Data-Efficient and Uncertainty-Aware RUL Prediction Using Physics-Informed Neural Networks: Application to Degraded Rubber Components

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ABSTRACT

This study presents a prognostic framework that integrates Physics-Informed Neural Network (PINN) with uncertainty quantification (UQ) techniques to enable probabilistic prediction of the Remaining Useful Life (RUL) of rubber components subjected to degradation. The framework utilizes data acquired from thermal Highly Accelerated Life Testing (HALT), replicating long-term material aging behavior under elevated temperature conditions within a shortened time frame. To address the high cost and time consumption of HALT experiments, the proposed approach aims to ensure accurate and reliable predictions even with limited data availability. An empirical degradation model is embedded within the PINN structure, enabling physically consistent and data-efficient estimation of degradation model parameters. The framework employs uncertainty quantification techniques based on Bayesian inference, in which data-driven approaches (e.g., Gaussian Process modeling, Bayesian neural networks) and physics-based methods (e.g., Markov chain Monte Carlo, particle filtering) are separately applied to quantify variations arising from material properties, experimental conditions, and measurement noise. These methods generate posterior distributions from which failure time and probabilistic RUL estimates are derived based on a predefined degradation threshold. Compared to deterministic optimization methods, the proposed approach improves prediction robustness and interpretability, offering a cost-effective and scalable solution for prognostic modeling in engineering systems.

INTRODUCTION

Rubber materials gradually degrade over time, affecting structural stability and performance (Wang et al., 2025). Especially in high-reliability fields such as aerospace, automotive, and industrial applications, degradation may lead to unexpected failures and seriously affect system safety and reliability (Brown, 2001). Therefore, remaining useful life (RUL) prediction is essential for implementing maintenance and obtaining the reliability of systems utilizing rubber materials (Ma et al., 2023). In addition, industry trends are increasing the need for shorter product development times, and RUL prediction is becoming increasingly important to address this issue.

Rubber degradation data used for RUL prediction is usually obtained by highly accelerated life testing (HALT). This method exposes materials to high-temperature conditions over extended periods to simulate long-term degradation and enable early lifetime prediction (Tayefi et al., 2023). Most studies have utilized HALT to analyze the effects of various environmental factors (e.g., stress, temperature, and humidity) on the degradation rate. Based on HALT, several approaches have been proposed to calibrate degradation models or predict the system's lifetime (Woo et al., 2010).

Previous research experimentally measured the degradation of rubber specimens under various temperature conditions and analyzed models for estimating degradation rates and lifetime. Based on these results, an empirical degradation model was constructed. And then, key factors parameterized such as initial strength, transition point, and degradation rate, which were subsequently used for lifetime prediction using metaheuristic optimization algorithms (e.g., Genetic Algorithms) (Kwon et al., 2007). However, the empirical degradation model based on HALT did not consider measurement noise, resulting in limitations in prediction accuracy and uncertainty quantification.

To enhance the accuracy and reliability of the empirical degradation model, it is essential to propose probabilistic ranges using uncertainty quantification rather than single predictions (Shi et al., 2025). Previous research has attempted to address real-world uncertainty (e.g., material heterogeneity, measurement error, variation in test conditions) by quantifying uncertainty due to various noise sources using a Bayesian framework. Bayesian-based methods such as Gaussian processes (GP), Bayesian neural networks (BNN), Markov chain Monte Carlo (MCMC), and particle filters are used to generate posterior distributions and support decision-making based on confidence intervals (Kim et al., 2017).

This means preventing resource waste caused by overly optimistic or conservative designs during the RUL predictions and establishing a reliability-based maintenance strategy. Accordingly, Bayesian-based methods that consider inherent uncertainties are essential in RUL prediction frameworks and require research expansion.

RUL prediction models primarily utilize data-driven regression methods. However, these methods typically lack physical consistency and rely on the quantity and quality of data. For HALT, which requires costly and repetitive experimental time, it is often difficult to obtain sufficient data. Recent studies focused on integrating physical knowledge into predictive models to address these limitations (Nascimento et al., 2023). For this purpose, some methods proposed integrating physical equations into the mean function of Gaussian process regression (GPR) (Cross et al., 2024), while others embed physical constraints directly into the training process using physics-informed neural network (PINN). Moreover, these frameworks have been extended to Bayesian-PINN (B-PINN) (Linka et al., 2022). Physics-informed methods can produce physically consistent predictions despite a lack of data and have demonstrated superior reliability compared to conventional regression models.

In this study, a case study was conducted to predict the RUL of the lifespan and dependability of rubber materials employed in automotive suspension systems. An empirical degradation model was applied to ensure physical feasibility, and physics-informed GPR (Phi-GPR), MCMC and B-PINN models were constructed and applied, considering uncertainty factors that may occur in real-world conditions. As a result, the lifetime and reliability of rubber material were analyzed for deterministic optimization methods, and each Bayesian-based method and the applicability of a real-world work site were evaluated by considering uncertainty factors.

1. DEGRADATION MODEL FOR RUBBER MATERIAL

Highly Accelerated Life Test for Rubber Material of Bushing

Long-term gradual thermal aging tests at room temperature are required to ensure rubber components' reliability in automobile systems. Evaluating material degradation and predicting product lifetime within short development periods is difficult. Therefore, to reduce the time cost, HALT is commonly employed. HALT exposes the product to extreme conditions, such as high stress and temperature, in a controlled laboratory environment to evaluate its durability and reliability (Kong et al., 2018).

