Remaining Useful Life Prediction for IGBT using LSTM with Monte Carlo Dropout

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1. Introduction

The instrumentation and control system of a Nuclear Power Plant (NPP) performs the function of protecting and controlling the NPP. It consists of several electronic components and circuits. Currently, the integrity of the instrumentation and control system is checked through self-diagnostics functions and periodical tests. However, self-diagnostics is performed on the card or system level rather than on individual components. Additionally, in the case of periodical tests, it is difficult to check integrity during normal operation. Therefore, it is necessary to develop a system that can diagnose potential component failures occurring during NPP operation, predict the Remaining Useful Life (RUL), and perform advanced maintenance. This enables preemptive responses in the event of failure, preventing unplanned reactor trip and accidents caused by component failures. This study aims to perform the RUL prediction for the electronic components constituting the Reactor Protection System (RPS), one of the instrumentation and control systems.

Because the acquisition of actual failure data for the RPS is limited, failure data is being acquired based on accelerated aging tests through a testbed. Accelerated aging tests are being conducted on 8 types of electronic components that are vulnerable to failure at the Korea Atomic Energy Research Institute and Soosan ENS. As failure data for RPS are currently being acquired, this study uses open-source data in terms of preliminary modeling to predict the RUL for electronic components. The open-source data are accelerated aging data for Insulated Gate Bipolar Transistors (IGBTs), subjected to various temperature and voltage conditions.

The RUL prediction for IGBT was conducted using Long Short-Term Memory (LSTM) [1] and Monte Carlo (MC) [2] dropout methods. The RUL prediction for IGBT is performed through LSTM, which is widely used in RUL prediction, and uncertainty about the prediction results is expressed through the MC dropout method. The proposed RUL prediction model is a preliminary model toward the development of a failure prediction model for RPS, the ultimate goal. It confirms the applicability of the utilized artificial intelligence methods.

2. Methods

2.1 LSTM

Recurrent Neural Network (RNN)-based methods are mainly used in RUL prediction research. LSTM, a type of RNN method, addresses the long-term dependency problem inherent in traditional RNNs [1]. LSTM selectively passes data through memory cells. It can learn information about long sequences. Specifically, the hidden state (h_t) and cell state (C_t) values are calculated through gates within the memory cell (refer to Fig. 1). The gates include the input (I_t), forget (F_t), and output (O_t) gates. These gates determine how much of the previous cell state to remember, how much new input information to store, and finally derive the result. Because these gates are automatically adjusted throughout the learning process, LSTM networks can effectively capture the temporal dependencies of time series data.

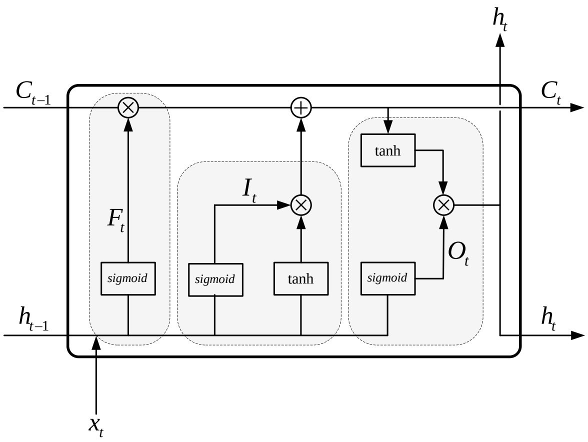

Fig. 1. Structure of LSTM cell [1].

2.2 MC dropout

MC dropout is a type of Bayesian deep learning that estimates prediction uncertainty by probabilistically utilizing the dropout technique within a neural network [2]. MC dropout learns the model by activating each dropout layer of the neural network. The general dropout is a technology that improves generalization performance by randomly deactivating some neurons during the learning process of a neural network. In contrast, MC dropout deactivates some neurons not only in learning but also in inference, resulting in multiple different outputs for the same input data. Based on the derived outputs, the mean and variance are calculated to estimate the uncertainty of predictions. In this study, a prediction model was developed by adding a dropout layer with a dropout rate of 0.5 between LSTM layers. Additionally, to estimate uncertainty, we obtained 100 results for the same input data and utilized their mean and variance values.

3. Data Preparation

The data used in this study are from the IGBT accelerated aging dataset provided by NASA [3]. IGBT data were acquired through thermal overstress accelerated aging experiments, performed by applying a square signal. The IGBT data are accelerated aging test data for 4 devices and include information such as supply temperature and voltage, collector-emitter current and voltage. The failure mode observed in the IGBT data is the transistor latch-up phenomenon, characterized by a rapid drop in collector-emitter voltage due to the high current between the collector and emitter. Therefore, in the IGBT accelerated aging data, the failure point is where the collector-emitter voltage rapidly drops. Fig. 2 shows the changes in collector-emitter voltage over time, and the failure point is at 2,460 seconds, when the voltage suddenly drops.

