

Development of an AI-based Condition Monitoring System for Critical Electronic Components in Reactor Protection Systems

Hye Seon Jo, Jin Seong Kim, Se Heon Lee, Man Gyun Na*

Department of Nuclear Engr., Chosun Univ., 10, Chosundae 1-gil, Dong-gu, Gwangju, 61452

*Corresponding author: magyna@chosun.ac.kr

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1. Introduction

Currently, integrity of Instrumentation and Control (I&C) systems rely on limited self-diagnostic functions for several modules during normal operation, with maintenance primarily conducted via periodic testing and overhauls. In addition to conventional preventive maintenance, predictive maintenance technologies are increasingly required to prevent potential failures and enhance maintenance efficiency. This involves the development of technologies to assess the condition and predict the Remaining Useful Life (RUL) of critical components and modules in I&C systems, even during normal operation. In this regard, previous studies [1-3] developed Artificial Intelligence (AI)-based models for condition diagnosis and RUL prediction of critical components in Reactor Protection System (RPS).

This study proposes an AI-based condition monitoring system that integrates separately developed models from previous studies [1-3] to comprehensively evaluate the overall state of the RPS. This system comprises three modules for training data diagnosis, condition diagnosis, and failure prediction. AI models were developed for three critical components: photocouplers, capacitors, and DC-DC converters. The primary input variables incorporated operating time and ambient temperatures around the RPS, which are obtainable from nuclear power plants. These AI models were trained and tested using accelerated aging data. Finally, the performance of each component-level model was evaluated, and all models were integrated into the RPS monitoring system interface to present the diagnosis and prediction results for each component.

2. Framework

The RPS monitoring system consists of three modules that perform component-level condition diagnosis and failure prediction. This section introduces the overall RPS monitoring system and describes the detailed function of each module.

2.1 Overall Architecture

Fig. 1 shows the flowchart of the proposed RPS monitoring system. In Fig. 1, the system first performs training data diagnosis using rule-based logic on the RPS ambient temperature and operating time. If the

input data fall within the distribution of the training data, the component condition is classified into three levels based on operating time, temperature, and their derived statistical features. These levels are defined as “normal”, “monitoring”, and “replacement recommended”. When the component is diagnosed as either “monitoring” or “replacement recommended”, the failure prediction module is activated to estimate the RUL of the component along with its associated uncertainty information.

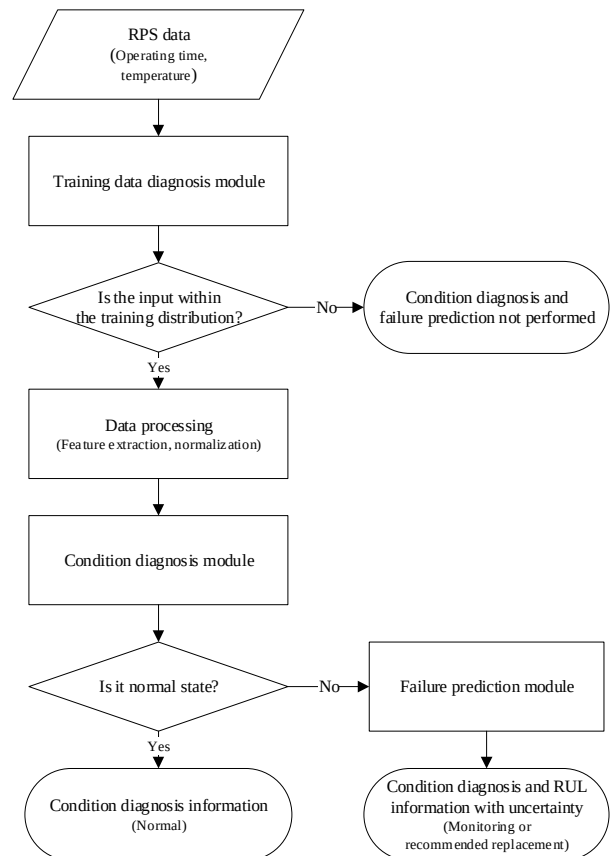


Fig. 1. Flowchart of the RPS monitoring system.

