Combining Statistical Models and AI for Predictive Maintenance: RUL Estimation of Reactor Protection System Components

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Abstract

Reliable operation of digital instrumentation in nuclear power plants depends heavily on accurate prediction of component degradation. This study proposes a hybrid framework for estimating the remaining useful life of photo-couplers used in reactor protection systems. Accelerated aging tests were performed under elevated thermal conditions to generate representative degradation data. Both statistical models and a neural network were developed to analyze long-term performance decline.

The AI model incorporates polynomial features and custom loss functions to reflect realistic monotonic and exponential degradation behavior. Its predictions closely matched those of the statistical models, with projected lifespans ranging from 22 to 24 years. A user-oriented software tool was also implemented to support real-time remaining useful life forecasting using field data, demonstrating the practical value of combining traditional and AI-based approaches for predictive maintenance in nuclear systems.

1. Introduction

Digital instrumentation and control (I&C) systems are essential for the safe and reliable operation of nuclear power plants (NPPs). These systems continuously monitor field signals, execute control actions, and activate protective responses in abnormal situations. Over the past two decades, digitalization has introduced advanced features such as self-diagnosis and automated testing, improving fault detection and operational efficiency.

However, this shift has also raised new challenges. Failures in electronic components—particularly in reactor protection systems (RPS)—remain a leading cause of plant incidents, often coupled with human errors. Traditional diagnostic methods, including periodic tests and self-check functions, struggle to detect hidden degradation or anticipate failures in real time. This highlights the urgent need for predictive maintenance solutions based on accurate estimation of component aging.

This study addresses this challenge by developing a hybrid remaining useful life (RUL) prediction framework combining statistical modeling and artificial intelligence. Through accelerated aging experiments on photo-couplers, we collected high-fidelity degradation data and trained both conventional life models and a neural network. Our goal is to bridge the gap between theoretical reliability models and field-deployable tools that support real-time predictive maintenance in nuclear environments.

2. Accelerated Aging Test Setup

2.1. Selection of Test Target

Among the digital components used in the RPS, photo-couplers were selected as the primary test target due to their critical role in signal isolation and frequent exposure to thermal stress. These devices convert electrical signals to optical signals, ensuring galvanic isolation between circuits. However, over time, they are prone to degradation mechanisms such as LED brightness loss, reduced phototransistor sensitivity, and insulation breakdown, all of which can compromise signal integrity. Given their functional importance and susceptibility to aging, photo-couplers are ideal candidates for RUL prediction model development and validation.

2.2. Accelerated Aging Test Environment

To simulate long-term operational stress within a shortened timeframe, accelerated aging tests were conducted under elevated temperature and electrical load conditions. Following IEC 62506 guidelines, photo-couplers were exposed to a constant ambient temperature of 130°C while operating under nominal voltage. Prior HALT (Highly Accelerated Limit Test) procedures ensured that these conditions induced degradation without causing immediate failure. This controlled environment enabled the collection of realistic degradation data for RUL modeling, reflecting aging patterns similar to those experienced over decades of actual plant operation.

2.3. Experimental Design

To replicate multi-year degradation within a feasible laboratory period, the test leveraged the Arrhenius acceleration model. Photo-couplers were continuously operated at 130°C for 2,597 hours (approximately 108 days), aiming for a tenfold acceleration of aging relative to standard 25°C conditions. The acceleration factor was calculated using component-specific activation energy values. Output voltage and related electrical properties were monitored over time to capture meaningful degradation signals suitable for RUL modeling.

A fully integrated testbed was developed to support real-time data acquisition and model validation. The system included a temperature-controlled chamber, waveform analyzer, LCR meter, and a control server with real-time data processing capabilities. Sensor signals were transmitted to a graphical user interface (GUI), allowing both engineers and researchers to visualize degradation trends and perform live RUL estimation. This setup bridged the gap between experimental testing and practical application in nuclear maintenance workflows.

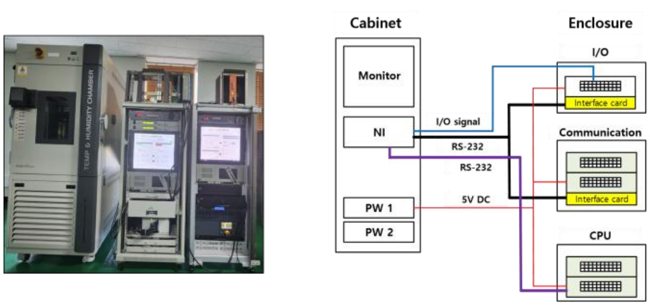

Figure 1. Experimental Setup for Thermal Stress Aging of Photo-Coupler Components.

3. METHODOLOGY

3.1. Statistical Model-Based Prediction

To establish a statistical baseline for RUL prediction, degradation data from the accelerated aging tests were preprocessed to remove noise, interpolate missing values, and stabilize voltage trends. This ensured that the time-series signals reflected consistent degradation patterns required for reliable lifetime estimation. A moving average filter was applied to reduce high-frequency noise while preserving the overall aging trend.

The onset of degradation was detected by analyzing the slope of the voltage curve. Specifically, the point at which the first derivative fell below a defined threshold was considered the beginning of meaningful degradation. This approach helped isolate the relevant portion of the data while excluding early signal fluctuations and noise.

Temporary signal recovery events—possibly caused by ion desorption or measurement artifacts—were identified and removed using second-derivative analysis. After cleaning the data, voltage decay curves were fitted to exponential models. The parameters were estimated using least squares, and the fitted lifetimes were evaluated for statistical validity using the Kolmogorov–Smirnov test.

