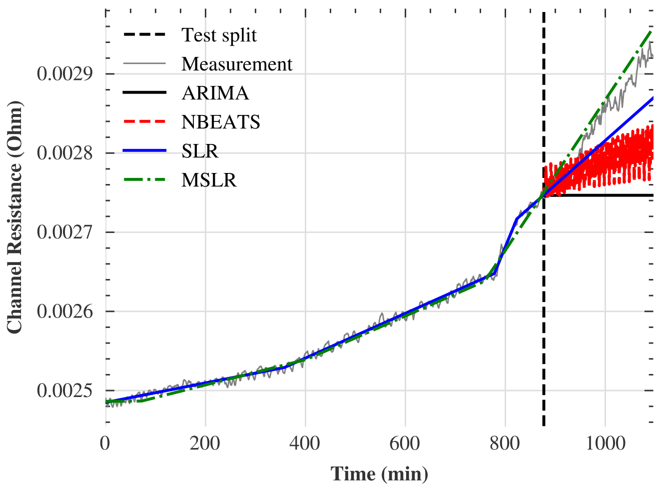

Figure 1: An example of PCB degradation prediction of various time series forecasting approaches

I. Introduction

The advent of electric cars is revolutionizing the automotive industry, paving the way for fully autonomous vehicles that promise to redefine transportation. These vehicles rely heavily on advanced semiconductor technologies that shape their software and electronic architectures. As the transition towards self-driving electric cars accelerates, the demand for cutting-edge electronic systems has grown exponentially. This shift not only enhances the capabilities of modern vehicles but also introduces significant complexities in their design and operation.

At the heart of these challenges lies the reliability and safety of electronic systems, which are critical to the performance of autonomous vehicles. The printed circuit boards (PCBs) and their solder interconnects, which form the backbone of these systems, are particularly vulnerable to degradation over time. Studies show that mechanical vibrations alone account for around one-fifth of solder joint failures, posing risks to mission-critical electronic components [1]. Ensuring the health of PCBs is therefore paramount. Effective real-time monitoring of solder joint degradation can help predict their remaining useful life, mitigating failures and enhancing system reliability. Moreover, predicting PCB degradation is also crucial in achieving the high safety of autonomous vehicles. Even though the degradation process ought to be monotonic, the strong noisy environment induces severe measurement noise, rendering reliable and accurate prediction.

Time series forecasting is an effective machine learning method for predicting trends based on previous measurements. Recent work [2] benchmarks the PCB degradation prediction task for various competitive time series forecasting approaches, including conventional statistical methods, like Auto-Regressive Integrated Moving Average (ARIMA) [3], and modern deep learning models, such as Neural Basis Expansion Analysis for Time Series (N-BEATS) [4]. ARIMA is a statistical model that combines autoregressive and moving average components with differencing to make the time series stationary before predicting future values. Its simplicity and interpretability make it a preferred choice for many forecasting tasks. N-BEATS, on the other hand, is a deep learning-based model designed to capture complex temporal patterns. It employs a

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stack-based architecture that uses neural networks to model the basis functions of the time series, achieving state-of-the-art performance in many benchmarking tasks.

However, both ARIMA and N-BEATS face significant limitations when applied to scenarios involving monotonic trends under strong measurement noise. ARIMA relies on assumptions of stationarity and linearity, which makes it ill-suited for capturing inherent monotonic behaviors. In contrast, N-BEATS, while powerful in learning complex patterns, lacks explicit constraints or inductive biases to enforce monotonicity in the predictions. This often results in overfitting to noisy data, especially in environments where the signal-to-noise ratio is low. Consequently, these methods struggle to reliably model monotonic degradation processes, underscoring the need for specialized approaches tailored to this task. Recent research demonstrates the effectiveness of introducing monotonic neural network [5] into degradation prediction in chip performance estimation at several testing time stamps [6], but there is a lack of such practice in PCB degradation forecasting for fine-grained time intervals.

To address these concerns, we propose Monotonic Segmented Linear Regression (MSLR), a tailored approach for modeling the degradation of solder joints in electronic systems with inherent monotonic trends. MSLR extends traditional Segmented Linear Regression (SLR) [7] by incorporating two key constraints: a constant value for the initial segment and a monotonic increase for subsequent segments. The constant segment captures the stable behavior typically observed at the start of the degradation process, while the monotonic constraint ensures that predictions reflect the non-decreasing nature of the underlying physical phenomenon.

