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Physics-Based Dynamic Data Synthesis Enabling Uncertainty-Aware RUL Prediction of Nuclear Digital Input Cards

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1. Introduction

Digital instrumentation and control systems are fundamental to ensuring the safe operation of nuclear power plants (NPPs). In particular, safety-related digital components within the reactor protection system (RPS) execute monitoring and trip functions that are directly associated with core safety. Therefore, the reliability of these safety-related digital components directly influences overall plant safety performance.

To maintain reliability, operating plants typically apply periodic preventive maintenance strategies. Under this approach, components are replaced or inspected at predefined intervals without explicit consideration of their actual degradation state. Although this strategy preserves conservative safety margins, it does not reflect device-specific aging progression. Consequently, maintenance actions may not represent the true health condition of individual components [1].

This limitation becomes more significant when considering the degradation characteristics of semiconductor-based digital components. In contrast to many analog systems, digital components exhibit a cliff-edge failure characteristic [2]. Internal degradation mechanisms accumulate gradually, while observable performance degradation remains minimal until a critical threshold is exceeded. Once that threshold is reached, performance deteriorates abruptly. As a result, time-based maintenance may either replace components prematurely or fail to prevent unexpected failures between inspection intervals.

Accordingly, condition-based maintenance strategies relying on remaining useful life (RUL) estimation have gained increasing attention in the nuclear field [1,3]. However, implementing reliable RUL prediction in nuclear environments presents a fundamental challenge. Real failure events are extremely rare, and degradation datasets reflecting diverse dynamic stress conditions are difficult to obtain from field operation alone.

Recent research has demonstrated the applicability of artificial intelligence techniques to digital safety systems. For example, Lee et al. reported that artificial intelligence-based condition monitoring of photocouplers enhances maintenance strategies in digital RPS applications [4]. While such work confirms the feasibility of intelligent monitoring, reliable RUL prediction under dynamically varying stress conditions still requires physically consistent degradation modeling and data generation.

In this context, this study proposes a physics-informed degradation modeling and synthetic data generation framework for RUL prediction with uncertainty quantification. Accelerated aging data from safety-related digital input (DI) cards are first analyzed to establish degradation criteria. Temperature-dependent lifetime behavior is then modeled using the Arrhenius relationship and a cumulative damage formulation. Based on this physical foundation, synthetic degradation trajectories reflecting dynamic operating conditions are generated and used to train a predictive model with uncertainty quantification.

2. Accelerated Aging Experiment and Degradation Characterization

The service lifetime of safety-related DI cards installed in the RPS extends over several decades under nominal operating conditions. Because degradation progresses slowly and actual failure events are extremely rare, field data alone are insufficient for establishing statistically meaningful degradation criteria. Therefore, a temperature-accelerated aging experiment was conducted to observe measurable degradation trends within a feasible experimental duration.

A constant temperature of 100°C was selected based on acceleration factor considerations derived from the Arrhenius relationship [3]. This temperature provides sufficient amplification of thermally activated degradation mechanisms while remaining within the material tolerance limits of the DI card components. The objective was to observe progressive electrical parameter drift associated with intrinsic semiconductor aging rather than inducing unrealistic overstress failure.

Thirty-two DI card channels were subjected to identical thermal stress conditions for approximately eight months. Rising threshold voltage was selected as the primary degradation indicator because it directly reflects transistor switching characteristics and gate oxide defect accumulation. Voltage measurements were recorded at a sampling rate of 1 Hz to capture transition behavior with adequate temporal resolution.

Fig. 1 illustrates the experimental configuration. All channels were exposed to uniform temperature conditions and continuously monitored. This configuration ensured statistical consistency across channels and minimized environmental bias.

Fig. 1. Experimental configuration of the accelerated aging test for safety-related digital input cards.

During the experiment, rising threshold voltage exhibited gradual drift followed by accelerated growth in certain channels. A distinct inflection was observed near 10.2 V, beyond which the voltage increase accelerated significantly. Fig. 2 presents representative threshold trajectories and highlights this transition region. The value of 10.2 V was therefore defined as the functional end-of-life boundary under accelerated conditions.

