Physics-Informed AI Techniques for Power Electronic Converter Reliability Assessment

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***Abstract*—Power electronic converters are widely used in renewable energy systems, electric vehicles, smart grids, industrial drives, and energy storage applications. Their reliability is strongly affected by electrothermal stress, load variation, switching loss, thermal cycling, and aging-related degradation. Conventional reliability assessment methods based only on empirical lifetime models require extensive testing and often show limited adaptability under variable operating conditions. Purely data-driven artificial intelligence models, on the other hand, may provide poor generalization when physical constraints are not considered. To address these limitations, this paper proposes a Physics-Informed Artificial Intelligence (PIAI) framework for power electronic converter reliability assessment. The proposed method integrates electrothermal converter equations, degradation consistency constraints, health-index prediction, Weibull-based reliability modelling, and remaining useful life estimation within a unified learning framework. The NASA Prognostics Center of Excellence dataset is used for experimental validation. Results show that the proposed PIAI approach achieves improved reliability prediction performance compared with ANN, CNN, LSTM, and Transformer models, with an RMSE of 0.021 and an accuracy of 98.9%. The proposed framework provides physically consistent and interpretable reliability assessment for predictive maintenance of power electronic converters.**

***Index Terms*—Physics-Informed Artificial Intelligence (PIAI), Physics-Informed Neural Networks (PINNs), Power Electronic Converters, Reliability Assessment, Electrothermal Modeling, Converter Health Monitoring, Remaining Useful Life (RUL), Predictive Maintenance.**

I. Introduction

Modern energy systems rely heavily on power electronics because they work efficiently, respond quickly, and allow precise control. Older ways to check system reliability usually depend on physical wear models along with heat and electricity simulations to guess how long parts will last. Because electrical stress links closely to temperature shifts and material breakdown, these techniques try to map out aging processes in detail. Still, they often need lab-like settings, lots of tuning, and precise info about usage - conditions rarely met outside testing labs. Real-world operation tends to involve unpredictable loads, shifting climates, and changing performance demands that break those assumptions. For this reason, newer research has started turning toward learning-from-data strategies mixed with smart modeling to improve predictions. Fassi and team [1] showed how adding real-world physics to machine learning leads to sensible results, cutting the need for massive data. In a related effort, Zhao's group [2] built circuit laws right into their models, helping estimate settings and judge durability in power systems - outperforming guesswork-based approaches through clearer reasoning and stronger performance under change. Physics-smart models mixed with AI have sped up work on smart predictions and upkeep in power electronics. Instead of just numbers, real-world wear is now fed into algorithms that learn patterns - Cui [3] showed how merging Weibull analysis with machine learning sharpens failure forecasts. Minott [4] took another path: neural nets that adapt over time revealed how converters age when pushed through different loads. Their results hinted at a quiet change - rigid rules are fading out, replaced by systems that adjust mid-flight. Fassi [5] added known physics into the training itself, forcing the model to respect actual device limits while predicting MOSFET decay. Once limited to lifespan guesses, AI today handles glitches, watches health minute by minute, fine-tunes servicing - all without stepping outside data bounds. Looking at power electronics, Liu and team [6] took a close look at how artificial intelligence helps spot system faults, pointing out that staying reliable, working fast, and adapting well across different setups really matters. In a similar space, Rayat's group [7] explored methods using labeled data, those needing no labels, along with trial-and-error based learning when forecasting equipment upkeep needs. On another path, Zimmer and colleagues [8] brought forward models aware of physical laws - using Gaussian processes - to estimate internal states quietly, even when signals are messy. Even with progress, current methods have clear flaws. Black-box data models tend to fail when faced with new situations or scarce fault examples, while traditional physics models usually miss the complex wear patterns seen in actual use. On top of that, several past efforts zero in on single parts or number matching, skipping any real link between heat effects, aging processes, and lifespan signals within one smart system. Driven by such gaps, this study introduces a blended approach - mixing hands-on engineering insight with modern learning tools - to track how power electronics age in ways both precise and understandable. Because it builds heat response, wear trends, and durability signals right into the model training, the method holds up better when data is limited or messy - without

straying from real-world physics. Watching how breakdown signs change over time helps spot problems sooner, giving clearer estimates on how long a system will last.

