AI-Based Preliminary Modeling for Failure Prediction of Reactor Protection System in Nuclear Power Plants

Hye Seon Jo[a], Ho Jun Lee[b], Ji Hun Park[c] and Man Gyun Na[d]

Department of Nuclear Engineering, Chosun University, 10, Chosundae 1-gil, Dong-gu, Gwangju, Republic of Korea

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Abstract: Nuclear power plants (NPPs), which generate electricity through nuclear fission energy, are crucial for safe operation due to the potential risk of exposure to radioactive materials. NPPs contain a variety of safety systems, and this study aims to develop an artificial intelligence-based failure prediction model that can predict and prevent potential failures in advance by targeting the reactor protection system (RPS). Currently, failure data for RPS are being collected through a testbed, so we conducted preliminary modeling using open-source data due to insufficient data acquisition. The applied open-source data are the accelerated aging data of insulated gate bipolar transistors (IGBTs), and the remaining useful life of IGBT was predicted using long short-term memory and Monte Carlo dropout technology. Also, physical rules were applied to improve their prediction performance and their applicability was confirmed through performance evaluation. Through performance evaluation of the developed prediction models, we explored the optimal model and confirmed the applicability of the applied methodologies and technologies.

1 INTRODUCTION

A nuclear power plant (NPP) is a facility that produces electricity by turning a turbine with steam generated through nuclear fission energy. NPPs have hundreds of systems with different functions, including several safety and control systems to ensure the safe operation of the NPP, even in the event of an accident. Among them, the reactor protection system (RPS) monitors safety-related variables and trips the reactor when the monitored variables reach the set values. The instrumentation and control system, including the RPS, consists of various electronic components and circuits, such as analog and digital. The instrumentation and control system checks its integrity through self-diagnostics at the system level or periodical tests. However, self-diagnostics is performed only for limited functionalities, or in the case of the periodical tests, it is difficult to check integrity during normal operation. In NPP, malfunction of the RPS is directly related to plant safety, so the prognostics and health management (PHM) technology that can prevent potential component failures during normal operation is required. It can be achieved through fault diagnosis and estimation of the remaining useful life (RUL) for major electronic components that are vulnerable to failure.

Currently, for the PHM of electronic components, many studies are being conducted to predict the RUL of electronic components using a data-driven approach in various fields, such as hard disks (Coursey et al., 2021), lithium-ion batteries (Rouhi Ardeshiri et al., 2021), and insulated gate bipolar transistors (IGBTs) (Lu et al., 2023). Through these studies, the effectiveness of data-driven approaches in the PHM field has been confirmed. Therefore, this study proposes a framework for predicting the RUL of electronic components in the RPS using artificial intelligence (AI) technology. Due to limitations in obtaining failure data on electronic components of the RPS in actual NPPs, accelerated aging tests are being conducted on major components by establishing a test bed. Accordingly, this study performed a preliminary

[a] https://orcid.org/0000-0002-4413-5244
[b] https://orcid.org/0009-0001-5155-9483
[c] https://orcid.org/0000-0001-6225-5621
[d] https://orcid.org/0000-0003-0097-3403

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modeling using open-source data to predict the RUL of electronic components. The preliminary modeling involves exploring and confirming methodologies using open-source data before developing a failure prediction model for electronic components within RPS. This process can identify effective approaches and derive a more optimal model for developing a failure prediction model based on actual data in the future. The open-source data utilized in this study are the IGBT accelerated aging data provided by NASA (Celaya et al., 2009). Previous studies (Ismail et al., 2020; Lu et al., 2023; Chen et al., 2024; He et al., 2021) on predicting the RUL of IGBTs have primarily used neural networks, such as feedforward neural networks, long short-term memory (LSTM), and random forest methods. So, this study utilized LSTM (Hochreiter & Schmidhuber, 1997) and Monte Carlo (MC) dropout (Gal & Ghahramani, 2016) based on these studies. RUL prediction was performed using LSTM, and uncertainty about the prediction results was estimated through MC dropout. Also, to enhance the performance of the LSTM, physical rules reflecting the characteristics of RUL were added to the loss function during model training.

The developed IGBT RUL prediction model was compared in performance with the basic LSTM with dropout, which does not include physical rules. It evaluates the applicability of the proposed method for the failure prediction model of RPS to be developed in the future.

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2 METHODS

This section describes the AI method and optimization used in this study. The AI method applied to predict RUL was LSTM, and MC dropout technology was used to estimate uncertainty. Then, the optimization procedure of the RUL prediction model was explained.