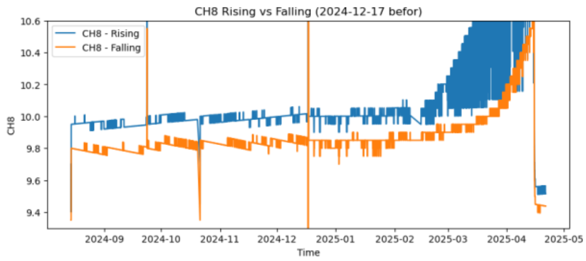

Fig. 2. Representative rising threshold voltage trajectories under accelerated aging conditions and identification of the 10.2 V functional boundary.

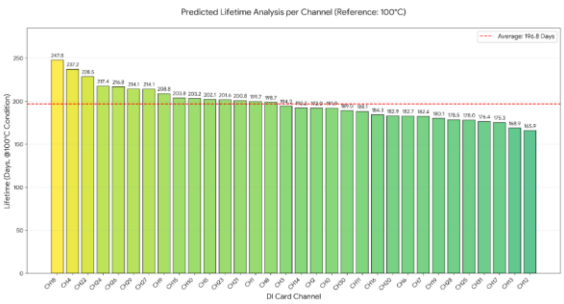

Fig. 3. Channel-wise lifetime distribution under 100°C accelerated aging condition showing inherent variability across DI card channels.

In addition to the voltage-based criterion, cumulative reversal events were evaluated using Rainflow counting. Rapid acceleration in cumulative event growth was observed between approximately 400 and 600 cycles. Based on this behavior, 500 cumulative events were defined as a conservative early-warning criterion indicating the onset of accelerated degradation. These two criteria establish both a functional boundary and a dynamic instability indicator for subsequent modeling.

In addition to the threshold-based characterization, variability among channels was analyzed under the accelerated condition. Fig. 3 shows the channel-wise lifetime distribution at 100°C, indicating inherent dispersion in degradation sensitivity across DI card channels. This observed variability provides empirical justification for incorporating stochastic parameter sampling in the dynamic data synthesis stage.

3. Physics-Informed Dynamic Data Synthesis

Although the accelerated experiment was conducted under constant temperature, actual plant operation involves dynamically varying stress conditions. Therefore, constant-temperature observations must be translated into degradation trajectories reflecting realistic operating histories.

Temperature-dependent lifetime behavior was modeled using the Arrhenius relationship [3] as expressed in Eq. (1):

$$L(T) = A\exp\left(\frac{E_a}{kT}\right) \quad (1)$$

where E_a denotes activation energy and k represents the Boltzmann constant. Eq. (1) provides a physically interpretable basis for extrapolating degradation rates across temperature levels.

To account for time-varying stress histories, cumulative damage was evaluated using Eq. (2).

$$D = \sum \frac{\Delta t}{L(T)} \quad (2)$$

Failure was assumed when cumulative damage reached unity. This approach maintains consistency between accelerated aging observations and long-term operational extrapolation.

Dynamic temperature profiles were constructed to represent stress, steady-state, and recovery phases observed in plant operation. Stress phases correspond to elevated thermal loading, steady-state phases represent nominal operating temperature, and recovery phases simulate cooling or reduced load conditions. Maintenance intervals were modeled as negligible damage accumulation periods. Consequently, degradation progression becomes dependent on both temperature magnitude and exposure duration. In addition, the dynamic profiles were designed to span realistic variability in exposure patterns so that synthesized trajectories cover both mild and severe thermal histories.

Fig. 4 illustrates the sequential mapping from dynamic temperature stress to cumulative damage accumulation and subsequent RUL estimation based on the Arrhenius–cumulative damage framework adapted from Jang and

Kim [3]. This representation clarifies the physical linkage between temperature variation, damage integration, and lifetime projection under realistic operating conditions.

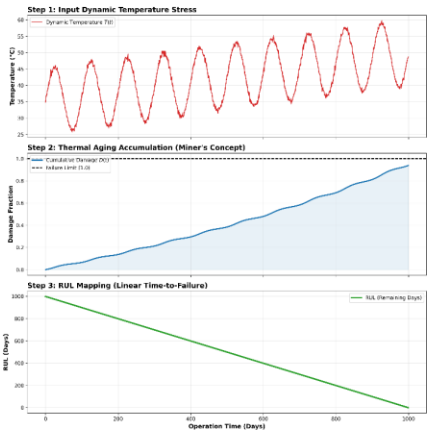

Fig. 4. Sequential mapping from dynamic temperature stress to cumulative damage accumulation and RUL estimation based on the Arrhenius–cumulative damage model.