The model achieves this by enforcing constraints on the segment slopes, ensuring they remain non-negative, and by using a Softplus projection to map free parameters into valid monotonic slopes. This approach embeds the monotonicity directly into the optimization process, preventing overfitting to noise and ensuring consistency with the expected trend. By dividing the time series into meaningful segments and explicitly encoding the monotonic behavior, MSLR captures the essential structure of degradation processes, even in the presence of significant measurement noise. This makes MSLR a robust and interpretable solution for time series forecasting in applications where monotonic trends are fundamental. In Fig. 1 we illustrate the prediction of our method and other baselines for PCB degradation. MSLR successfully captures the monotonically increasing trend under noisy measurement without overfitting.

To further enhance the reliable uncertainty quantification of MSLR, we adopt Adaptive Conformal Inference (ACI) [8] for upper bound estimation. ACI is a recent Conformal Prediction (CP) approach [9], which is able to provide confidence intervals for designed coverage rates under distribution shift scenarios, such as time series forecasting. ACP dynamically adjusts the coverage rate to account for changes in data distribution, enabling MSLR to produce adaptive prediction intervals that maintain valid coverage under varying conditions. By leveraging recent residuals through a sliding window, ACI calibrates the upper bounds of resistance degradation predictions to reflect the underlying uncertainty. This integration is particularly valuable for monotonic trends, as it ensures the model's predictions remain robust to noise while quantifying the confidence in its upper bounds. With ACI, MSLR not only captures the monotonic increase in degradation but also provides reliable bounds that are critical for safety-critical applications like predictive maintenance in autonomous electric vehicles.

The main contributions of this work are as follows:

- We propose MSLR, a novel method designed to capture monotonic trends in time series data, even under significant measurement noise. By embedding monotonic constraints into the model, MSLR effectively models degradation processes with non-decreasing behavior.
- We introduce ACI to MSLR, enabling the estimation of reliable upper bounds for resistance degradation. ACI dynamically adjusts to data variability, providing statistically valid prediction intervals with high confidence.
- Through extensive experiments on real-world PCB degradation datasets, we demonstrate that MSLR, combined with ACI, achieves superior forecasting performance compared to state-of-the-art baselines, including ARIMA and N-BEATS, in terms of both accuracy and reliability.

II. Preliminaries

A. Basics of Board Level Vibration Testing

Vibration testing can be broadly categorized into two types based on the type of vibration stress application: swept sine testing and random vibration testing. Swept sine testing is preferred for understanding the solder degradation process due to fatigue, as its outcomes are more interpretable. This type of testing is based on key theoretical concepts.

Firstly, PCB resonance occurs when the board vibrates at its natural frequency f_0, leading to amplified vibrations and increased stress on solder joint interconnects. The natural frequency is mathematically defined as [10]:

$$f_0 = \lambda \left(\frac{1}{l^2} + \frac{1}{w^2} \right) \sqrt{\frac{Eh^3}{12\rho\left(1-\upsilon^2\right)}}, \tag{1}$$

where λ is a constant dependent on clamping, l and w are the board's length and width, E is Young's modulus, h is the board thickness, ρ is the density, and υ is Poisson's ratio.

Secondly, the peak-to-peak displacement d measures the maximum movement experienced by the PCB during vibration testing. Excessive displacement or acceleration a can damage the PCB-solder interface. It is expressed as [10]:

$$d = \frac{a}{2\pi^2 f_0^2}. \tag{2}$$

These two parameters—resonance frequency and peak-to-peak displacement—constitute the PCB dynamic response, which refers to the reaction of the board to external mechanical stimuli. To capture this dynamic response, a 4-wire resistance measurement circuit, as proposed in [2], is employed to collect time-series resistance measurements of the solder joints on the board.

B. Problem Definition

Let $\mathcal{D} = \{(t_i, y_i)\}_{i=1}^{N}$ be the dataset of a time series of N observations, where $x_i \in \mathbb{R}$ represents the i-th timestamp, and $y_i \in \mathbb{R}$ the electrical resistance, assumed to be the noisy measurement of a monotonically increasing physical model f:

$$y(t) = f(t) + \epsilon, \tag{3}$$

where

$$f(t_i) <= f(t_j), \quad \forall\ t_i < t_j,$$

and ϵ represents the error term, assumed to be independently and identically distributed following a zero-mean Gaussian distribution.