In this study, the synthetic rubber of the Bushing series from automobile suspension components was used, generally subjected to continuous exposure to external stress and high temperatures. The primary failure mechanism of rubber bushings is gradual thermal aging caused by temperatures, and their lifetime can be predicted using HALT and the Arrhenius equation. For HALT, rubber specimens were prepared according to the KS M 6518 and exposed to various temperatures (70 °C, 100 °C, 120 °C, and 140 °C) for durations ranging from 24 to 408 hours. After each aging condition and time interval, rubber specimens were retrieved and subjected to tensile testing using a Universal Testing Machine (UTM). The tensile strength at failure was measured to quantify the degradation, and the resulting data were collected for analysis. To consider experimental uncertainty, three rubber specimens were utilized at each condition. The tensile strength was calculated using a weighted average of the measured values, ordered from highest to lowest: $0.7T_1 + 0.2T_2 + 0.1T_3$ (where $T_1 \geq T_2 \geq T_3$). The experimental results showed that the mechanical material properties declined as degradation progressed, leading to a gradual decrease in tensile strength. Moreover, as aging temperatures increased, the degradation rate accelerated, resulting in a more rapid reduction in tensile strength.

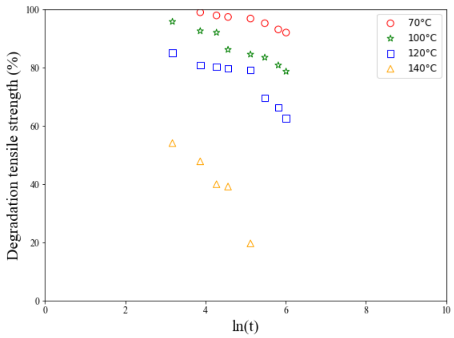


Figure 1. The results of HALT

Before performing the lifetime prediction for rubber material, it is necessary to select a degradation behavior model to confirm the overall time-dependent degradation characteristics of the rubber. Based on previous research, an empirical piecewise degradation model was proposed to quantitatively describe the degradation behavior of rubber material under high-temperature conditions, and its validity was demonstrated (Kwon et al., 2014). This model was constructed using tensile strength data obtained from HALT and characterizes the degradation of rubber material in two distinct phases, separated by a transition point (t_0), which can be expressed by:

$$f(t) = \begin{cases} 100 - (100 - f_0) \times e^{(t-t_0)k_1}, if\ t < t_0 \\ f_0 \times e^{-(t-t_0)k_2} \qquad\qquad\quad , if\ t \geq t_0 \end{cases} \tag{1}$$

Elastic polymers (e.g., EPDM, NBR) exhibit a decline in mechanical performance when exposed to high-temperature conditions for extended periods. In this study, tensile strength was selected as a representative degradation indicator. The degradation model curve generally follows a nonlinear piecewise function depending on the transition point, which allows us to represent the degradation behavior of a rubber material that degrades rapidly and non-linearly. This behavior has been experimentally observed using HALT and is attributed to the combined effects of polymer chain scission, oxidation, and curing/degradation processes.

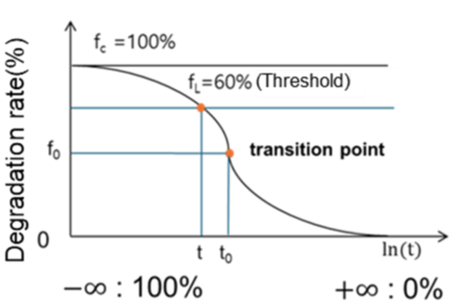


Figure 2. Empirical degradation model for rubber material

2. CONSTRUCTING AN EMPIRICAL DEGRADATION MODEL FOR PARAMETER PREDICTION

2.1. Deterministic optimization PINN

PINN is a neural network-based model that directly integrates physical information into the loss function, enabling physically consistent predictions even with a lack of data (Raissi et al., 2019). In this study, the degradation behavior of rubber material was represented using an empirical nonlinear model, and the parameters (t_0, f_0, k_1, k_2) were determined using the PINN model. The training process of PINN integrates not only a data-driven loss term but also a physics-based loss term derived from domain knowledge (Wang et al., 2024). Additionally, in this study, the total loss function of the PINN was defined by combining the following three loss functions.

Data loss term: Minimize the difference between the time-tensile strength data obtained from HALT and the model output. It consists of the mean squared error.

Physical constraint loss term: This term guides the physical conditions required by the model, such as the continuity of the degradation curve and the continuity of the differentiation at the transition point. (e.g., at the transition time t_0, the left and right derivatives of the degradation curve must be equal.)

Boundary conditions loss term: This term guided the model to satisfy known tensile strength at a specific time based on experimental observations. (e.g., it includes conditions such as that the tensile strength at the initial time is satisfied 100%)

$$\mathcal{L}_{Total} = \alpha \times \mathcal{L}_{Data} + \beta \times \mathcal{L}_{Phys} + \gamma \times \mathcal{L}_{BC} \tag{2}$$

Here, α, β, and γ are hyperparameters that control the weights of each loss term. These parameters are tuned to balance data fidelity and physical consistency in the model. The parameters obtained by training have a physical meaning related to the degradation mechanism, and including physical constraints enables the model to derive a generalized degradation curve rather than merely fitting the data. However, the PINN provides only a single deterministic prediction value. Thus, it does not provide information on the confidence interval of the prediction value. Furthermore, the approach may exhibit sensitivity to such disturbances because experimental noise and environmental variability in the observations are not modeled. To address this challenge, this study introduced B-PINN, Phi-GPR, and BNN-based complementary methods utilizing Bayesian structure to perform probabilistic parameter estimation.