2.1 LSTM with MC Dropout

Figure 1 shows the structure of LSTM with MC dropout for RUL prediction of IGBT in this study. LSTM (Hochreiter & Schmidhuber, 1997) is a modified recurrent neural network-based methodology that can learn information about long sequences as well as short sequences. LSTM regulates the flow of information through gates within its memory cells. Figure 2 shows the LSTM cell at the t-13 step, and the gates include the input, forget, and output gates. These gates determine how to reflect new information, whether to maintain or discard previous cell state information, and ultimately, how to derive the final output based on input data and the cell state. In other words, LSTM learns the input sequence data and derives results. In this study, the time sequence of the LSTM model was empirically set to 15.

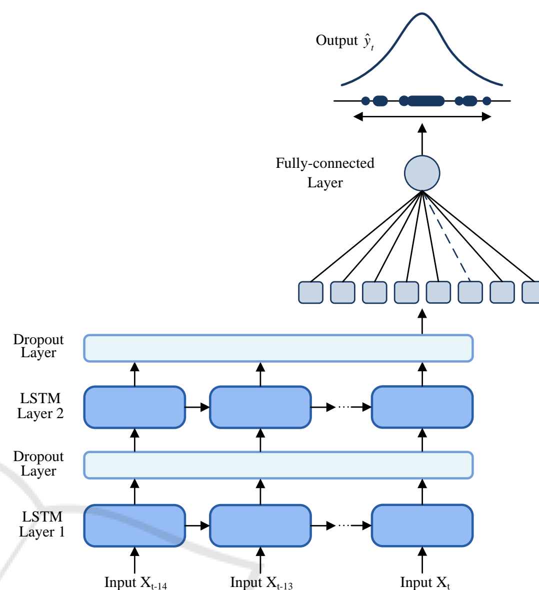

Figure 1: Model structure for RUL prediction of IGBT.

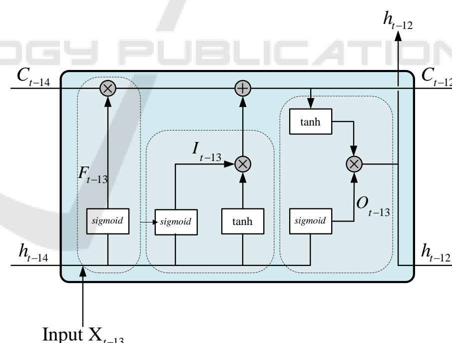

Figure 2: LSTM cell structure at the t-13 step.

Also, the MC dropout (Gal & Ghahramani, 2016) technology was used to estimate the uncertainty in the prediction results. MC dropout involves applying the dropout technique to neural networks during training and keeping the dropout active during evaluation, thereby producing prediction results in the form of a distribution for the same input data. The mean and standard deviation values of the predicted distribution are used to perform the prediction value and uncertainty estimation, respectively. Applying MC dropout to the neural networks enhances

generalization performance and allows for the assessment of the reliability of the prediction results.

In this study, the dropout rate was set to 0.1 to estimate uncertainty, and the results were derived 100 times for the same input data. The dropout rate was experimentally applied to various values, with 0.1 identified as the optimal value, so this study presented the RUL prediction results applying that value.

As a result, RUL prediction using LSTM with MC dropout proceeds through the following steps. First, the LSTM with MC dropout model is trained based on the train data. Second, 100 prediction results are generated for the same input data using the trained model. At this time, dropout is also activated. Finally, the mean and standard deviation of the prediction results for the same input data are calculated. This allows for the evaluation of the final predicted RUL value and its uncertainty.

2.2 Optimization of the RUL Prediction Model

Hyperparameter optimization was performed to develop an optimal RUL prediction model using LSTM with MC dropout. The hyperparameters of the model are listed in Table 1, which indicates the specific ranges for each hyperparameter. Network training and comparative evaluation were performed for all hyperparameter combinations. Here, RUL prediction is a regression problem and generally uses mean squared error (MSE) as the loss function. In addition, based on a previous study (Lu et al., 2023) where physics-informed regularization was applied to improve RUL prediction performance, it was also used in this study.

Table 1: Model hyperparameters and value ranges.