To convert test-based results into real-world lifespan estimates, the Arrhenius model was used to compute acceleration factors. Based on the applied thermal stress and the activation energy from component datasheets, the predicted mean time to failure (MTTF) under nominal conditions was approximately 22 to 23 years. These results provide a robust statistical foundation for cross-validating AI-based predictions.

3.2. AI Model-Based Prediction

To complement the statistical approach, an AI model was developed using a feedforward neural network enriched with polynomial regression features. This architecture was selected for its ability to learn nonlinear voltage degradation patterns observed in the accelerated aging data. The model was trained on time-series data filtered to exclude temporary recoveries and focused exclusively on monotonic degradation segments. The predicted RUL was defined as the time point at which the model's projected voltage dropped below a critical threshold of 2.2 V.

To ensure physically meaningful predictions, a composite loss function was designed that combined mean squared error (MSE), exponential decay regularization, and a monotonicity constraint. These components encouraged the model to follow realistic aging trends while minimizing error. The model showed excellent agreement with statistical estimates, predicting a mean RUL of approximately 24 years. Evaluation metrics, including MAE of 9.8 and RMSE of 12.1, confirmed its competitive accuracy.

For conservative and explainable RUL inference, a Monte Carlo sampling strategy was employed to generate multiple predictions and compute a 95% confidence interval. The lower bound of this interval was used to define a safe and robust RUL estimate. This approach enhances the model's applicability in safety-critical nuclear environments, aligning with digital twin and predictive maintenance strategies currently gaining traction in the nuclear industry.

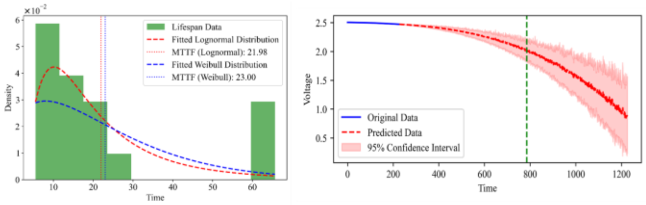

Figure 2. Comparison of RUL Predictions: Statistical vs. AI-Based Models.

4. Software Development

To bridge the gap between model development and field usability, a GUI-based software tool was created to support real-time RUL prediction. The software is tailored for use by nuclear maintenance engineers, allowing intuitive interaction with both statistical and AI-based models without requiring AI expertise. It was designed to enable rapid degradation analysis, live inference, and integration with existing instrumentation systems.

The system architecture consists of four key layers: data input and preprocessing, AI model execution, user interface, and result management. Users can upload sensor data, configure model parameters, execute RUL predictions, and export results in standard formats like CSV and JSON. Real-time visualization of voltage trends and predicted RUL enhances interpretability and operational relevance.

Three main functional modules were developed. The preprocessing module handles data cleaning, smoothing, and visualization. The AI model module allows for configurable neural network training and performance monitoring using metrics like MAE and RMSE. Finally, the prediction module supports real-time application using live or batch data, producing confidence-bounded RUL estimates for field decision-making.

Implemented in Python with PyTorch and PyQt5, the software was validated on the experimental testbed and demonstrated near-real-time performance. This platform enables proactive maintenance planning by offering interpretable, data-driven RUL forecasting, representing a practical step toward digital transformation in nuclear predictive maintenance.

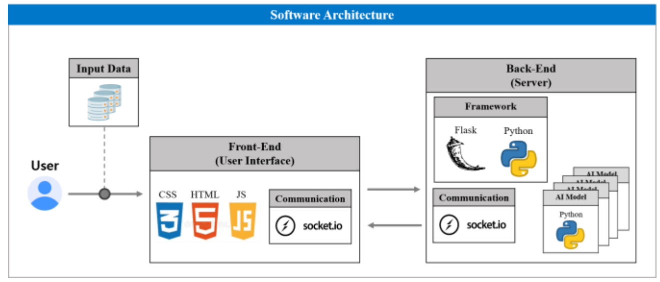

Figure 3. Modular Architecture of the AI-Based RUL Prediction Software.

5. Results

The accelerated aging test revealed clear exponential voltage degradation in photo-couplers, with a significant drop observed after approximately 840 hours. Using a fixed failure threshold of 2.2 V, both statistical and AI models produced consistent RUL predictions: 22 years (lognormal), 23 years (Weibull), and 24 years (AI model). The AI model further achieved a low prediction error, with MAE of 9.8 and RMSE of 12.1, and provided a 95% confidence interval of [23.95, 24.17] years, highlighting its robustness.

These results demonstrate strong agreement between physics-based statistical methods and the AI approach, validating the hybrid framework's reliability. While the statistical models offer interpretability and stability, the AI model captures nonlinear degradation more effectively, particularly during the late-life phase. This mutual cross-verification supports the use of AI and statistical models in tandem for safety-critical applications like nuclear I&C systems.

In line with established standards (e.g., IEC TR 62380), the predicted lifetimes are realistic and align with industry expectations for photo-copuplers. The developed GUI-based software further enhances practical applicability, allowing field engineers to conduct real-time RUL estimation. Nonetheless, maintaining data quality and avoiding model overfitting are essential for deployment. Future implementations should incorporate techniques like early stopping, real-world validation, and adaptive learning to ensure sustained performance in dynamic plant environments.

6. Conclusions

This study proposed a hybrid RUL prediction framework combining statistical models and physics-informed neural networks to assess the long-term reliability of photo-couplers in the RPS. Through accelerated aging experiments and model validation, the approach demonstrated high accuracy and consistency across methods. A GUI-based software tool was also developed to support real-time application in field environments, enhancing the practicality of predictive maintenance in nuclear I&C systems.

Looking ahead, future research will aim to generalize the framework by applying it to a broader range of safety-critical components and operational conditions. Efforts will also focus on incorporating online learning capabilities for real-time model adaptation and conducting scenario-based validation to ensure reliability under dynamic plant environments.

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