We aim to train a time series forecasting model that is able to predict the degradation of resistance in the future T timestamps of measurement $\{(t_i, y_i)\}_{i=N+1}^{N+T}$.

C. Segmented Linear Regression

Segmented Linear Regression (SLR) aims to partition the time series into $K+1$ segments and fit a separate linear function to each segment, such that:

$$y(t) = \alpha + \beta_0 t + \sum_{i=1}^{K} (\beta_i - \beta_{i-1})(t - \tau_i)H(t - \tau_i) + \epsilon, \tag{4}$$

where:

- K is the number of segments (predetermined or to be optimized);
- α represents the intercept parameter;
- $\tau_1, \cdots, \tau_K$ are the breakpoints between segments such that $\tau_1 < \cdots < \tau_K$;
- $\beta_0, \cdots, \beta_K$ are the slope parameters for the k-th segment;
- $H(\cdot)$ is the Heaviside step function.

This formulation ensures that the fitted segments form a continuous piecewise linear function, with potential changes in slope at the breakpoints while maintaining continuity of the regression function.

The objective is to find the optimal parameters $\{\beta_{k,0}, \beta_{k,1}\}_{k=1}^{K}$ and breakpoints $\{\xi_k\}_{k=1}^{K-1}$ that minimize Mean Absolute Percentage Error (MAPE) $\mathcal{L}_{mape}$ between true values y and model predictions $\hat{y}$ in the training set $\mathcal{D}$:

$$\mathcal{L}_{mape}\ (\%) = 100 \times \frac{1}{N} \sum_{i=1}^{N} \mid 1 - \frac{\hat{y}_i}{y_i} \mid . \tag{5}$$

D. Conformal Prediction

Conformal prediction [9] is a framework for quantifying the uncertainty of model predictions by providing prediction intervals that are guaranteed to have a specified coverage level under mild assumptions. The key idea is to assess the conformity of a new observation with respect to a given dataset and model, leveraging nonconformity measures to identify how unusual or outlying a new prediction might be.

In the context of time series forecasting, conformal prediction can be used to construct prediction intervals for future observations. Let $\hat{y}(t)$ represent the model's point prediction for the resistance at time t. A conformal prediction interval for the true value $y(t)$ at a specified confidence level γ is defined as $\mathcal{C}(t) = [\hat{y}(t) - \hat{q}, \hat{y}(t) + \hat{q}]$, where $\hat{q}$ is chosen to ensure that the interval contains the true value $y(t)$ with probability at least γ.

The process involves using a calibration dataset $\mathcal{D}_{\text{cal}}$ to compute nonconformity scores, which measure the difference between observed values and model predictions. For example, a simple nonconformity score can be the absolute residual:

$$s_i = |y_i - \hat{y}(t_i)|, \quad (t_i, y_i) \in \mathcal{D}_{\text{cal}}. \tag{6}$$

The threshold $\hat{q}$ is then determined as the $(1 - \gamma)$ quantile of the nonconformity scores in the calibration set.

Conformal prediction makes minimal assumptions about the data distribution and is compatible with any underlying predictive model, making it a versatile tool for reliable uncertainty quantification. By applying conformal prediction, we can complement the point forecasts of the resistance degradation model with rigorous uncertainty intervals, enhancing the interpretability and trustworthiness of the predictions [11].

III. Methodology

A. Monotonic Segment Linear Regression

In this section, we present the proposed Monotonic Segment Linear Regression (MSLR). To better model the degradation of PCB channel resistance, we introduce two constraints into Segmented Linear Regression (SLR):

- A constant value in the first segment;
- A monotonically increasing trend in the remaining segments.

The first constraint captures the stable functional value during the initial period of degradation, while the second constraint models the non-decreasing resistance during the degradation process. The mathematical formulation is as follows:

$$y(t) = \alpha + \sum_{i=1}^{K} (\beta_i - \beta_{i-1})(t - \tau_i)H(t - \tau_i) + \epsilon, \tag{7}$$

$$\text{subject to} \begin{cases} \beta_i = 0, & \text{if } i = 0, \\ \beta_i > 0, & \text{if } i \in \{1, \cdots, K\}, \\ \tau_i < \tau_j, & \text{if } i < j, \end{cases} \tag{8}$$

where $H(t - \tau_i)$ is the Heaviside step function, ϵ is noise, β_i are segment slopes, and τ_i are breakpoint locations.