2.2 Training Data Diagnosis Module

The training data diagnosis module is developed using rule-based logic. Using rules defined for the operating time and temperature information, this module determines the validity of the input data. Input data are classified as in-distribution when the operating time increases from the previous time step and the

temperature remains within the predefined minimum-maximum range. The rule-based approach provides a baseline criterion for screening the valid data range, and its diagnostic performance is expected to be progressively enhanced by incorporating data-driven techniques such as k-nearest neighbors in future work.

2.3 Condition Diagnosis Module

Once the input data are determined to be within the training data distribution by the training data diagnosis module, the condition diagnosis module assesses the state of the component based on the input data. The condition of the components is classified into three levels considering the overhaul cycle and the period.

The condition diagnosis models were developed for each component using Gated Recurrent Units (GRUs). GRUs learn both short- and long-term temporal dependencies while requiring fewer parameters than Long Short-Term Memory (LSTM), resulting in high computational efficiency. These characteristics make GRUs well suited for assessing the macroscopic condition of components in plant environments with limited computational resources.

The condition diagnosis model for each component was evaluated in terms of both diagnostic accuracy and computational efficiency, quantified by the number of model parameters. The optimal configuration for each component was determined empirically among various hyperparameter combinations, including the number of layers, the number of units, and the set of input variables.

2.4 Failure Prediction Module

The failure prediction module is activated when a component is classified as non-normal state by the condition diagnosis module. In this case, it provides the estimated RUL of the component along with its uncertainty, expressed as a 95% confidence interval.

Unlike the condition diagnosis model, the failure prediction model provides detailed RUL information for each component. Therefore, it was developed by combining an LSTM with Monte Carlo (MC) dropout. The LSTM precisely tracks time series degradation trends, while MC dropout quantifies the predictive uncertainty. The failure prediction model for each component was evaluated using the Mean Absolute Error (MAE) and accuracy. As with the condition diagnosis model, the optimal hyperparameter configuration was determined empirically among various combinations.

3. Data Collection and Preprocessing

Photocouplers, capacitors, and DC-DC converters were selected as the critical components in the RPS based on circuit analysis and reliability analysis. These components are critical because their failure can

cascade to the module level and subsequently to the RPS itself. Since failure data are difficult to obtain from actual plants, the testbeds were constructed, and the data were collected through accelerated aging test.

3.1 Accelerated Aging Test

The accelerated aging tests were conducted by the Korea Atomic Energy Research Institute and SOOSAN ENS at a high temperature of 130°C. Component-specific testbeds were constructed and operated in a high-temperature chamber. Table I presents the detailed test conditions and degradation indicators for each component.

For photocouplers and capacitors, the lowest 20% of the data was set as the representative baseline. Due to unclear degradation trends, DC-DC converters adopted a conservative baseline criterion. Failure thresholds were determined for each component based on their degradation indicator. The data were then transformed into 66 constant-temperature cases using the Arrhenius equation. In addition, 1440 temperature-varying scenarios were generated to account for seasonal effects and transient heat generation of the components.

Table I: Accelerated aging test conditions

Parameters	Components		
	Photocoupler	Capacitor	DC-DC converter
Aging temperature	130°C	130°C	130°C
Acquisition frequency	5 sec	2 sec	5 min
No. of parts	40	40	10
Degradation indicators	Current transfer ratio	Capacitance	Total regulation

3.2 Feature Extraction and Preprocessing

Operating time, temperature, and derived statistical features were used as input variables for developing the condition diagnosis and failure prediction models. The derived statistical feature is exponentially dependent on temperature according to the Arrhenius relationship, incorporating cumulative damage over operating time. The condition diagnosis model used two variables (operating time and cumulative damage), whereas the failure prediction model used five variables (operating time, temperature, cumulative damage, and minimum and maximum temperatures).

The static and dynamic temperature scenarios generated for model training were split into training, validation, and test datasets. Data normalization was then performed using min-max scaling and standardization.

4. Results and Interface Implementation

The condition diagnosis and failure prediction models were selected by considering the trade-off between accuracy and the number of model parameters.

4.1 Condition Diagnosis Results

The condition diagnosis model was evaluated using balanced accuracy. Fig. 2 shows the highest-performance and lightweight condition diagnosis models for each component. In Fig. 2, the number of parameters was reduced by more than 90%, whereas the change in diagnosis accuracy was less than 0.1%. This demonstrates that the model complexity can be substantially reduced while effectively learning the diagnosis problem.