Hyperparameters	Value ranges
Number of units	[16, 32, 64, 128]
Number of layers	[2, 3]
Batch size	[8, 16, 32, 64]

In this study, model development was performed individually using four different loss functions, and performance was compared for each applied loss function. Among these, two loss functions utilized were MSE and a scoring function. When MSE and scoring functions are used as loss functions, the model is trained to ensure that these values converge to lower values. The scoring function is an evaluation metric related to RUL prediction proposed at the International Conference on Prognostics and Health Management (PHM08) Data Challenge (Saxena & Goebel, 2008). In the case of the scoring function, a larger penalty is imposed when the RUL prediction is higher than the real value in terms of maintenance. That is, if the predicted RUL is lower than the real RUL, the failure can be prevented in advance through preventive maintenance, but if not, the failure cannot be prevented. The other two loss functions were based on them and included physical rules. The four loss functions are shown in Eqs. (1) to (4). In Eqs. (3) and (4), E_{MDC} represents the monotonic decreasing condition for the RUL prediction. Here, the rectified linear unit (ReLU) is a function that outputs the input value as is if it is greater than 0, and outputs 0 if it is less than 0. Considering that the RUL value typically decreases over time, E_{MDC} imposes a penalty when the difference between the current predicted RUL ($\hat{Y}_k$) and the previously predicted RUL ($\hat{Y}_{k-1}$) is positive. This ensures that the RUL prediction adheres to the natural characteristic of decreasing over time. E_{BCC} represents the boundary condition that the normalized RUL cannot be less than 0 or greater than 1. Also, α, γ, and β are constants that adjust the proportions of each term. These values were the same as those used in the previous study (Lu et al., 2023). By applying various hyperparameters and loss functions, the RUL prediction model for IGBT was developed, and the performance of each was evaluated.

$$E_{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left(Y_k - \hat{Y}_k\right)^2 \tag{1}$$

$$E_{score} = \begin{cases} \sum_{k=1}^{N} e^{-\left(\frac{\hat{Y}_k - Y_k}{13}\right)} - 1, \; for\ \hat{Y}_k - Y_k < 0 \\ \sum_{k=1}^{N} e^{\left(\frac{\hat{Y}_k - Y_k}{10}\right)} - 1\,, \; for\ \hat{Y}_k - Y_k \geq 0 \end{cases} \tag{2}$$

$$E_{PINN(MSE)} = (1-\alpha)\cdot E_{MSE} + \alpha\cdot\gamma\cdot E_{MDC} + \beta\cdot E_{BCC} \tag{3}$$

$$E_{PINN(Score)} = (1-\alpha)\cdot E_{score} + \alpha\cdot\gamma\cdot E_{MDC} + \beta\cdot E_{BCC} \tag{4}$$

where

Y_k: Real RUL values

$\hat{Y}_k$: Predicted RUL values

α, γ, β: Constants

$E_{MDC} = \frac{1}{N-1}\sum_{k=2}^{N}\left[ReLU\left(\hat{Y}_k - \hat{Y}_{k-1}\right)\right]^2$

$E_{BCC} = \frac{1}{N}\sum_{k=1}^{N}\left[ReLU\left(-\hat{Y}_k\right)\right]^2 + \sum_{k=1}^{N}\left[ReLU\left(\hat{Y}_k - 1\right)\right]^2$

$ReLU(x) = \max(0, x)$

3 DATA PREPARATION

The IGBT accelerated aging data provided by the NASA Ames Laboratory Prognostics Center of Excellence were used (Celaya et al., 2009). The data were obtained by performing accelerated aging under thermal overstress conditions with a square signal bias at the gate. That is, accelerated aging was performed as temperature and voltage conditions changed over time until failure occurred. The failure criterion in IGBT accelerated aging data is defined by the occurrence of the transistor latch-up phenomenon. This phenomenon is confirmed based on the characteristic that the collector-emitter voltage of the provided data drops rapidly. In this study, IGBT accelerated aging data for 4 devices with supply and measurement information were used. It includes supply temperature and voltage, collector-emitter current and voltage, etc.

The failure time is determined based on the time of latch-up occurrence, and the difference between the current time and the failure time is calculated as the RUL value. This is expressed in Eq. (5).

$$RUL = t_f - t_i \tag{5}$$

where t_f and t_i represent the failure time and current time, respectively.

As input variables, environmental variables that were considered to be obtainable were selected because it is difficult to acquire information on electronic components within the RPS in actual NPPs. Environmental variables include operation time, temperature, and voltage. Also, mean and weighted average values were utilized as additional input variables. The input variable groups are divided into three groups as follows:

1. Operation time, Temperature, and Voltage
2. Operation time, Temperature, Voltage, and Mean Temperature/Voltage
3. Operation time, Temperature, Voltage, Mean Temperature/Voltage, Weighted Average Temperature/Voltage

The data were divided into train, validation, and test datasets. Three devices (Device 2, 3, and 4) were used as train and validation datasets, and the remaining device (Device 5) was used as test datasets. The data for the selected input variables were transformed into a normal distribution using a standardization method. The data for the output variable (i.e., RUL value) were normalized to a value between 0 and 1 to apply physical rules.