We minimize the Mean Absolute Percentage Error (MAPE) loss as defined in Eq. (5) on the training time series $\mathcal{D}$. This optimization problem is nonlinear and constrained. To address this, we employ latent variables to eliminate the constraints and optimize the resulting unconstrained problem using a gradient-based method.

We introduce two sets of real-valued latent variables, $\{\theta_1, \cdots, \theta_K\}$ and $\{\delta_1, \cdots, \delta_K\}$, which map to $\{\beta_1, \cdots, \beta_K\}$ and $\{\tau_1, \cdots, \tau_K\}$, respectively, via a softplus projection $sp : \mathbb{R} \to (0, +\infty)$:

$$\beta_i = sp(\theta_i), \quad \tau_i = \sum_{j=1}^{i} sp(\delta_j), \tag{9}$$

$$sp(x) = \log(1 + \exp(x)). \tag{10}$$

The softplus projection embeds the constraints into the latent variables. For large inputs, the softplus function approximates an identity mapping, ensuring numerical stability during training and testing.

Gradient-based optimization efficiently updates the latent variables. The initial values are set to $\theta_i = -10$ (yielding $\beta_i \approx 4.5 \times 10^{-5}$) and δ_i as the i-th quantile of the time span $[t_1, t_N]$. Updates follow the rule $\theta_i \leftarrow \theta_i - \eta\nabla_{\theta_i}\mathcal{L}_{mape}$ and $\delta_i \leftarrow \delta_i - \eta\nabla_{\delta_i}\mathcal{L}_{mape}$, where η is the learning rate.

B. Optimal Breakpoint Selection via Information Criterion

While MSLR determines optimal breakpoint locations for a predefined number of segments, practical applications often lack prior knowledge of the number of breakpoints, particularly in PCB degradation prediction. To address this, we adopt a model selection framework using the Bayesian Information Criterion (BIC) [12]. The BIC balances model complexity with goodness of fit and is defined as:

$$\mathrm{BIC} = -2\ln(\mathcal{L}) + k\ln(n), \tag{11}$$

where $\mathcal{L}$ is the maximized likelihood of the model, k is the number of parameters (including breakpoints and segment coefficients), and n is the sample size. The first term evaluates the model fit, while the second penalizes model complexity to mitigate overfitting.

For a series of candidate models $\mathcal{M}_1, \cdots, \mathcal{M}_m$ with varying numbers of breakpoints, the optimal model is selected as:

$$\mathcal{M}_{\text{optimal}} = \underset{i\in\{1,\ldots,m\}}{\arg\min}\ \mathrm{BIC}(\mathcal{M}_i). \tag{12}$$

This framework enables the automatic selection of models that balance complexity and goodness of fit, practically effective for PCB resistance degradation prediction.

C. Extending MSLR to Upperbound Estimation with Adaptive Conformal Prediction

To extend MSLR for predicting the upper bounds of resistance degradation with high reliability at a specified confidence level, we incorporate Adaptive Conformal Inference (ACI) [8], a recent Conformal Prediction (CP) approach [9]. ACI provides a distribution-free framework for uncertainty quantification, producing confidence intervals with statistical coverage guarantees.

For a specific timestamp, the conformal score $s(t_i)$ is computed as the residual between the observed and predicted values:

$$s(t_i) = y_i - \hat{y}_i. \tag{13}$$

Using the L-sized time window preceding the current timestamp, we calculate $\hat{q}_\gamma(t_i)$, the $\frac{\lceil\gamma(t_i)\cdot(L+1)\rceil}{L}$-quantile of the conformal scores:

$$\hat{q}_\gamma(t_i) = \text{Quantile}_{\frac{\lceil\gamma(t_i)\cdot(L+1)\rceil}{L}}(s(t_1), \ldots, s(t_L)), \tag{14}$$

where the adaptive coverage rate $\gamma(t_i)$ is sequentially updated with a step size hyper-parameter ν:

$$\begin{cases}\gamma(t_{N+1}) = \gamma \\ \gamma(t_i) = \gamma(t_{i-1}) + \nu\cdot(\gamma - \mathbf{1}_{y(t_{i-1})<\hat{y}(t_{i-1})+\hat{q}_\gamma(t_{i-1})})\end{cases} \tag{15}$$

The upper bound for the resistance degradation is then given by:

$$\hat{y}_\gamma(t_i) = \hat{y}(t_i) + \hat{q}_\gamma(t_i), \tag{16}$$

where $\hat{y}_\gamma(t_i)$ has a confidence level γ of being greater than or equal to the true resistance $y(t_i)$. This approach ensures robust and reliable interval predictions for PCB resistance degradation.