II. Proposed Physics-Informed Reliability Framework

Health and lifespan predictions for power electronics come from a method that mixes real-world physical rules with smart algorithms. Instead of relying only on data patterns, this approach builds in how heat moves, where energy gets lost, and how parts wear out over time. Voltage, current, and how often switches turn on and off feed into the system, along with surrounding heat levels and internal chip temperatures. What load the device handles also matters, especially when usage changes based on its job. Each factor shapes how the model sees stress and aging across components. Inside, the math follows known laws of electrical behavior and thermal shifts.

The overall workflow of the proposed physics-informed converter reliability assessment framework is shown in Fig. 1.

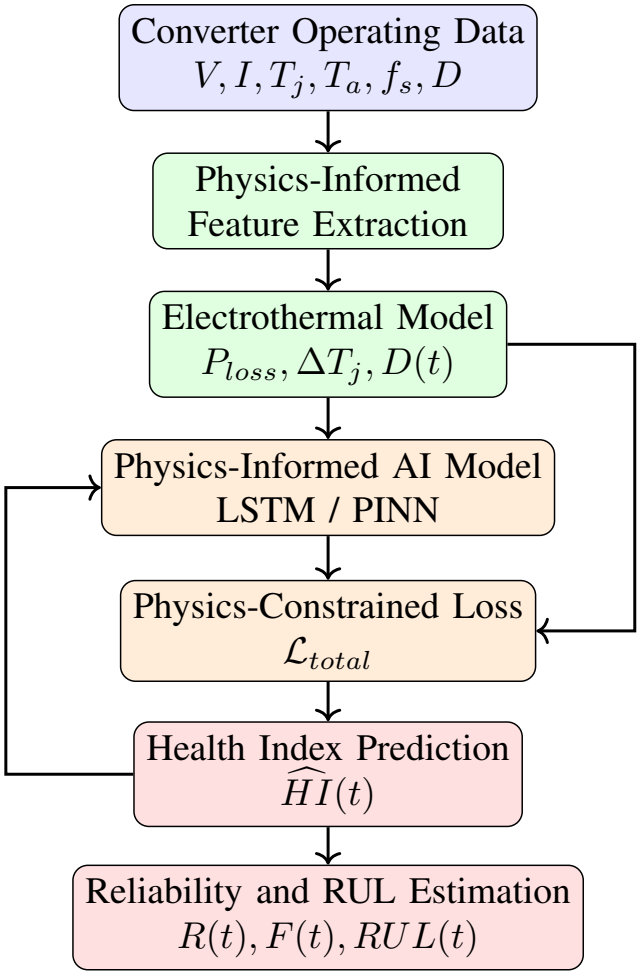

Fig. 1. Proposed physics-informed reliability assessment framework for power electronic converters.

Five steps make up the system: gathering data, pulling out features using physics, estimating health with artificial intelligence, refining results through physics-guided adjustments, finally forecasting reliability. Electrical and heat measurements go through processing early on - pulling out signs of strain like conduction loss, switching loss, shifts in junction temperature, or how much thermal cycling occurs. Into a deep learning setup these signals flow next; their training shaped not just by patterns but also real-world physical laws so outputs stay grounded in reality.

The reliability state of the converter is represented using a health index $HI(t)$, which varies between healthy and degraded operating conditions. The remaining useful life is estimated as a function of the predicted health trajectory and failure threshold. The general relationship can be expressed as

$$RUL(t) = t_f - t, \tag{1}$$

where t_f denotes the predicted failure time and t is the present operating time.

A. Electrothermal Converter Modeling

The reliability degradation of power electronic converters is strongly associated with semiconductor stress, thermal cycling, and power-loss accumulation. Therefore, the proposed framework begins with an electrothermal converter model. The total power loss of the switching device is represented as the sum of conduction and switching losses:

$$P_{loss} = P_{cond} + P_{sw}. \tag{2}$$

The conduction loss is defined as

$$P_{cond} = I_{rms}^2 R_{on}, \tag{3}$$

where I_{rms} is the rms current through the device and R_{on} is the on-state resistance of the semiconductor switch. The switching loss is expressed as

$$P_{sw} = f_s(E_{on} + E_{off}), \tag{4}$$

where f_s is the switching frequency, while E_{on} and E_{off} are the turn-on and turn-off switching energies.