4 RESULTS

Using the LSTM with MC dropout method, the RUL prediction models for IGBT were developed according to the input variable group and applied loss function. A total of 12 prediction models were developed, and for each model, the combination of hyperparameters that exhibited the best performance was selected as the final model for each model. Mean absolute error (MAE) and R-square (R^2) were used as prediction performance evaluation metrics, which are calculated as Eqs. (6) and (7). MAE indicates better performance as its value decreases, while R^2 indicates better performance as it approaches 1.

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|Y_k - \hat{Y}_k\right| \tag{6}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(Y_k - \hat{Y}_k)^2}{\sum_{k=1}^{N}(Y_k - \bar{Y})^2} \tag{7}$$

Table 2 shows the RUL prediction results of IGBT according to all input variable groups and applied loss functions. The performance was progressively improved in the order of input variable groups 1, 2, and 3. It indicates that utilizing mean and weighted average values when predicting RUL is more meaningful than using only temperature and voltage values. Based on the applied loss functions, the prediction performance on the train and validation datasets was similar for the other three models, except for the LSTM (MSE) model. However, the prediction performance on the test datasets was relatively better for the LSTM (MSE) model.

Figure 3 shows the RUL prediction results according to the input variables. The prediction error decreases as the input variable group number increases from 1 to 3. Figure 4 shows the prediction results with confidence intervals for input variable group 3. This demonstrates that a model incorporating physical rules exhibits lower uncertainty in predictions than a model that does not incorporate physical rules. This study reviewed the input variables and AI methods to be applied as preliminary modeling of the failure prediction model for RPS in the future. So, we expect to utilize these input variables and methods when developing failure prediction models in practice.

Table 2: Prediction results for all input variable groups.

Input variable group	Model	Train datasets		Validation datasets		Test datasets	
		MAE	R^2	MAE	R^2	MAE	R^2
Group 1	LSTM (MSE)	50.73	0.9856	44.54	0.9888	**65.04**	**0.9788**
	PI-LSTM (MSE)	40.36	0.9903	36.64	0.9920	80.14	0.9681
	LSTM (Score)	**31.88**	**0.9924**	**25.08**	**0.9962**	85.64	0.9625
	PI-LSTM (Score)	37.34	0.9919	35.81	0.9942	93.99	0.9587
Group 2	LSTM (MSE)	56.82	0.9835	54.27	0.9863	**53.54**	**0.9854**
	PI-LSTM (MSE)	**20.49**	**0.9981**	23.49	0.9975	83.50	0.9523
	LSTM (Score)	23.49	0.9973	**19.50**	**0.9977**	71.59	0.9606
	PI-LSTM (Score)	24.57	0.9965	24.83	0.9967	78.15	0.9555
Group 3	LSTM (MSE)	33.24	0.9946	31.22	0.9952	**43.58**	**0.9909**
	PI-LSTM (MSE)	**21.51**	**0.9978**	**22.77**	**0.9978**	47.99	0.9838
	LSTM (Score)	35.56	0.9936	36.62	0.9933	54.58	0.9850
	PI-LSTM (Score)	35.76	0.9939	37.31	0.9938	46.56	0.9893