IV. Experimental Results

A. Experimental Settings

a) Physics-Based Degradation Analysis through Vibration Testing: The experimental apparatus for board-level vibration analysis comprises three primary components: an electromagnetic shaker system, a digital controller, and a power amplifier, operating in a closed-loop feedback configuration. The controller generates precise waveforms that are amplified and transmitted to the shaker, enabling accurate reproduction of predetermined vibration profiles. The mechanical interface between the shaker and the test specimen consists of a custom-designed vibration fixture equipped with four precision-machined mounting pillars that ensure uniform load distribution and consistent boundary conditions for the PCB under test.

We conducted swept-sine vibration tests, whose frequency sweep range is specifically tailored to encompass $\pm 20\%$ of the fundamental resonance frequency of the test board, allowing for comprehensive characterization of the dynamic response near the critical frequency.

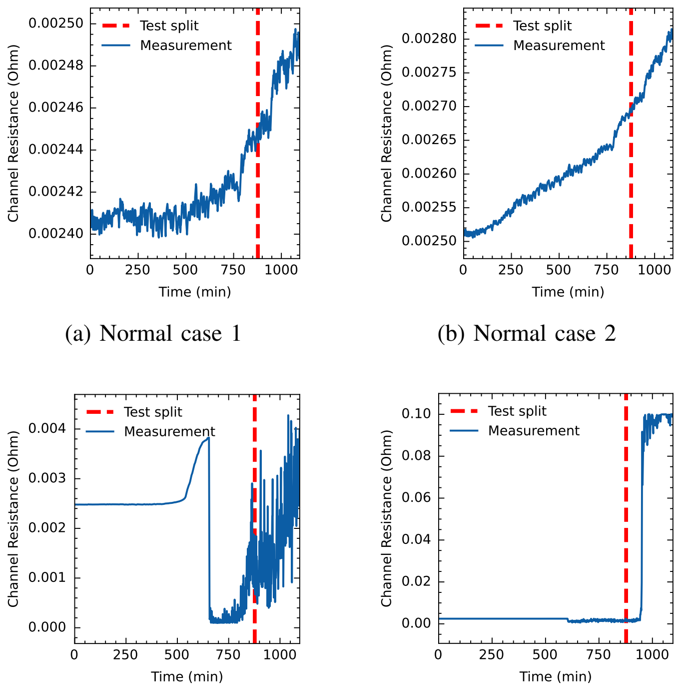
The test vehicles consist of Quad Flat No-Lead (QFN) packages [13] with dimensions of 9 mm $\times$ 9 mm, incorporating 56 peripheral input/output (I/O) pins. These packages are specially instrumented with wire-bonded circuits configured for four-wire resistance measurements, enabling high-precision monitoring of structural degradation at the solder-PCB interface. The measurement architecture facilitates real-time assessment of the physics of degradation through electrical signature analysis. The experimental design implements simultaneous resistance monitoring at all eight corner joints of each QFN package.

b) Dataset and Preprocessing: We utilized data from two PCB boards, each containing 22 channels. The total testing period spanned from 14:55 on July 5, 2023, to 9:11 on July 6, 2023. The resistance of each channel was measured simultaneously at varying time intervals, ranging from 10 seconds to 30 seconds. To standardize the measurements, we preprocessed the data by calculating the mean resistance value for each channel, averaged over one-minute intervals.

Subsequently, we split the time-series data into training and validation datasets, with the first 80% of the data allocated for training and the remaining 20% for testing. During the preprocessing stage, domain experts meticulously examined each time series and excluded those exhibiting irregular patterns in the training phase. These anomalies were identified as resulting from physical failures during degradation tests, which rendered them unpredictable based on prior observations. Examples of normal and failure channels are illustrated in Fig. 2.