To incorporate variability among DI card channels, Latin Hypercube Sampling was applied to thermal resistance and degradation sensitivity parameters. Ten thousand synthetic degradation trajectories were generated. These trajectories reflect stochastic variability while remaining constrained by physically derived degradation laws.

Fig. 5 presents the distribution of synthesized degradation trajectories. The distribution includes both early-failure and extended-lifetime scenarios. This diversity ensures that the predictive model is trained on physically consistent yet statistically varied degradation behavior.

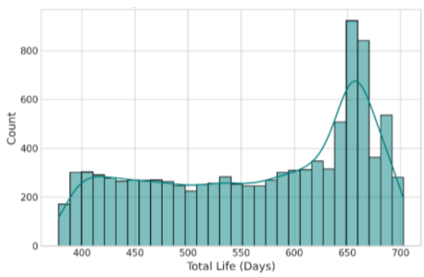

Fig. 5. Distribution of synthetic degradation trajectories generated using physics-informed dynamic data synthesis with stochastic variability.

4. RUL Prediction with Uncertainty Quantification

The synthetic degradation dataset generated in the previous section provides a physically constrained and statistically diverse basis for RUL prediction. Because the degradation trajectories were derived from temperature-dependent lifetime modeling and cumulative damage evaluation, the dataset preserves consistency with underlying semiconductor aging mechanisms. Building upon this foundation, a predictive framework was developed to estimate RUL under dynamic operating conditions.

A bidirectional long short-term memory network (Bi-LSTM) was adopted for time-series modeling. Degradation under dynamic thermal stress exhibits cumulative and history-dependent behavior. Therefore, capturing both forward and backward temporal dependencies improves representation of nonlinear degradation progression. By processing bidirectional context within each input window, the model enhances predictive reliability compared with architectures that rely solely on forward temporal information.

To improve prediction stability near the end-of-life region, the RUL target variable was log-transformed during model training. This transformation reduces the relative dominance of large early-life values and enhances sensitivity to degradation acceleration as the component approaches failure.

To validate the model selection, comparative experiments were conducted using several time-series architectures, including a deep neural network, a standard long short-term memory network, a temporal convolutional network, and a Transformer-based model. Among these candidates, the Bi-LSTM model achieved the lowest mean absolute error of 3.13 days and a root mean square error of 5.88 days. The maximum prediction error was limited to 39.51 days, which was smaller than that observed for the other models. Accuracy metrics defined over normalized tolerance thresholds further confirmed stable performance under stricter tolerance levels. These findings indicate that the proposed model maintains predictive consistency across different evaluation criteria and further support the use of the Bi-LSTM architecture for nonlinear and history-dependent degradation sequences under dynamic stress conditions.

The input features were constructed from physically meaningful quantities rather than arbitrary signal transformations. These features include temperature statistics within sliding windows, cumulative exposure measures, and degradation indicators derived from the cumulative damage model. By maintaining alignment between feature construction and physical degradation mechanisms, the learning process avoids purely empirical pattern fitting and remains grounded in interpretable degradation behavior.

While accurate point estimation of RUL is essential, uncertainty quantification is equally critical in nuclear applications. Maintenance decisions for safety-related components must remain conservative, particularly when approaching functional instability. Accordingly, Monte Carlo (MC) dropout was applied during inference to approximate predictive uncertainty [5]. One hundred stochastic forward passes were performed for each input sequence. The mean prediction was interpreted as the estimated RUL, whereas the variance across stochastic passes was used as an uncertainty indicator.

Fig. 6 illustrates representative RUL predictions with corresponding uncertainty intervals under dynamic operating conditions. Wider intervals appear during periods of rapid degradation acceleration, reflecting increased instability in degradation dynamics.