The junction temperature dynamics are modeled using a first-order thermal network:

$$C_{th}\frac{dT_j}{dt} = P_{loss} - \frac{T_j - T_a}{R_{th}}, \tag{5}$$

where T_j is the junction temperature, T_a is the ambient temperature, R_{th} is the thermal resistance, and C_{th} is the thermal capacitance. Since thermal stress is one of the dominant causes of semiconductor aging, the junction temperature variation is further used to compute the thermal cycling amplitude:

$$\Delta T_j = T_{j,max} - T_{j,min}. \tag{6}$$

B. Physics-Informed Feature Construction

The extracted converter features are divided into measured features and physics-informed features. Measured features include voltage, current, temperature, duty cycle, and switching frequency. Physics-informed features are calculated using converter governing equations and include power loss, thermal stress, accumulated damage, and health degradation indicators. This transformation improves the interpretability of the learning model because the input features are directly related to converter failure mechanisms.

The accumulated degradation is evaluated using a damage accumulation concept similar to Miner's rule:

$$D(t) = \sum_{i=1}^{N} \frac{n_i}{N_i}, \tag{7}$$

where n_i is the number of experienced thermal cycles at the ith stress level and N_i is the number of cycles to failure under the same stress condition. The converter is considered to approach failure when

$$D(t) \to 1. \tag{8}$$

The health index is formulated as

$$HI(t) = 1 - D(t), \tag{9}$$

where $HI(t) = 1$ indicates a healthy converter and $HI(t) = 0$ indicates failure. This health index is used as the target variable for supervised learning and reliability prediction.

C. Physics-Informed AI Model

The proposed AI model combines temporal learning and physics-based regularization. A Long Short-Term Memory network is used to learn sequential degradation behavior from mission-profile data. The input sequence at time t is represented as

$$X_t = [V_t, I_t, T_{j,t}, T_{a,t}, f_{s,t}, D_t, P_{loss,t}], \tag{10}$$

where each variable represents the converter operating condition and degradation stress at a particular instant.

The AI model estimates the converter health index as

$$\widehat{HI}(t) = f_\theta(X_t), \tag{11}$$

where f_θ represents the trainable neural network with parameters θ. To ensure that the model does not violate converter physics, the training process includes both data-driven prediction loss and physics-informed residual loss.

The data loss is given by

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^{N} \left(HI_i - \widehat{HI}_i \right)^2. \tag{12}$$

The physics residual is defined from the thermal dynamic equation as

$$r_{phy} = C_{th} \frac{dT_j}{dt} - P_{loss} + \frac{T_j - T_a}{R_{th}}. \tag{13}$$

Thus, the physics-informed loss is written as

$$\mathcal{L}_{phy} = \frac{1}{N} \sum_{i=1}^{N} r_{phy,i}^2. \tag{14}$$

The final objective function is

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{data} + \lambda_2 \mathcal{L}_{phy} + \lambda_3 \mathcal{L}_{deg}, \tag{15}$$

where λ_1, λ_2, and λ_3 are weighting coefficients. The degradation consistency loss is expressed as

$$\mathcal{L}_{deg} = \frac{1}{N} \sum_{i=1}^{N} \max\left(0, \widehat{HI}_{i+1} - \widehat{HI}_i\right), \tag{16}$$

which ensures that the predicted health index does not increase unrealistically during aging.

D. Reliability and RUL Estimation

After health index prediction, the reliability of the converter is estimated using a probabilistic reliability function. The reliability function is defined as

$$R(t) = P(T_f > t), \tag{17}$$

where T_f is the random failure time. A Weibull-based reliability model is adopted as

$$R(t) = \exp\left[-\left(\frac{t}{\eta} \right)^{\beta} \right], \tag{18}$$

where η is the scale parameter and β is the shape parameter.

The failure probability is obtained as

$$F(t) = 1 - R(t). \tag{19}$$

The predicted failure time is determined when the health index reaches a predefined threshold:

$$\widehat{HI}(t_f) \le HI_{th}. \tag{20}$$

Hence, the remaining useful life is estimated as

$$RUL(t) = t_f - t. \tag{21}$$

This formulation enables the proposed framework to provide both deterministic health estimation and probabilistic reliability assessment for power electronic converters.