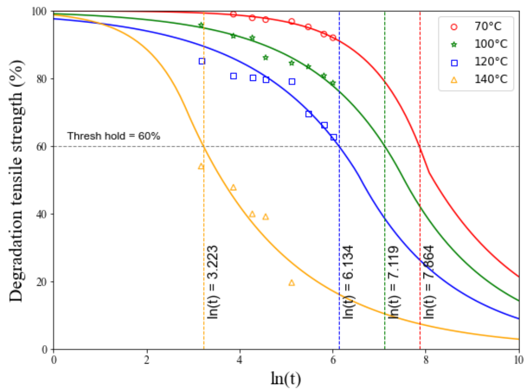


Figure 3. DO-PINN estimation results of degradation model parameters

2.2. Physics-Informed Gaussian Process Regression

GPR is a non-parametric Bayesian regression method where a function is considered to follow a GP if any finite set of its evaluations follows a joint gaussian distribution (Kim et al., 2025; Qiang et al., 2023; Wang, 2023). A GP is defined as an input matrix $X \in \mathbb{R}^{N\times d}$, and the output vector is defined as $y \in \mathbb{R}^{N\times 1}$. In a GPR model, the function $f(x)$ is characterized by a mean function and a covariance function (kernel function) defined over any two inputs x and x', which can be expressed by:

$$f(x) \sim GP(m(x), k(x,x')) \tag{3}$$

where,

$$m(x) = E[f(x)] \tag{4}$$

$$k(x,x') = E\left[\big(f(x)-m(x)\big)\big(f(x')-m(x')\big)\right] \tag{5}$$

In this study, we choose the radial basis function (RBF) kernel, which is widely used in GPR for its smoothness and flexibility (Jäkel et al., 2007). The RBF kernel is defined as:

$$k(x,x') = \sigma_f^2 * exp\left(-\frac{\|x-x'\|^2}{2l^2}\right) \tag{6}$$

where σ_f^2 and l represent the signal variance and length-scale hyperparameter, respectively. Adjusting the hyperparameters can be the variability of the resulting function (Schulz et al., 2018). In the real world, noise is usually observed due to various environmental factors. In this case, by considering the noise observations σ_n^2 in the observation value, it can be expressed by $y = f(x) + \varepsilon$, $\varepsilon \sim N(0, \sigma_n^2)$, GP can be expressed for a finite set of observation values (Sun et al., 2024).

$$y \sim GP(m(x), k(x,x') + \sigma_n^2) \tag{7}$$

According to the definition of GP (Tartakovsky et al., 2023), the observation value and predicted value at the new test point follow the joint Gaussian prior distribution, can be expressed by:

$$\begin{bmatrix} y \\ f' \end{bmatrix} \sim N\left(\begin{matrix} m(X) \\ m(x')' \end{matrix}\begin{bmatrix} K(X,X)+\sigma_n^2 I & K(X,x') \\ K(x',X) & K(x',x') \end{bmatrix}\right) \tag{8}$$

where $K(X,X)$ and $K(x',x')$ represent the covariance matrices between merely training inputs and merely test inputs, respectively, and $K(x',X) = K(X,x')$ represents the covariance matrices between training and test inputs.

$$P(f'|X,f,x') \sim N\left(f'\middle|\bar{f}', cov(f')\right) \tag{9}$$

where,

$$\bar{f}' = m(x') + K(x',X)[K(X,X)+\sigma_n^2 I]^{-1}(y-m(X)) \tag{10}$$

$$cov(\bar{f}') = K(x',x') - K(x',X)[K(X,X)+\sigma_n^2 I]^{-1}K(X,x') \tag{11}$$

where the $\bar{f}'$ is the posterior mean of f', and $cov(f')$ represents its posterior variance. Moreover, the 95% confidence interval (CI) can be calculated as follows to evaluate the uncertainty of the prediction results:

$$95\%\mathrm{CI} = \bar{f}' - 1.96 \times \sqrt{cov(\bar{f}')}, \bar{f}' + 1.96 \times \sqrt{cov(\bar{f}')} \tag{12}$$

Therefore, GPR models are used not only as regression models, but also to quantify uncertainty by considering confidence intervals. Regression methods have limitations because they require large amounts of high-quality data. To address these issues, a method to incorporate physical information into GPR has been proposed. In this study, we utilized physical knowledge along with parameter estimates obtained from the deterministic PINN performed earlier to build a pre-averaging function for GPR. As a result, we were able to simultaneously estimate the variance of the estimates and derive confidence intervals for each estimated parameter.