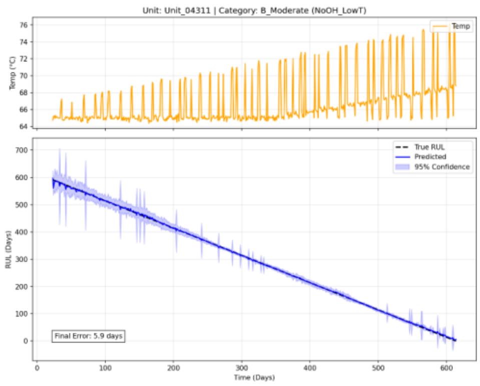

Fig. 6. Representative RUL prediction results with uncertainty intervals under dynamic operating conditions.

When interpreted together with the early-warning threshold based on cumulative events, the uncertainty-aware prediction framework provides complementary safety indicators. The functional boundary reflects proximity to performance degradation, whereas the expansion of predictive uncertainty reflects increasing variability in degradation progression. Consequently, the integration of physics-informed modeling and uncertainty quantification supports conservative maintenance decision-making for safety-related DI cards in NPPs.

5. Discussion and Conclusion

The results demonstrate that physics-informed dynamic data synthesis provides a technically viable solution to the data scarcity problem inherent in nuclear applications. By grounding synthetic degradation trajectories in temperature-dependent lifetime modeling and cumulative damage theory, the proposed framework ensures that generated data remain physically consistent with semiconductor aging mechanisms. This physical constraint is essential for maintaining interpretability when extrapolating beyond accelerated test conditions.

At the same time, the integration of data-driven learning enables flexible modeling of nonlinear degradation behavior under dynamic stress profiles. Purely physics-based lifetime estimation may not adequately capture stochastic variability among individual components. Conversely, purely data-driven models trained on limited degradation datasets may lack extrapolation reliability. The present framework balances these two approaches by preserving physical structure while allowing the predictive model to learn complex temporal dependencies.

An additional contribution lies in the explicit incorporation of uncertainty quantification. In nuclear engineering practice, maintenance strategies for safety-related components must remain conservative. Therefore, RUL prediction should not be interpreted solely as a point estimate. The predictive intervals derived from MC dropout provide supplementary information regarding confidence in the estimated lifetime. Notably, the expansion of uncertainty intervals during accelerated degradation phases suggests that predictive variance can serve as an additional indicator of increasing instability.

From a maintenance perspective, the combination of functional boundary identification and early-warning criteria based on cumulative damage offers a layered safety margin. When interpreted together, these indicators enhance safety margin visibility and support proactive maintenance planning.

Although the proposed framework demonstrates promising results, certain limitations should be acknowledged. The accelerated aging experiment was conducted under a single elevated temperature condition, and additional environmental stress factors were not explicitly modeled. Furthermore, validation was performed using physics-informed synthetic datasets rather than field failure data. Future work should incorporate multi-stress environments and validate predictive performance against operational data as it becomes available.

In summary, this study demonstrates that physics-informed dynamic data synthesis combined with uncertainty-aware RUL prediction can improve reliability management of safety-related DI cards in NPPs.

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REFERENCES

[1] M. Sethu, B. Kotla, D. Russell, M. Madadi, N. A. Titu, J. B. Coble, A. Bhojwani, H. Salehi, N. S. Balakrishnan, and A. Khojandi, Application of artificial intelligence in detection and mitigation of human factor errors in nuclear power plants: A review, Nuclear Technology, Vol. 209, pp. 276–294, 2023.
[2] International Electrotechnical Commission, IEC 61513: Dependability of digital instrumentation and control systems in nuclear power plants, IEC, 2011.
[3] I. Jang and C. H. Kim, Prediction of remaining useful life of electronic components in the POSAFE-Q PLC platform under NPP dynamic stress conditions, Nuclear Engineering and Technology, Vol. 56, pp. 1863–1873, 2024.
[4] H. J. Lee, H. S. Jo, M. G. Na, and C. H. Kim, AI-based condition monitoring of photocouplers to enhance the maintenance strategy for digital reactor protection systems, Nuclear Engineering and Technology, Vol. 57, 103958, 2025.
[5] Y. Gal and Z. Ghahramani, Dropout as a Bayesian approximation: Representing model uncertainty in deep learning, Proc. 33rd International Conference on Machine Learning, 2016.