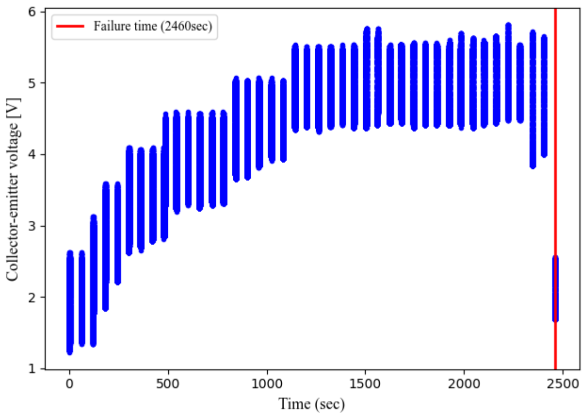

Fig. 2. Collector-emitter voltage values and failure time over time.

The RUL value is calculated according to Eq. (1), and the calculated value is utilized as the target variable in the RUL prediction model.

$$RUL = t_f - t_k \quad (1)$$

where t_f is failure time and t_k is the current time.

The research on IGBT RUL prediction is still actively conducted, and in existing studies [4-6], IGBT RUL prediction was performed using variables such as the collector-emitter voltage from Fig. 2, working time, supply voltage and temperature, and turn-off peak voltage as input variables. In this study, IGBT RUL prediction is performed using only environmental variables. This is because the variables that can be easily obtained from NPPs are environmental variables. In addition, as additional input variables, both environmental variables and their respective means and exponential moving averages were used. The mean value represents the average of each variable up to the current time, while the exponential moving average assigns higher weights to values at the current time to reflect dynamic conditions. Table I shows the input variable groups and data standardization was performed based on the selected input variables. The time sequence of the input data for application to LSTM was 2, 5, 10, and 15.

Table I: Input Variable Groups

No.	Input variables
1	Aging time, Temperature, Voltage
2	Average temperature and voltage including variables from group 1
3	Exponential moving average temperature and voltage including variables from group 2

4. RUL Prediction Results for IGBT

The IGBT RUL prediction model was developed using LSTM with MC dropout according to the input variable groups in Table I. The developed prediction model is the one with the best performance among various hyperparameter combinations. Performance evaluation was performed using Mean Absolute Error (MAE), R-square (R^2), and scoring function [7]. MAE is a metric that measures the mean absolute error between the real and predicted values; lower values indicate better performance. R^2 is a measure indicating how well the variance in the dependent variable (real values) is explained by the independent variable (predicted values) in a regression model, ranging from 0 to 1. Since the purpose of RUL prediction is to prevent device failure in advance, it is generally better to predict the time of failure early rather than late. So, the scoring function considers the usefulness of early predictions and the inadequacy of late predictions, imposing a larger penalty on late predictions compared to early ones. The lower the score calculated through the scoring function, the better the prediction performance. These evaluation metrics are calculated as in Eqs. (2)-(4).

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|y_k - \hat{y}_k\right| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N} \left(y_k - \hat{y}_k \right)^2}{\sum_{k=1}^{N} \left(y_k - \bar{y} \right)^2} \qquad (3)$$

$$score = \begin{cases} \sum_{k=1}^{N} e^{-\left(\frac{\hat{y}_k - y_k}{13}\right)} - 1 & \text{for } \hat{y}_k - y_k < 0 \\ \sum_{k=1}^{N} e^{\left(\frac{\hat{y}_k - y_k}{10}\right)} - 1 & \text{for } \hat{y}_k - y_k \geq 0 \end{cases} \qquad (4)$$

where, y_k is the normalized real RUL value and $\hat{y}_k$ is the predicted value. $\bar{y}$ is the mean value of the real RUL values.

The performance of the developed prediction model was compared with Deep Neural Network (DNN), a basic deep learning method. The DNN model also applied the MC dropout technique, similar to the LSTM with MC dropout model, and used the model with the best-performing hyperparameter combination. Tables II-IV show the IGBT RUL prediction results for prediction models developed with each input variable group. Overall, the LSTM model showed slightly better performance compared to the DNN model. Additionally, it was observed that the prediction performance of the LSTM with MC dropout model improved gradually as the time sequence increased. Additionally, as a result of comparing prediction performance by the model of input variable group, prediction performance was slightly improved in the order of group 1, group 2, and group 3. This indicates the meaningfulness of utilizing not only environmental variables but also mean values and dynamically adaptable exponential moving average values as input variables.