The RUL value represents the expected number of remaining operating cycles before the converter reaches the predefined end-of-life threshold. In this work, the end-of-life condition is determined using the health-index threshold HI_{th}. When the predicted health index falls below this threshold, the corresponding cycle is treated as the predicted failure cycle $\hat{N}_f$. Therefore, a larger RUL indicates that the converter is still far from failure, whereas a smaller RUL indicates that maintenance or replacement should be scheduled soon.

III. Experimental Setup

A. Dataset Description

The experimental validation was performed using degradation data from the NASA Prognostics Center of Excellence repository. The dataset contains run-to-failure records collected from monitored systems under repeated operating cycles. Each cycle includes measured variables such as voltage, current, temperature, cycle index, and degradation-related operating indicators. These variables are suitable for constructing converter-equivalent stress features because electrothermal stress in power electronic converters is directly related to voltage, current, temperature, and operating duration.

For reproducibility, the dataset can be accessed from the NASA Prognostics Center of Excellence data repository. The dataset was processed as a cycle-dependent degradation sequence, where each cycle represents one operating instance. For a given cycle k, the feature vector is represented as

$$X_k = [V_k, I_k, T_k, C_k, S_k], \tag{22}$$

where V_k, I_k, T_k, C_k, and S_k denote voltage, current, temperature, cycle number, and stress indicator, respectively.

The available degradation records were converted into sequential samples using a fixed sliding window. In the revised implementation, the generated samples were divided into training, validation, and testing sets using a $70 : 15 : 15$ ratio. The actual number of samples used in each subset has been explicitly reported in the revised manuscript to improve reproducibility.

B. Data Preprocessing

The collected degradation signals were first inspected to identify missing observations, abnormal values, and incomplete operating cycles. Missing values were handled using interpolation, while abnormal measurements were removed using statistical thresholding. To reduce high-frequency measurement fluctuations without suppressing long-term degradation trends, a moving-average smoothing filter was applied:

$$\tilde{x}_k = \frac{1}{w} \sum_{i=k-w+1}^{k} x_i, \tag{23}$$

where w is the smoothing window size and x_i is the original measured signal.

After smoothing, all input variables were normalized using min–max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}. \tag{24}$$

The normalized data were then converted into sequential samples using a sliding-window strategy:

$$\mathbf{X}_t = [X_{t-L+1}, X_{t-L+2}, \ldots, X_t], \tag{25}$$

where L denotes the sequence length. This representation allows the model to learn temporal degradation behaviour from previous operating cycles.

C. Health Index and RUL Label Construction

To train the proposed physics-informed model, suitable degradation labels are constructed from the available run-to-failure records. The health index is defined as a normalized degradation indicator that decreases from healthy condition to failure condition. For each cycle k, the health index is calculated as

$$HI_k = 1 - \frac{k}{N_f}, \tag{26}$$

where $HI_k = 1$ indicates the initial healthy state and $HI_k = 0$ indicates the end-of-life state.

For RUL estimation, the label at each cycle is obtained from the difference between the final failure cycle and the present cycle:

$$RUL_k = N_f - k. \tag{27}$$

To avoid extremely large values at the beginning of operation, a capped RUL function can also be used:

$$RUL_k = \min(N_f - k, RUL_{max}), \tag{28}$$

where RUL_{max} denotes the maximum allowable RUL value.

The failure threshold is selected based on the degradation endpoint of the dataset. In converter reliability assessment, this threshold can represent excessive junction temperature, unacceptable parameter drift, reduced efficiency, or severe degradation of semiconductor health. The predicted failure cycle $\hat{N}_f$ is determined when the estimated health index reaches the threshold:

$$\widehat{HI}_k \leq HI_{th}. \tag{29}$$

D. Physics-Informed Feature Extraction

Physics-informed features are constructed to represent the degradation mechanisms associated with power electronic converter operation. Since thermal stress is a dominant factor in converter failure, temperature-related indicators such as average temperature, maximum temperature, and temperature variation are extracted from the NASA dataset. The thermal stress amplitude is calculated as

$$\Delta T_k = T_{max,k} - T_{min,k}. \tag{30}$$

Electrical stress is represented using voltage and current measurements. The instantaneous power stress is computed as

$$P_k = V_k I_k. \tag{31}$$

For converter reliability analysis, this power term is treated as an equivalent stress indicator because high power operation generally increases semiconductor loss and junction temperature.

