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Prediction of Remaining Useful Life of Photocoupler for Failure Prediction in Reactor Protection System

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1. Introduction

The Reactor Protection System (RPS) is one of the instrumentation and control systems that monitors the status of the safety-related variables and trips the reactor when these values reach predetermined setpoints. RPS consists of several processors and devices such as bistable processors, coincidence processors, and interface and test processors based on electronic components and circuits. In the case of the RPS in the APR-1400 Nuclear Power Plants (NPPs), POSAFE-Q PLC is utilized for these processors. Currently, these instrumentation and control systems are checking their integrity through self-diagnostic functions, periodical tests according to maintenance plans, and function and performance checks during the overhaul period to prevent accidents due to failures. However, integrity can only be checked for limited functions, and there are limitations in assessing integrity during the operation of the NPPs. Since malfunctions in the RPS are closely related to the safety of NPPs, Prognostics and Health Management (PHM) technologies are necessary to prevent potential component failures during normal operation. PHM technologies include device diagnostics and prediction, and this study focuses on the prediction aspect.

Therefore, in this study, the Remaining Useful Life (RUL) prediction using data-based methods was performed for the electronic components of the POSAFE-Q PLC in the RPS. The POSAFE-Q PLC in the RPS consists of 12 modules and hundreds of electronic components. Among them, the RUL prediction was performed for the photocoupler, which is a component with a high probability of failure. The data are accelerated aging data obtained by performing accelerated aging tests under high-temperature conditions. The RUL prediction was performed using the Long Short-Term Memory (LSTM) with Monte Carlo (MC) dropout method, which was utilized for preliminary modeling in a previous study [1-3]. However, the data obtained from accelerated aging under a single temperature condition corresponds to a linear equation where the RUL value changes over time. Therefore, a genetic algorithm [4] was additionally utilized to estimate the slope and intercept of the linear equation, and RUL prediction was performed based on these parameters. In this study, the RUL prediction results of the derived linear equation and the LSTM with MC dropout model were compared and evaluated. We also discuss the future works for performing artificial intelligence-based RPS failure prediction.

2. Methods

In this study, two methods were utilized to perform RUL prediction for photocouplers, which is a component vulnerable to failure, for predicting RPS failures. The two methods are LSTM with MC dropout and genetic algorithm. LSTM with MC dropout was previously used for preliminary modeling in RUL prediction [3], and this method was applied based on the acquisition of RPS failure data. This method provides both RUL prediction results and their uncertainties. The genetic algorithm was applied to estimate the optimized coefficients for a linear equation by assuming that the variation in RUL values based on the given data follows linearity.

2.1 LSTM with Monte Carlo Dropout

LSTM with MC dropout has a structure in which dropout layers are added between LSTM layers, allowing for the estimation of uncertainty in the prediction results. The structure of LSTM with MC dropout is shown in Fig. 1. LSTM is a widely used method in the RUL prediction field, specialized for processing sequence data [1]. LSTM can effectively learn long-sequence information by regulating the flow of sequence information through its memory cells. This regulation is achieved through input, forget, and output gates within the memory cells. The gates selectively combine new and past information to ultimately derive the output for the current sequence. RUL prediction is performed based on the structural characteristics of LSTM, and the uncertainty of the prediction results is estimated by adding dropout layers between LSTM layers. Unlike conventional dropout techniques, MC dropout activates dropout layers during both training and testing [2]. It means that dropout layers remain active during inference, leading to different prediction results for the same input data. These prediction results have a distribution form, and their mean and standard deviation are used to estimate the final prediction value and its uncertainty. In this study, 100 prediction results were derived for the same input data, and uncertainty was estimated using these results.