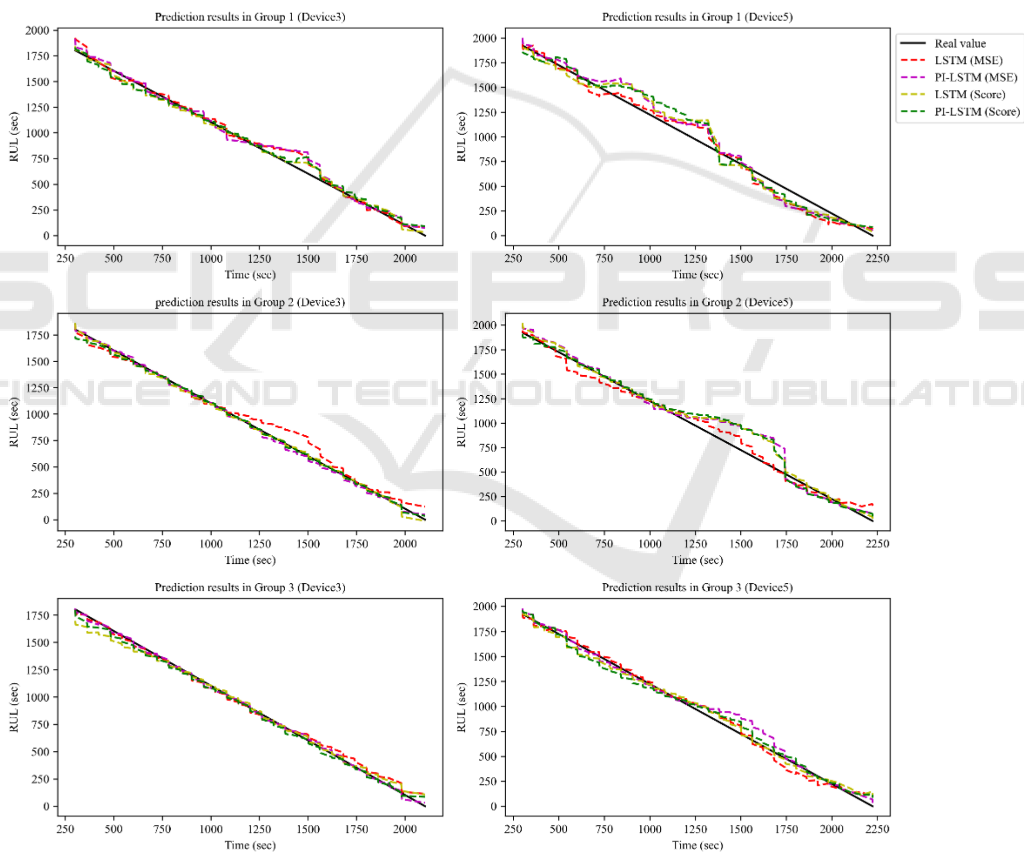

Figure 3: IGBT RUL prediction results according to input variable groups.

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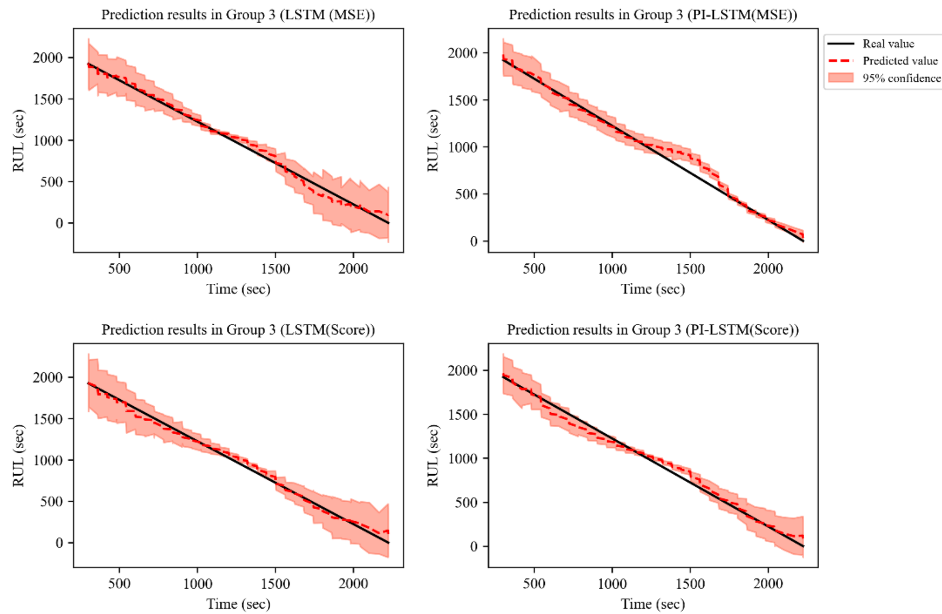

Figure 4: Prediction results for device 5 in input variable group 3.

5 CONCLUSIONS

In this study, prior to developing a failure prediction model for RPS, a preliminary modeling was performed using IGBT accelerated aging data to develop a failure prediction model and evaluate its performance. In the IGBT accelerated aging data, the failure point is defined based on the occurrence of the transistor latch-up phenomenon, and the RUL value was calculated based on this. In addition, variables that were judged to be obtainable in real NPPs, such as operation time, temperature, and voltage, were selected as input variables. Based on the selected environmental variables, model development and performance evaluation were conducted by dividing into three input variable groups. RUL prediction was performed through a combination of LSTM and MC dropout technology. Additionally, to enhance prediction performance, the model development incorporated physical rule constraints into the loss function for RUL prediction. As a result, using mean and weighted average values, rather than just temperature and voltage values, led to better RUL prediction performance. Among these, the performance of the model developed using a loss function including physical rules was slightly better. The results of preliminary modeling are expected to be useful when developing fault prediction models based on accelerated aging data for major electronic components within the RPS in the future.

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