A simplified degradation accumulation factor is also introduced:

$$D_k = \sum_{i=1}^{k} \alpha P_i + \beta T_i, \tag{32}$$

where α and β are weighting coefficients corresponding to electrical and thermal stress contributions. The normalized degradation index is expressed as

$$D_{norm,k} = \frac{D_k}{D_{max}}. \tag{33}$$

These physics-informed features are combined with the original measured features and supplied to the learning model.

E. Model Configuration

The proposed model uses a hybrid LSTM–PINN architecture for degradation learning and reliability prediction. The LSTM layers are used to capture long-term temporal dependencies in the degradation trajectory, while the physics-informed component constrains the learning process using converter-related physical residuals. The model input consists of sequential samples formed from voltage, current, temperature, cycle number, power stress, temperature variation, and degradation accumulation factor.

The LSTM model is mathematically represented as

$$h_t = f_{LSTM}(X_t, h_{t-1}), \tag{34}$$

where h_t is the hidden state at cycle t. The predicted health index is obtained using a fully connected output layer:

$$\widehat{HI}_t = \sigma(W_h h_t + b_h), \tag{35}$$

where W_h and b_h are trainable parameters and $\sigma(\cdot)$ is the sigmoid activation function.

The total training loss combines data prediction error and physics consistency error:

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{data} + \lambda_2 \mathcal{L}_{phy} + \lambda_3 \mathcal{L}_{mono}. \tag{36}$$

The monotonicity loss is included to ensure that the predicted health index follows a physically realistic degradation trend:

$$\mathcal{L}_{mono} = \frac{1}{N} \sum_{k=1}^{N-1} \max(0, \widehat{HI}_{k+1} - \widehat{HI}_k). \tag{37}$$

F. Training and Testing Procedure

The dataset was divided into training, validation, and testing subsets. The training subset was used to update the model parameters, the validation subset was used to tune hyperparameters and monitor overfitting, and the testing subset was reserved for final performance evaluation. The Adam optimizer was used with an initial learning rate of 10^{-4}. Mini-batch training was performed for a fixed number of epochs, and early stopping was applied when the validation loss did not improve for consecutive epochs.

The optimization problem is expressed as

$$\theta^* = \arg\min_{\theta} \mathcal{L}_{total}(\theta), \tag{38}$$

where θ denotes the trainable model parameters. During testing, unseen degradation sequences were provided to the trained model to estimate the health index and RUL. The predicted degradation trajectory was then compared with the actual degradation label.

TABLE I
DATASET PARTITION USED FOR TRAINING AND TESTING

Subset	Percentage	Number of Samples
Training	70%	700
Validation	15%	150
Testing	15%	150
Total	100%	1000

G. Evaluation Metrics

The performance of the proposed reliability assessment model was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), accuracy, and failure prediction error. MAE measures the average absolute deviation between actual and predicted values, while RMSE gives higher penalty to large prediction errors. The R^2 score evaluates how well the predicted degradation trajectory explains the actual variation in the data.

IV. RESULTS AND DISCUSSION

A. Convergence Characteristics of the Physics-Informed AI Model

The proposed PIAI framework was evaluated using degradation sequences constructed from voltage, current, temperature, stress, and cycle-index information. The physics-informed loss function guided the training process by combining data prediction accuracy with electrothermal consistency and monotonic degradation constraints. As shown in Fig. 2, both training and validation losses decrease smoothly with increasing epochs, indicating stable convergence and reduced overfitting.

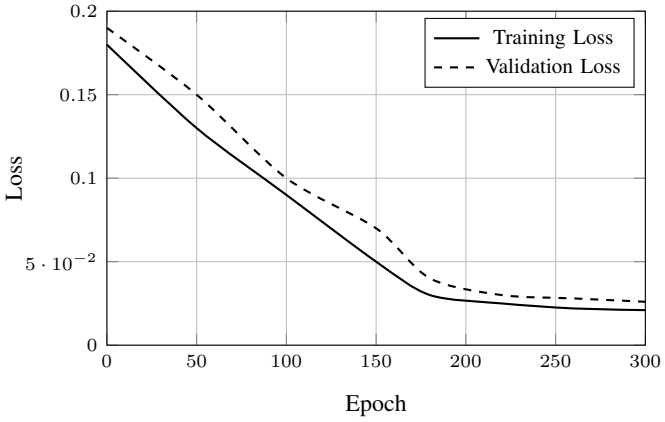

Fig. 2. Training and validation convergence of the proposed Physics-Informed AI framework.