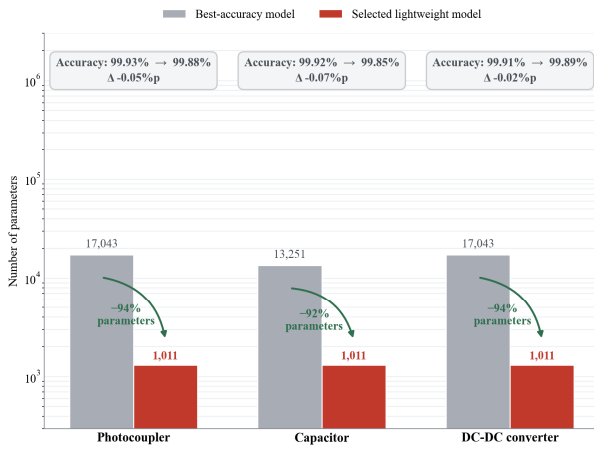


Fig. 2. Comparison of the highest-performance and the selected lightweight condition diagnosis models for each component.

4.2 RUL Prediction Results

Failure prediction model was evaluated in terms of MAE and accuracy. Here, the accuracy was defined as the metric where at least 90% of the predicted probability distributions are within $\pm 10\%$ of the actual value. Fig. 3 shows the highest-performance and lightweight failure prediction models for each component. In Fig. 3, the lightweight models achieved an accuracy degradation of less than 0.5% relative to the highest performance models, despite a parameter reduction of more than 70%. This indicates that sufficient prediction performance can be achieved without using the excessively large models. Nevertheless, the prediction models generally retain a larger number of parameters than the diagnosis models, which is attributed to the fact that RUL prediction is a relatively difficult problem requiring the precise estimation of time-series degradation trends.

Table II shows the MAE values of the selected lightweight models, indicating that the predictions are

performed with a mean error of approximately one day. Consequently, such model compression is expected to be advantageous in terms of computational efficiency and scalability when multiple components models are integrated and operated as a single system.

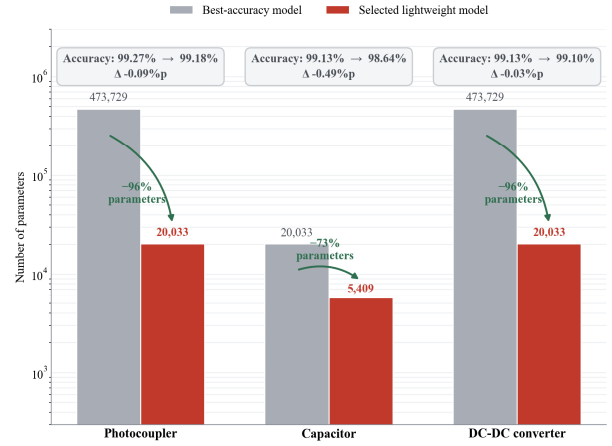


Fig. 3. Comparison of the highest-performance and the selected lightweight failure prediction models for each component.

Table II: Performance of failure prediction for each components

Components	No. of parameters	MAE (days)	
		Train data	Test data
Photocoupler	20,033	0.95	0.93
Capacitor	5,409	0.61	0.61
DC-DC converter	20,033	1.28	1.24

4.3 Condition Monitoring System Interface

Based on the lightweight models, a monitoring system interface was implemented to providing visualization of condition diagnosis and RUL predictions. The system interface was designed based on the testbed constructed by SOOSAN ENS, our collaborating institution. Additionally, to reflect the multi-channel redundancy characteristic of real plants, the interface was designed with 4 independent channels, each containing 3 separate cabinets.

Fig. 4 shows the example dashboard of the RPS monitoring system. The system provides module-level conditions with component diagnosis. Components classified as “monitoring” or “replacement recommended” are displayed on the right panel. The “View” button triggers a detailed popup (refer to Fig. 5) showing temperature profiles and RUL predictions for the selected component.