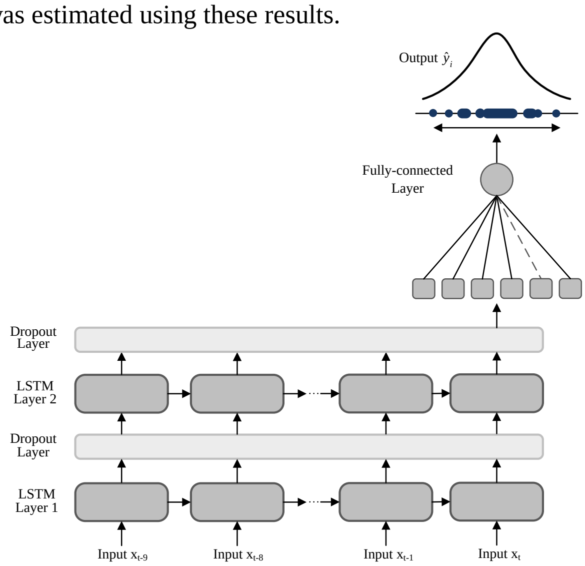

Fig. 1. Structure of LSTM with MC dropout.

2.2 Genetic Algorithm

The genetic algorithm is an optimization method that imitates the evolutionary processes of biological organisms to find optimal solutions [4]. In this study, a genetic algorithm was utilized to optimize the slope and intercept values based on the assumption that the RUL values exhibit linearity over time. The genetic algorithm proceeds in initialization, fitness evaluation, termination condition verification, and population generation. Specifically, the initial population of chromosomes is randomly generated, and their fitness is evaluated. Here, the initial chromosome set consists of random values representing the slope and intercept of the linear equation. The fitness function is an indicator that measures how well a chromosome solves a problem. In this study, Mean Squared Error (MSE) was used as a fitness function. Since a higher fitness value indicates a solution closer to the optimal values, the negative value of MSE was used as the fitness function. The fitness function utilized is expressed as Eq. (1).

$$\text{Fitness function} = -\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (1)$$

where, y_i is the real RUL value and $\hat{y}_i$ is the predicted value.

After evaluating the fitness of the initial population, the termination condition is checked. If the termination condition is not met, genetic operations such as selection, crossover, and mutation are performed to generate the next generation of the population. The fitness of the generated population is then evaluated, and the termination condition is checked again. This process is repeated until the termination condition is satisfied. The algorithm progressively finds better solutions, with termination conditions that can include reaching a maximum number of generations or observing no change in fitness values. In this study, the termination condition was set to reach the maximum number of generations. After termination, the solution corresponding to the highest fitness value is identified as the optimal solution.

3. Data Preprocessing

The photocoupler is a component vulnerable to failure within RPS, and the accelerated aging data were utilized. Due to limitations in obtaining failure data from actual NPPs, Korea Atomic Energy Research Institute established the testbed and performed accelerated aging tests on the photocouplers. The accelerated aging tests were conducted for approximately three months on 40 photocouplers under 130℃ conditions. Table I shows the detailed data description. The photocoupler is a component that transmits electrical signals as light, and its performance degradation can be assessed through the current transfer ratio (CTR). CTR is the ratio of the current in the light-emitting element to that in the light-receiving element. The failure criteria for photocouplers vary between manufacturers.

Table I: Data description

Accelerated aging test information	Description
Test period	About 92 days
Number of parts	40
Acquisition frequency	5 seconds

The accelerated aging data for the 40 photocoupler components used in this study showed a noticeable drop in CTR values over time for only some components rather than all. This is expressed as a distribution at each time interval. In this study, a conservative approach was adopted by converting the CTR values corresponding to the 20th percentile of the CTR values at each time point among the 40 components. Fig. 2 shows the distribution at each time interval, and the red line shows the 20th percentile of the CTR value. Based on this converted data, the failure criterion is defined as 95% of the CTR value when reaching 130℃. The failure time derived through this is approximately 88 days at 130℃. However, the failure criterion in this study is a value set based on the acquired data and may differ from the actual life of the photocoupler. The failure criterion needs to be continuously reviewed and refined in the future.