Table I: MAPE Error for Board Resistance Degradation Prediction

Model	Board 1			Board 2		
	Mean (↓)	Median (↓)	Std (↓)	Mean (↓)	Median (↓)	Std (↓)
ARIMA	1.09%	0.94%	0.58%	0.92%	0.92%	0.25%
N-BEATS	0.85%	0.70%	0.32%	0.93%	0.80%	0.28%
SLR	14.43%	0.58%	40.34%	29.85%	0.54%	54.15%
MSLR	**0.48%**	**0.43%**	**0.20%**	**0.48%**	**0.52%**	**0.24%**



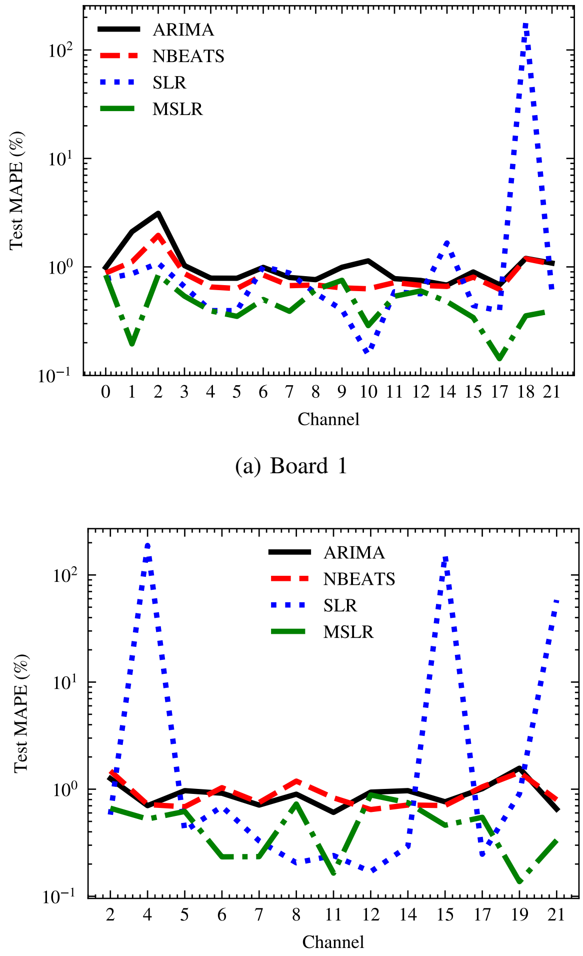
(a) Normal case 1

(b) Normal case 2

(c) Failure case 1

(d) Failure case 2

Figure 2: Visualization of normal and failure examples in PCB resistance measurements



(a) Board 1

(b) Board 2

Figure 3: PCB resistance degradation forecasting results

c) Baselines: We compared our proposed approach, MSLR, against three competitive baselines: ARIMA, Segmented Linear Regression (SLR), and N-BEATS. ARIMA (Auto-Regressive Integrated Moving Average) is a classical statistical model commonly used for time series forecasting. In our experiments, we configured ARIMA with parameters (12, 1, 0), representing the order of the autoregressive terms, the degree of differencing, and the order of the moving average terms, respectively. Segmented Linear Regression (SLR) models the time series as a set of linear segments and does not require specific hyperparameter tuning, as it directly applies piecewise linear regression based on a predefined number of breakpoints. Its maximum number of breakpoints is 6, and we report the testing result of the model with the lowest BIC score. N-BEATS (Neural Basis Expansion Analysis for Time Series) is a deep learning-based model specifically designed for univariate time series forecasting. For this baseline, we used the following configuration: an input chunk length of 48, an output chunk length of 10, 10 epochs, 3 stacks, 3 blocks per stack, 4 layers per block, a layer width of 128, an expansion coefficient dimension of 5, and the LeakyReLU activation function. Each baseline was trained and evaluated on the same training and testing datasets to ensure a fair and consistent comparison.

d) MSLR Configurations: The proposed model is configured with hyperparameters optimized for accurate point predictions of PCB resistance degradation. The key hyperparameters for point prediction include a learning rate $\eta = 0.05$, a total of 50,000 iterations, and the Adam optimizer for efficient gradient-based optimization. The bias term α is initialized as the mean of the first one hour (60 minutes) of resistance data, ensuring the model effectively captures the initial stable phase of degradation. For upper bound estimation with ACI, we use a

Table II: Results for Board Resistance Degradation Upperbound Estimation of MSLR with ACI

Design	Board 1 Interval Coverage			Board 1 Interval Length			Board 2 Interval Coverage			Board 2 Interval Length		
Coverage	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
70%	69.90%	70.23%	1.78%	0.45%	0.42%	0.22%	68.07%	66.84%	2.43%	0.43%	0.40%	0.26%
80%	80.28%	80.23%	1.57%	0.47%	0.46%	0.24%	78.72%	77.72%	2.43%	0.46%	0.37%	0.28%
90%	89.90%	90.23%	1.84%	0.52%	0.55%	0.26%	87.84%	88.08%	3.61%	0.49%	0.40%	0.31%

window size $L = 100$ to compute conformal scores, balancing adaptation to recent data with robustness against noise. The step size $\nu = 0.05$ is set as per the standard ACI implementation, ensuring a controlled adjustment of the miscoverage rate.