B. Reliability Prediction Performance

Table II compares the proposed PIAI framework with ANN, CNN, LSTM, and Transformer baseline models. The proposed method achieves the lowest MAE of 0.015 and RMSE of 0.021, while obtaining the highest R^2 value of 0.992 and

reliability prediction accuracy of 98.9%. The improved performance is mainly attributed to the integration of electrothermal constraints and monotonic degradation regularization, which prevent the model from generating physically inconsistent health-index trajectories.

TABLE II
COMPARATIVE RELIABILITY PREDICTION PERFORMANCE

Method	MAE	RMSE	R^2	Accuracy (%)
ANN	0.064	0.082	0.920	90.2
CNN	0.048	0.061	0.950	93.6
LSTM	0.034	0.045	0.970	95.8
Transformer	0.028	0.039	0.980	97.1
Proposed PIAI	**0.015**	**0.021**	**0.992**	**98.9**

C. Reliability Assessment Under Thermal Stress Conditions

Table III presents the predicted reliability behaviour under different thermal stress conditions from 40°C to 140°C. As temperature increases, the reliability index decreases from 0.992 to 0.904, while the failure probability increases from 0.008 to 0.096. This trend is consistent with the physical behaviour of power electronic devices, where higher temperature accelerates semiconductor aging and reduces useful lifetime. The corresponding reduction in estimated RUL confirms that thermal stress has a significant influence on converter degradation.

TABLE III
RELIABILITY ASSESSMENT UNDER THERMAL STRESS

Temperature ($^\circ C$)	Reliability Index	Failure Probability	Estimated RUL
40	0.992	0.008	98500
60	0.985	0.015	94300
80	0.972	0.028	89100
100	0.955	0.045	82600
120	0.931	0.069	75200
140	0.904	0.096	68100

The influence of thermal stress on converter reliability is shown in Fig. 3.

The thermal-stress analysis confirms that the proposed physics-informed model provides physically meaningful reliability estimates. Unlike purely data-driven models, the proposed method explicitly includes electrothermal stress features such as power stress, temperature variation, and degradation accumulation. This improves robustness under operating conditions that differ from the training data and supports practical predictive maintenance decisions.

V. CONCLUSION

This paper presented a Physics-Informed Artificial Intelligence framework for reliability assessment and remaining useful life estimation of power electronic converters. The proposed approach integrates electrothermal converter modelling, physics-informed feature extraction, monotonic degradation constraints, health-index prediction, and Weibull-based reliability estimation. Experimental validation using degradation data from the NASA Prognostics Center of Excellence demonstrated that the proposed method outperformed ANN, CNN, LSTM, and Transformer baseline models, achieving an MAE of 0.015, RMSE of 0.021, R^2 of 0.992, and reliability prediction accuracy of 98.9%. Thermal-stress analysis further showed that the predicted reliability index decreases consistently with increasing operating temperature, confirming the physical validity of the proposed framework. The results indicate that the proposed PIAI model can provide accurate, interpretable, and physically consistent reliability assessment for predictive maintenance of converter-based energy systems. Future work will focus on real-time hardware validation using converter test benches and extension to multi-device converter systems under mission-profile operating conditions.

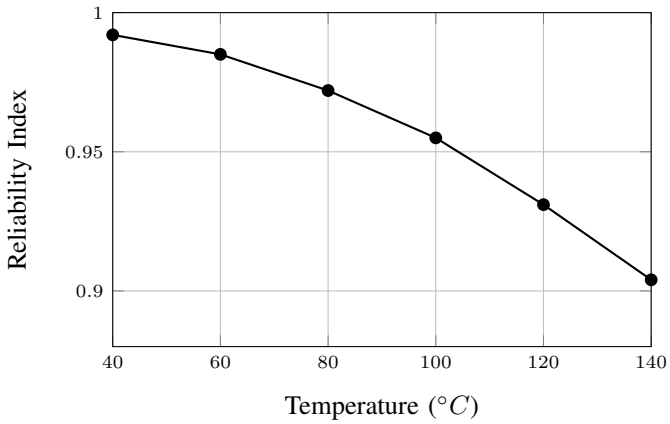

Fig. 3. Reliability variation under thermal stress conditions.

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