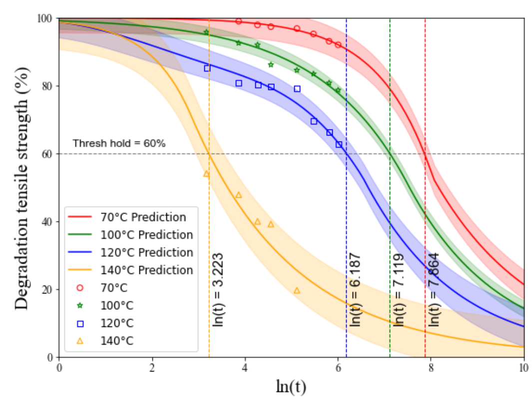
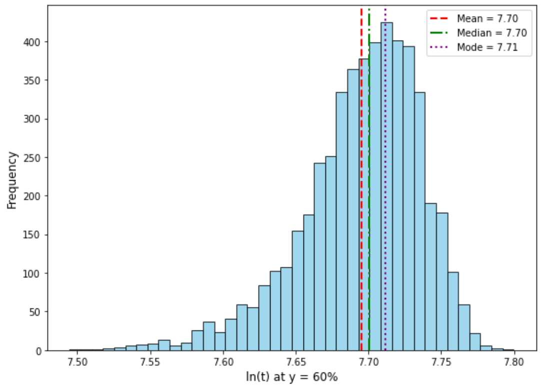
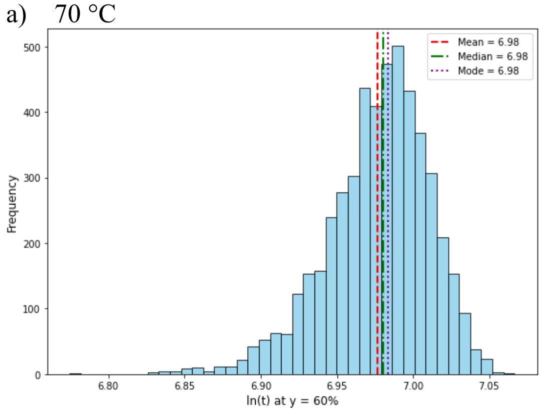


Figure 4. Phi-GPR estimation results integrating the governing equation into the prior mean function

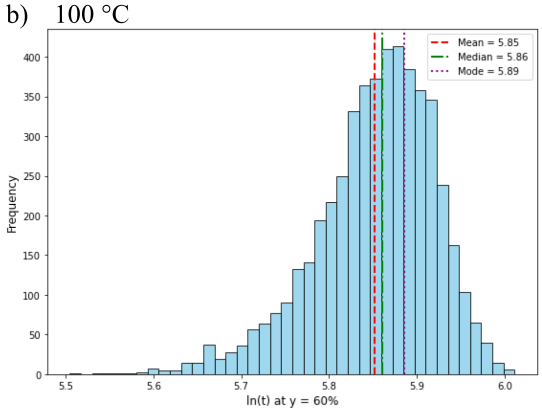
To quantify the uncertainty in the estimated thresholds, we drew 5,000 samples from the posterior predictive distribution of the Phi-GPR model. Based on the posterior inference of the degradation model, we estimated the distribution of ln(t), defined as the time to reach 60% of the initial tensile strength, for each temperature condition.



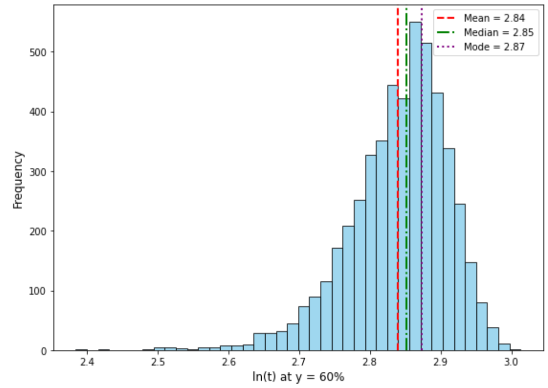
a) 70 °C



b) 100 °C



c) 120 °C



d) 140 °C

Figure 5. Posterior Distribution of ln(t) Estimated by Phi-GPR at the Failure Threshold

2.3. Markov Chain Monte Carlo

In this study, a Bayesian inference-based MCMC method was applied to estimate the parameters of a degradation model that characterizes the thermal aging behavior of rubber materials (Andrieu et al., 2003). While traditional deterministic optimization methods yield only single-point estimates, Bayesian frameworks can combine observational data and prior knowledge to derive posterior distributions for model parameters, allowing you to quantify uncertainty.

1. Generate initial sample θ^0
2. For i = 1 to n_s
 - Generate sample form proposal distribution $\theta^* \sim g(\theta^* | \theta^{i-1})$
 - General acceptance sample u ~ U (0,1)
 - if $u < Q(\theta^{i-1}, \theta^*) = min\left\{1, \frac{f(\theta^*|y)g(\theta^{i-1}|\theta^*)}{f(\theta^{i-1}|y)g(\theta^*|\theta^{i-1})}\right\}$

$$\theta = \theta^*$$

else

$$\theta^i = \theta^{i-1}$$

$$Q(\theta^{i-1}, \theta^*) = \min\left\{1, \frac{f(\theta^*|y)}{f(\theta^{i-1}|y)}\right\}$$

MCMC sampling was performed using the Metropolis-Hastings (M-H) algorithm, a basic MCMC technique. This algorithm allows asymptotic sampling from a complex probability distribution by constructing a Markov chain with a normal distribution corresponding to the target posterior distribution. By repeating this procedure in several steps, a representative sample set that approximates the posterior distribution can be obtained. Rejected samples are replaced with samples that replicate previously accepted states, thereby maintaining the continuity of the Markov chain. The prior distribution was set to a Gaussian distribution based on the deterministic parameter estimation derived from the DO-PINN framework. Based on this prior distribution, MCMC sampling was performed to obtain the posterior distribution, which enabled confidence intervals and quantitative evaluation of the predicted behavior of the degradation model.