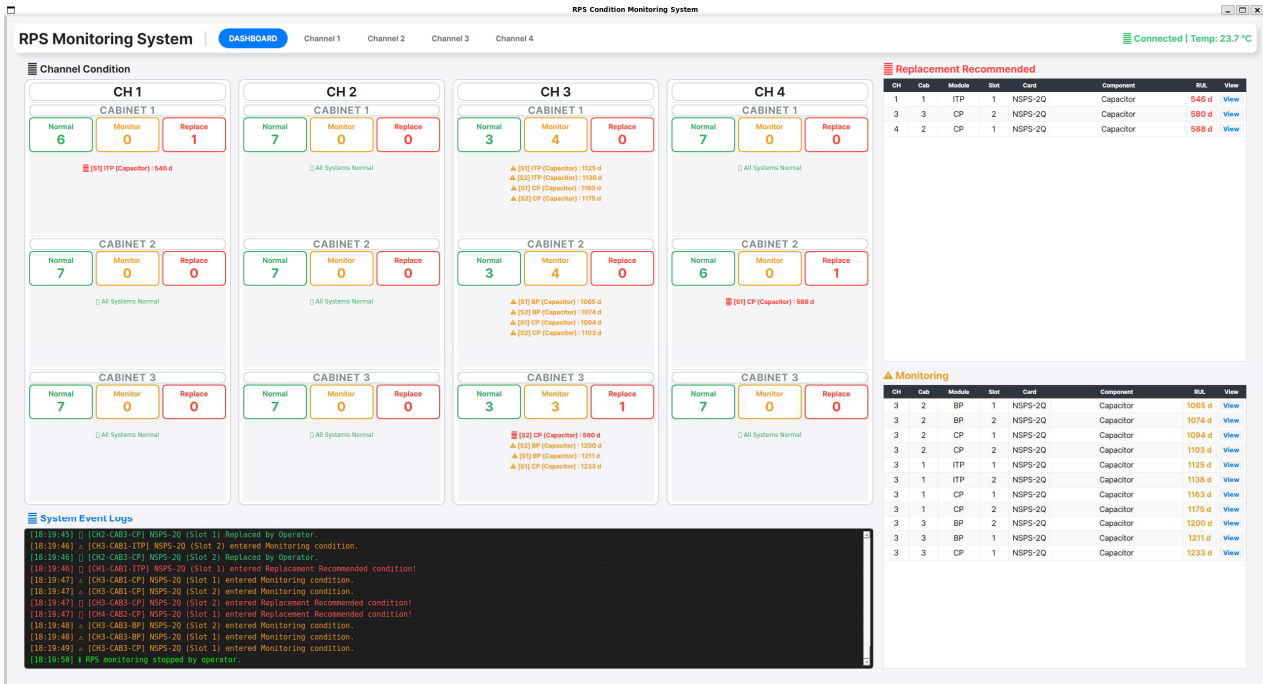


Fig. 4. Example dashboard of the RPS monitoring system.

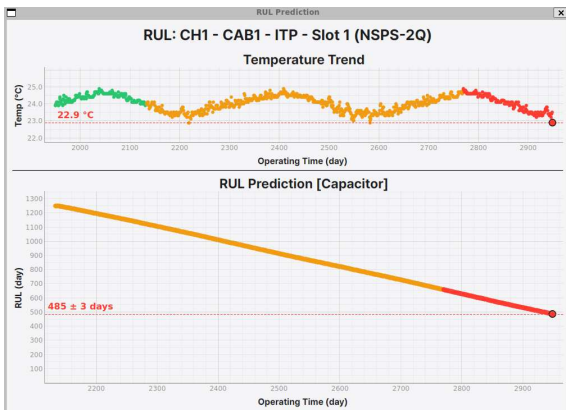


Fig. 5. Example of popup displaying temperature trends and RUL predictions for selected components.

5. Conclusions

In this study, an RPS monitoring system was constructed by integrating the previously developed condition diagnosis and failure prediction models for photocouplers, capacitors, and DC-DC converters. Additionally, model optimization reduced parameters by over 90% for diagnosis models and over 70% for prediction models, while maintaining performance within 0.5% degradation. Furthermore, a monitoring system interface was developed to visualize the health states and the RUL of each component over time. While this study focuses on three components, developing models for additional components in future work would provide more comprehensive evaluation of the overall RPS condition. Also, this system is expected to support operators in detecting early component degradation and planning timely maintenance.

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