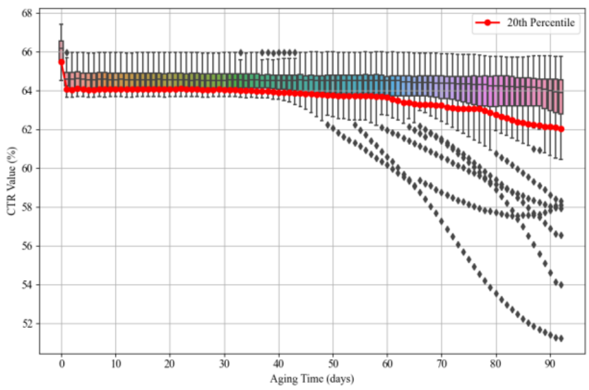

Fig. 2. CTR values of photocouplers according to the accelerated aging time at 130℃.

The RUL values according to the aging time were calculated based on the derived photocoupler failure occurrence time. The RUL values are calculated through the difference between the failure occurrence time and the aging time. The input and output variables for predicting the RUL of the photocoupler are aging time and RUL values, respectively. Data for developing a prediction model were converted to 1-minute interval data and divided into train and test data. The test data corresponded to 10% of the total data and were extracted at a specific interval. Also, the data were normalized using the standardization method to apply to the LSTM with MC dropout model. The normalized input data were in the form of (No. of data, time sequence, aging time) and were input to the LSTM with MC dropout model to finally derive the RUL value.

4. Results and Discussion

RUL prediction of photocoupler was performed using LSTM with MC dropout and genetic algorithm. LSTM with MC dropout model was developed by varying the number of units and layers in 10 input sequences. The genetic algorithm found the optimal values for the slope and intercept of the linear equation for maximizing the fitness function. The RUL prediction results based on these two methods were derived from the model and parameters that exhibited the best performance.

4.1 Evaluation Metrics

Mean Absolute Error (MAE) and R-square (R^2) were used as performance evaluation metrics for RUL prediction. These evaluation metrics were used to evaluate and compare the performance of RUL predictions derived from two different methods applied in this study. Each metric is calculated as in Eqs. (2) and (3).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2} \quad (3)$$

where, $\bar{y}$ is the mean value of the real RUL values. Lower values of MAE and higher values of R^2 indicate better performance.

Also, α-λ accuracy [5] was additionally utilized to evaluate the accuracy of RUL prediction. α-λ accuracy evaluates the performance of a model by assessing whether the predicted RUL values are within a specific allowable error margin. α-λ accuracy is calculated as in Eq. (4) and has a binary value. Accordingly, the accuracy of the total data is calculated as the mean value.

$$\alpha - \lambda\ \mathrm{Accuracy} = \begin{cases} 1 & \text{if } \pi[y_i]_{-\alpha}^{+\alpha} \geq \beta \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where, $\pi[y_i]_{-\alpha}^{+\alpha}$ is the probability mass of the predicted probability density function within the α-bounds. α-bound set in this study is $\pm 10\%$ of the real RUL value. β is the minimum desired probability threshold, which is a value between 0 and 1.

4.2 RUL Prediction Results of Photocoupler

Table II shows the RUL prediction performance in the optimal model and linear equation. The RUL prediction performance based on the optimized linear equation using the genetic algorithm is shown to outperform that of the LSTM with MC dropout model. Since the RUL value is calculated based on the difference between the fault time and the current time, and only the acceleration time is used as an input variable, it corresponds to a straightforward linear equation. Although deep learning methods generally perform well in handling nonlinear problems, the current problem is inherently linear. Therefore, a simple linear approach may be more appropriate than a complex deep learning method. Nevertheless, the performance difference between the two methods is not significant. Both methods predict accurately with low errors. In actual NPPs, temperature variations are expected. Therefore, in the future, it is necessary to address the nonlinear problems that account for both time and temperature variations.