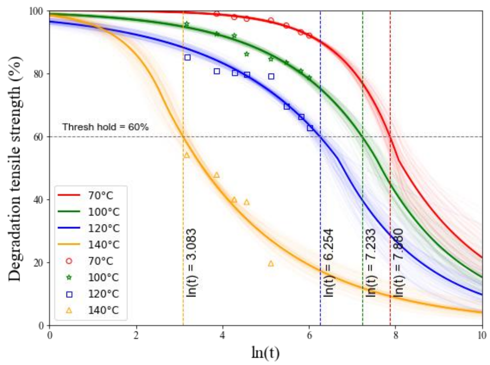
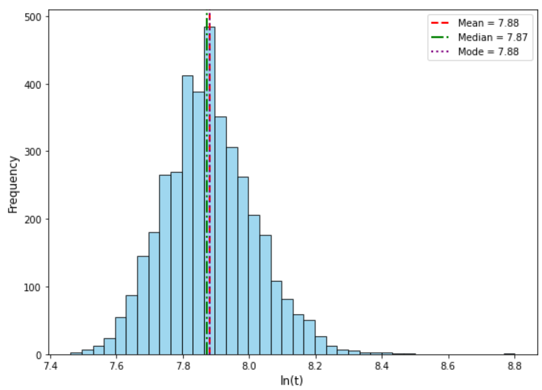
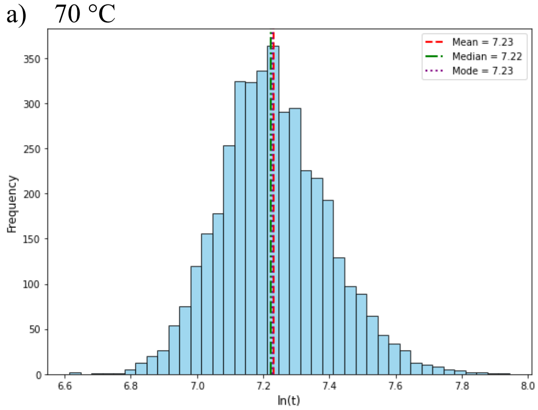


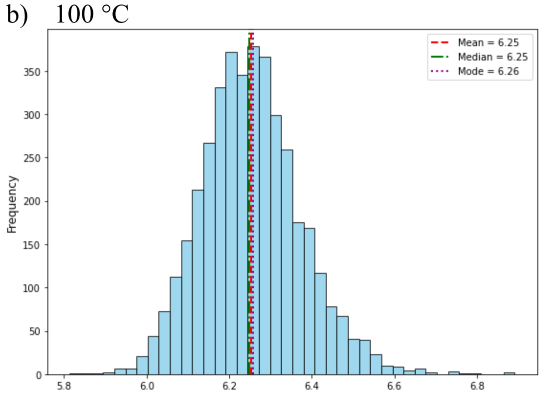
Figure 6. MCMC sampling-based estimation results of degradation model parameters



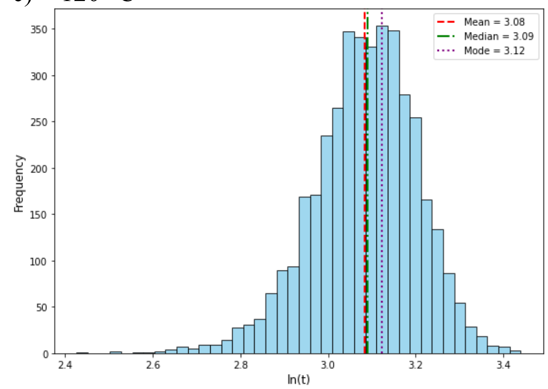
a) 70 °C



b) 100 °C



c) 120 °C



d) 140 °C

Figure 7. Posterior Distribution of ln(t) Estimated by MCMC at the Failure Threshold

The MCMC framework visualized the thresholds corresponding to 60% performance degradation as a histogram to show the probabilistic distribution of predicted failure times.

2.4. Bayesian Neural Network PINN

Unlike conventional deterministic neural networks, the BNN assumes probabilistic prior distributions over weights and biases, and infers posterior distributions based on training data (Rivas et al., 2022). This structure has the advantage of being able to quantify the uncertainty of the model in essence and providing the mean value and confidence interval of the prediction at the same time. BNN enables quantification of uncertainty in prediction by modeling the weights of the neural network as a probability distribution. Unlike deterministic neural networks that rely on fixed parameter values, BNN defines a prior distribution for each weight w and bias b, and infers their posterior distribution through learning. In this study, BNN was employed to approximate the thermal degradation behavior of rubber materials using neural networks, generating not only predictive outputs but also associated confidence intervals (Yang et al., 2021). Each linear layer of the model is implemented as a Bayesian linear layer, where the weights and biases are parameterized by the mean (μ) and log standard deviation (logσ), and forward propagation is performed by sampling. For example, the weights are sampled as follows:

$$\omega = \mu_\omega + \sigma_\omega \times \epsilon, \epsilon \sim N(0, I) \quad (13)$$

B-PINN builds on top of the probabilistic structure of BNN by incorporating physical constraints to enable probabilistically consistent modeling that is consistent with physical knowledge. In this study, we applied a hybrid framework by incorporating the structural constraints of a degradation model into the loss function of a BNN architecture. This contributed not only to accurate fitting but also to increased confidence in predicting degradation trends.