B. Point Prediction of Board-Level Degradation

In this section, we evaluate the performance of our proposed method, MSLR, for point prediction of board-level resistance degradation. The evaluation metrics include the Mean Absolute Percentage Error (MAPE) for mean, median, and standard deviation (Std) of the resistance predictions. Table I summarizes the results for both Board 1 and Board 2, and Fig. 3 illustrates the results of each channel.

From the table, MSLR consistently outperforms all baselines across all metrics. For Board 1, MSLR achieves a mean MAPE of 0.48%, a median MAPE of 0.43%, and a standard deviation MAPE of 0.20%. In comparison, NBEATS, the closest competitor, achieves 0.85%, 0.70%, and 0.32%, respectively. Similarly, for Board 2, MSLR achieves a mean MAPE of 0.48%, a median MAPE of 0.52%, and a standard deviation MAPE of 0.24%. N-BEATS follows with values of 0.93%, 0.80%, and 0.28%, respectively. ARIMA demonstrates relatively high errors and variations, while SLR exhibits significantly higher errors in mean and standard deviation metrics, indicating its unsuitability for modeling the monotonic degradation process in PCB resistance.

The results highlight the robustness and accuracy of MSLR in capturing the degradation dynamics at the board level. The superior performance of MSLR can be attributed to its ability to model monotonic degradation trends while remaining resistant to noise and outliers, as evidenced by its consistently low error metrics across both boards. This suggests that MSLR is a reliable method for predictive maintenance applications in PCB systems.

C. MSLR Upper Bound Estimation

This section evaluates the performance of MSLR with Adaptive Conformal Inference (ACI) in estimating upper bounds for PCB resistance degradation. The results in Table II present the interval coverage and interval length across different confidence levels at 70%, 80%, and 90%. We quantify the interval length by MAPE $\mathcal{L}_{mape}$.

The interval coverage shows that MSLR with ACI consistently achieves values close to the desired confidence levels for both boards. At any confidence level, the designed coverage rate falls into the 1 standard deviation interval around the mean coverage, indicating the model's effectiveness in maintaining valid statistical coverage while adapting to the dynamic nature of resistance degradation. The results confirm that the predicted intervals reliably contain the true resistance values, even in varying operational conditions.

In terms of interval length, MSLR with ACI produces compact prediction intervals, around the same value of MAPE ($\sim$0.5%) in point prediction. It means that we are able to achieve 90% coverage with only 1-σ interval started from the mean prediction. The method avoids overly conservative predictions while maintaining consistency across different confidence levels. Low standard deviations in interval lengths further underscore the stability of the model's predictions, ensuring consistent performance over time.

These results demonstrate that MSLR with ACI effectively balances reliability and efficiency in upper bound estimation. By producing accurate and statistically valid intervals without being excessively wide, the method is well-suited for predictive maintenance applications in PCB systems. Its ability to handle dynamic conditions and provide reliable uncertainty quantification makes it a robust tool for degradation modeling.

V. Conclusion

This paper introduces a Monotonic Segmented Linear Regression (MSLR) method to address the challenges in predicting resistance degradation of electronic packages under vibration loads. Our proposed approach successfully overcomes the limitations of traditional time series forecasting methods when dealing with strong measurement noise. By modeling the degradation process as a series of monotonically increasing segments, MSLR provides a more accurate and physically meaningful representation of the degradation behavior. The results demonstrate that MSLR improves prediction accuracy. This is particularly crucial for automotive applications where component reliability directly impacts safety.

Future work sheds the light on extending MSLR to handle multiple degradation indicators simultaneously, and investigating the correlation between identified segments and specific failure mechanisms. These developments will further enhance our ability to ensure the reliability of electronic packages in safety-critical automotive applications.

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