Table II: Comparison of RUL Prediction Performance

Method	Train data		Test data	
	MAE (days)	R^2	MAE (days)	R^2
LSTM with MC dropout	0.1345	0.9996	0.1336	0.9996
Genetic algorithm	0.0934	0.9999	0.0934	0.9999

Fig. 3 shows the prediction results for the developed LSTM with MC dropout model and its uncertainty region. The prediction results of the LSTM with MC dropout model are derived in the form of a distribution at each time. It allows evaluation of the α-λ accuracy described in Eq. (4). Since the α-λ accuracy also depends on the β value, this study evaluated accuracy based on various β values. Fig. 4 shows α-λ accuracy according to β value for test data. Due to the characteristics of α-λ accuracy calculation, the accuracy decreases as the β value increases. This is because the prediction accuracy is considered accurate only if the probability that the predicted distribution falls within the α-bounds must be greater than or equal to the β value. In Fig. 4, the RUL prediction accuracy of the photocoupler was over 80% for most β values, indicating excellent prediction performance.

α-λ accuracy is also a key performance metric for determining the performance of the optimal model. It is important to set appropriate α-bound and β values. When developing RUL prediction models in the future, utilizing this metric to select the optimal model is expected to improve performance in RUL predictions.

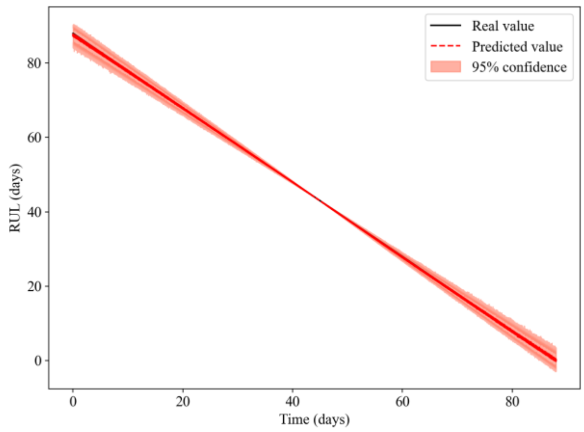

Fig. 3. RUL prediction results using the LSTM with MC dropout method.

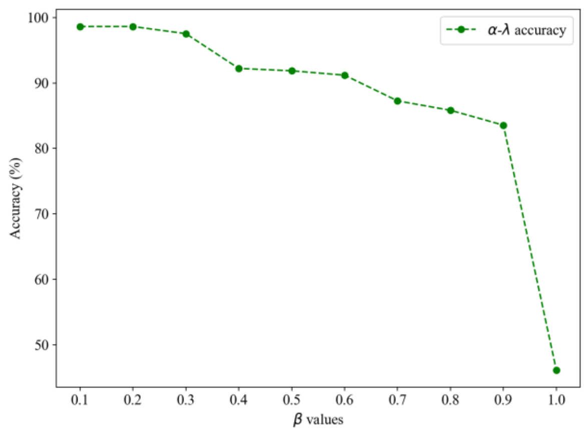

Fig. 4. α-λ accuracy according to the β value for the test data.

5. Conclusions and Future Work

In this study, RUL prediction was performed for the photocoupler, which is a component with a high probability of failure, to predict failures in RPS based on data-based methods. The data were obtained by accelerated aging tests of 40 photocouplers under 130℃. The failure criterion was defined as the CTR value corresponding to 95% of the CTR value when the accelerated aging temperature reached 130℃. Since RUL prediction was performed using only the aging time as an input variable, it is expressed as a linear equation. LSTM with MC dropout and genetic algorithm were used to predict RUL values, and the performance comparison was performed for predicted RUL values. Both methods accurately predicted RUL, and the potential for improving performance was evaluated by reviewing and applying performance evaluation metrics for RUL prediction.

However, the photocoupler accelerated aging data used in this study do not account for temperature variations, and additional steps are required to convert these accelerated aging data into equivalent time under usage conditions. Furthermore, the failure criterion also needs to be discussed in more detail. In the future, RUL predictions should be performed considering temperature variants and usage conditions. Additionally, we plan to develop models for overall RPS failure prediction by utilizing accelerated aging test data for significant components and modules, which is currently being performed.

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