B-PINN is a probabilistic extension of PINN that incorporates loss terms based on physical information into the basic structure of BNN. This makes B-PINN particularly effective for reliability prediction of degrading systems such as rubber-based components, as it ensures both predictive uncertainty and physical realizability.

B-PINN consists of the following three core components:
Probabilistic Parameterization: Key material parameters (t_0, f_0, k_1, k_2) are defined not as fixed scalar values but as random variables assumed to follow normal distributions with mean μ and variance σ^2. Sampled values from these distributions are used to construct physics-informed degradation curves and generate predictions.
Variational Inference-based Learning: To address the intractability of computing the exact posterior, this study employs Variational Inference (VI) to learn an approximate posterior distribution $q(\theta)$. A Kullback-Leibler (KL) divergence term, measuring the difference between the approximate posterior and the prior distribution $p(\theta)$, is integrated into the loss function for regularization.
Integration of Physics-based Loss: The core of the PINN framework is that physics-based terms such as PDE, , ODE, continuity, gradient smoothness, and boundary condition satisfaction are directly incorporated into the model. This ensures that what is learned is not simply a control effect on the data but exists in a special valid solution space. All parameters are assumed to follow a standard normal prior N (0,1), and the KL divergence is appropriately computed to prevent excessive dispersion while promoting convergence based on prior knowledge.

$$\mathcal{L}_{KL} = \sum_i D_{KL}[q(\theta_i|\mu_i, \sigma_i)\|N(0,1)] \tag{14}$$

$$D_{KL} = -\frac{1}{2}\sum_i \left(1 + \log \sigma_j^2 - \mu_j^2 - \sigma_j^2\right) \tag{15}$$

Combining physical consistency and prediction confidence, the B-PINN framework serves as an effective modeling approach for model parameter estimation under uncertainty. In particular, the inference phase allows for the construction of estimated confidence intervals through iterative sampling to support RUL prediction.

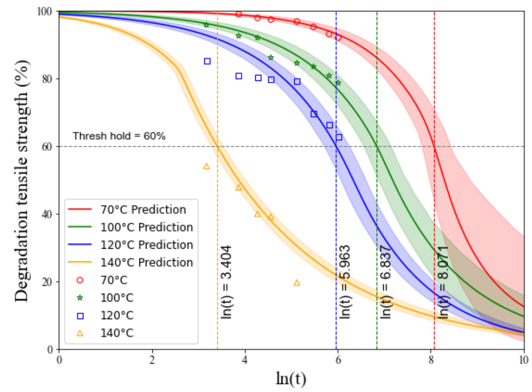
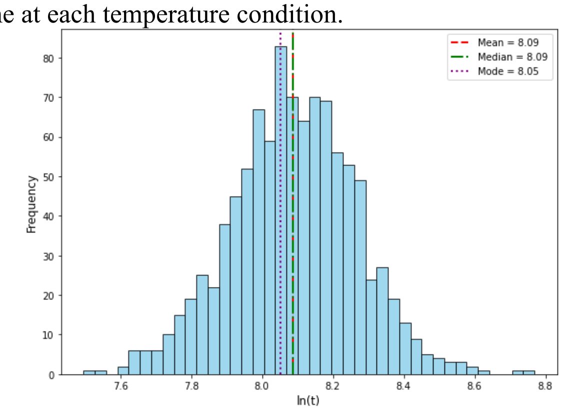
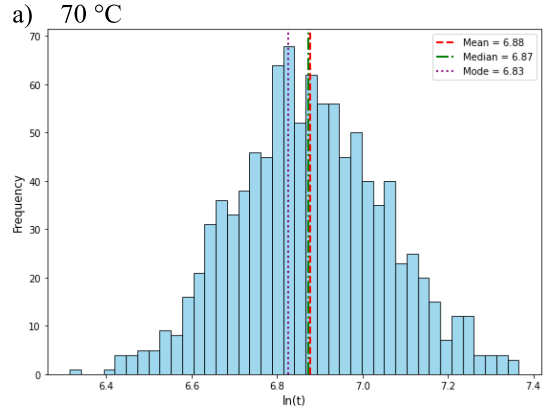


Figure 8. B-PINN estimation results of degradation model parameters

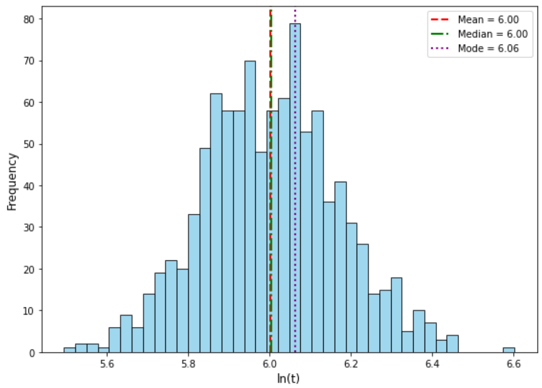
After training, 1,000 prediction curves were extracted from the learned variation distribution of the model parameters and sampled from the posterior of the B-PINN. The resulting posterior samples of thresholds were visualized as a histogram to represent the uncertainty of the predicted failure time at each temperature condition.



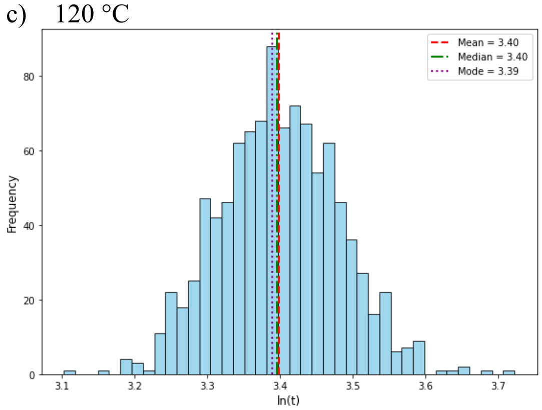
a) 70 °C



b) 100 °C



c) 120 °C



d) 140 °C

Figure 9. Posterior Distribution of ln(t) Estimated by B-PINN at the Failure Threshold

3. ARRHENIUS REGRESSION FOR LIFETIME PREDICTION OF RUBBER MATERIAL

To predict failure life under thermal degradation of rubber, this study adopted the Arrhenius model—a widely used framework in temperature stress life testing that characterizes the relationship between reaction and temperature. The model was constructed by defining the lifetime based on a specified reduction in the initial tensile strength of rubber specimens at each temperature, thereby establishing a time–temperature relationship. This approach can be used to convert HALT data to expected life at room temperature due to natural aging.

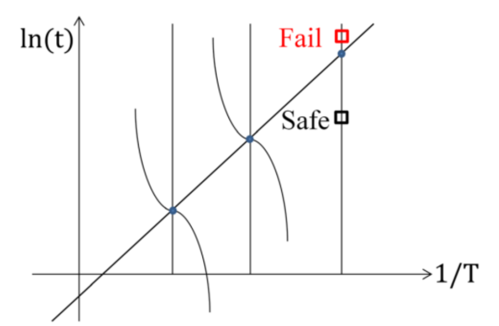


Figure 10. Arrhenius model-based lifetime prediction

Here, K is the rate constant, A is a pre-exponential factor, E_a is the activation energy (KJ/mol), R is the gas constant (8.314J/mol*K), T is the absolute temperature (K), and t is the lifespan (hour).

$$K = Ae^{\frac{-Ea}{RT}} \tag{16}$$

$$\ln(K) = \ln(A) - \frac{E_a}{R}\left(\frac{1}{T}\right) \tag{17}$$

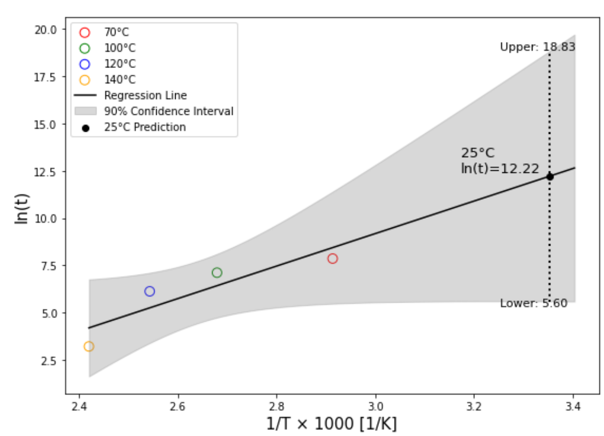
$$\ln(t) = \ln\left(\frac{1}{A}\right) + \frac{E_a}{R}\left(\frac{1}{T}\right) \tag{18}$$

In this study, the lifetime was defined as the time required for tensile strength to degrade to 60% of its initial value, and the lifetime at each temperature was predicted using four distinct methods: DO-PINN, Phi-GPR, MCMC, and B-PINN. Subsequently, Arrhenius regression analysis was conducted to derive linear regression coefficients corresponding to each method.

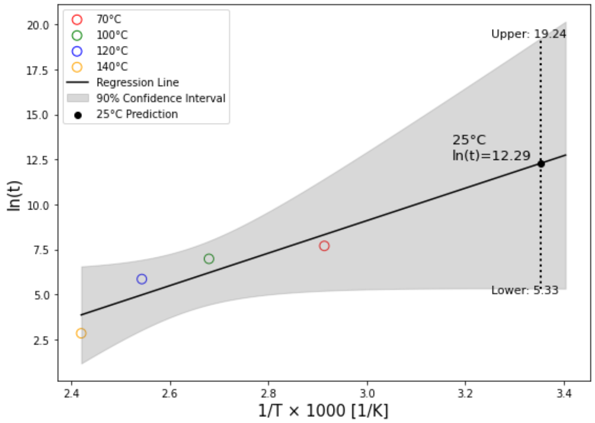
To quantify the uncertainty associated with the estimated lifetime at room temperature (25°C), a confidence interval was calculated based on the standard error of the predicted ln(t) obtained through linear regression of the Arrhenius model. For each method (DO-PINN, Phi-GPR, MCMC, and B-PINN), a regression line was fitted to the ln(t) values derived from the predicted 60% failure times at elevated temperatures (70°C–140°C), and extrapolated to 25°C.

To construct the confidence interval, the standard formula for the prediction of a mean response in simple linear regression was employed:

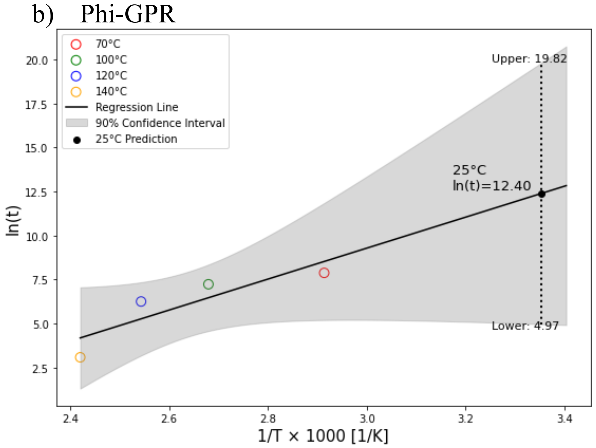
$$\hat{y}(x) \pm t_{a/2,n-2} \cdot \sigma \cdot \sqrt{\frac{1}{n} + \frac{(x_i - \bar{x})^2}{\sum(x_i - \bar{x})^2}} \tag{19}$$



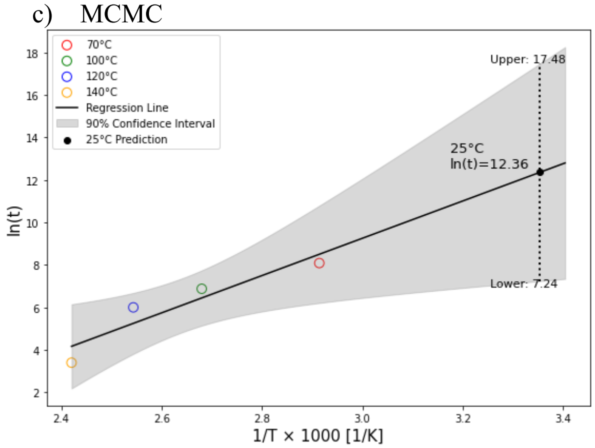
a) DO-PINN



b) Phi-GPR



c) MCMC



d) B-PINN

Figure 11. The results of lifetime prediction using Arrhenius regression

Table 1. The comparison of Arrhenius regression-based lifetime prediction

Method	**Regression equation**	**ln(t) at 25°C**	**t at 25°C (hour)**
DO-PINN	8.5845 * (1/T*1000) -16.5739	12.22	202,804
Phi-GPR	9.0223 * (1/T*1000) -17.9734	12.29	217,509
MCMC	8.7937 * (1/T*1000) -17.0987	12.40	242,801
B-PINN	8.7785 * (1/T*1000) -17.0794	12.36	233,281

At 25°C, the ln(t) estimates values were relatively consistent across all four methods, ranging from about 12.22 to 12.40. While DO-PINN provided deterministic point estimate values based on physics-based modeling, Phi-GPR, MCMC, and B-PINN incorporated a probabilistic inference framework to quantify the uncertainty.

Each probability model reflected the difference in posterior variance and model assumptions through confidence intervals for the estimated ln(t) values. This framework not only provides accurate extrapolation based on the Arrhenius relationship, but also significantly improves life prediction by allowing interpretation of uncertainty, confidence intervals, and distributional characteristics of model results, which are essential for robust and risk-aware decision making in reliability engineering.

4. CONCLUSION

In this study, an empirical degradation behavior model is used to predict the thermal response of rubber materials, and both deterministic and probabilistic approaches are utilized to evaluate the reliability and interpretability of the model. Most of the existing metaheuristic-based degradation curve fitting methods are deterministic methods that focus on single-point prediction, and have inherent limitations in confidence intervals and uncertainty quantification. To overcome these limitations, this study preferentially applied the PINN structure that directly integrates physical constraints into the loss function. This enabled deterministic degradation modeling and optimal parameter estimation (DO-PINN), and successfully predicted the degradation behavior of rubber with only a small amount of data.

We also quantify the prediction uncertainty and confidence intervals of the fitted degradation curves using various model-based techniques, including Phi-GPR, MCMC, and B-PINN. A comparative analysis of RUL predictions shows that all four approaches consistently predict lifetime at room temperature conditions. These results demonstrate not only similar predictive capabilities to existing models, but also the ability to infer uncertainties, confidence intervals, and distributional properties of model parameters, increasing the interpretability and reliability of RUL predictions.

The key conclusions of this study are as follows:

1) DO-PINN inserted physical constraints into the loss function to effectively identify performance degrad ation and accurately estimate optimal model param eters.

2) Phi-GPR, MCMC, and B-PINN produced RUL predictions that were compar able to deterministic models, while further quantify ing the predictive uncertainty in the lifespan estima tes.

3) Comparative Arrhenius regression analysis showed that all four methods produced consistent lifetime predictions at room temperature, with Phi-GPR, MCMC, and B-PINN providing additional insight into confidence i ntervals and distributional reliability.

In summary, this study utilized a framework that combines PINN and Bayesian Berlin quantification to support deterioration modeling and explanation. This methodology is easily conditionally extensible to other material properties or conditions and promises to provide interesting predictions and state predictions (PHM) depending on the data context. In future work, we will extend the hybrid framework proposed in this study to incorporate probabilistic uncertainty quantification even at the Arrhenius regression stage to enable full probabilistic lifetime prediction at all modeling stages. We also plan to extend the B-PINN-based framework to different degradation prediction mechanisms such as mechanical fatigue and chemical corrosion, and to further enhance its practicality as a PHM system through demonstrations using real sensor-based monitoring data.

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