Table II: Prediction Results in the Model of Group 1

Method	Time sequence	Train data		Test data	
		MAE	R^2	MAE	R^2
DNN	-	0.1691	0.9546	**0.0818**	**0.9895**
LSTM	2	0.1515	0.9647	0.0923	0.9870
	5	0.1394	0.9658	0.0944	0.9862
	10	0.1275	0.9690	0.1005	0.9824
	15	**0.1107**	**0.9728**	0.0857	0.9851

Table III: Prediction Results in the Model of Group 2

Method	Time sequence	Train data		Test data	
		MAE	R^2	MAE	R^2
DNN	-	0.1317	0.9723	0.0706	0.9906
LSTM	2	0.1515	0.9647	0.0923	0.9870
	5	0.1394	0.9658	0.0944	0.9862
	10	0.1440	0.9597	0.1232	0.9688
	15	**0.1011**	**0.9764**	**0.0555**	**0.9922**

Table IV: Prediction Results in the Model of Group 3

Method	Time sequence	Train data		Test data	
		MAE	R^2	MAE	R^2
DNN	-	0.1070	0.9811	0.0791	**0.9910**
LSTM	2	0.1233	0.9752	0.0743	0.9907
	5	0.1301	0.9711	0.0809	0.9897
	10	**0.0748**	**0.9878**	0.0946	0.9836
	15	0.1024	0.9783	**0.0699**	0.9895

Figs. 3-5 show the IGBT RUL prediction results for test data using the LSTM with MC dropout model in each input variable group. In Figs. 3-5, black line and dotted red line represent the real and predicted values, respectively. The light red shaded area represents the uncertainty of the prediction results, indicating the 95% confidence interval. This confidence interval is calculated based on the standard deviation of 100 prediction results for the same input data. It shows that the IGBT RUL is predicted according to the trends of the real values in all groups for input variables. However, as the failure point approaches, both the prediction error and uncertainty values increase.

In particular, through Tables II-IV and Figs. 3-5, the MAE value in the model with group 2 input variables is the smallest; however, as the actual failure time approaches, the prediction error increases more significantly in this group compared to other groups. When predicting RUL, it is more important in terms of preventive maintenance to predict the time of failure early rather than predicting it later. So, the score was calculated for the test data using a scoring function. Table V shows the scores for each input variable group, with lower score values indicating better performance. The model with group 2 input variables which showed the lowest MAE value, had the highest score calculated through the scoring function compared to the models with other input variable groups, indicating a diminished prediction performance relative to the other groups. As a result, considering all evaluation metrics, the model with group 3 input variables showed the best prediction performance. Also, it is considered that applying various dropout rates in the future may alleviate some prediction performance.

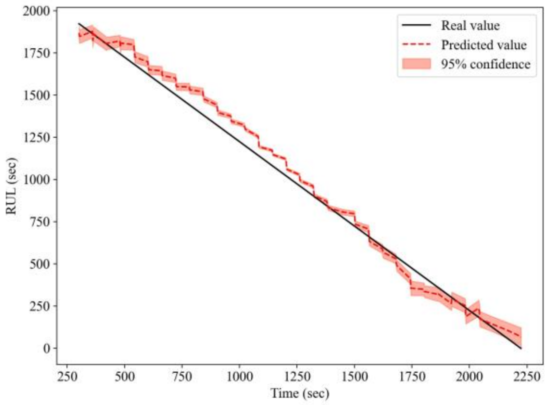

Fig. 3. IGBT RUL prediction results for test data in the model of group 1 (in the case of 15 sequences).

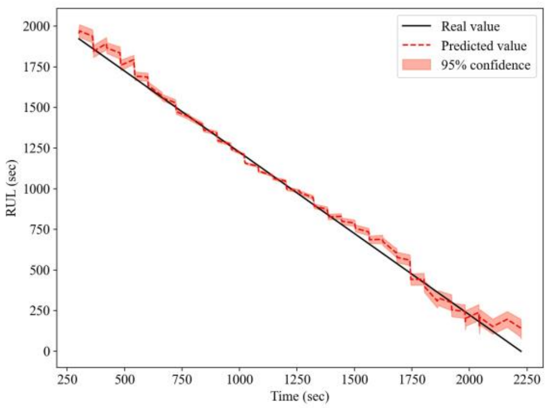

Fig. 4. IGBT RUL prediction results for test data in the model of group 2 (in the case of 15 sequences).

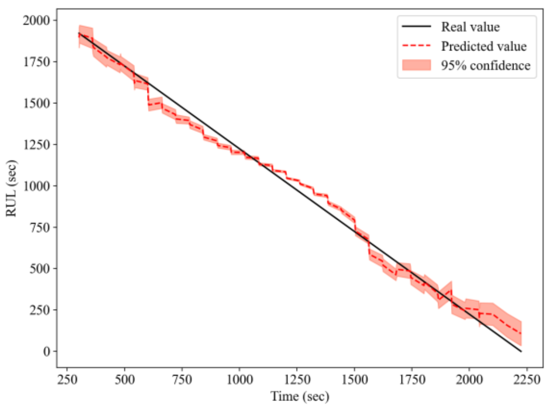

Fig. 5. IGBT RUL prediction results for test data in the model of group 3 (in the case of 15 sequences).

Table V: Score in the Models of All Input Groups

Method	Time sequence	Group 1	Group 2	Group 3
DNN	-	2.2E+06	1.1E+07	4.8E+05
LSTM	2	2.8E+07	2.8E+07	6.5E+06
	5	2.4E+06	**2.4E+06**	1.2E+06
	10	6.3E+06	2.0E+10	1.4E+07
	15	**1.8E+06**	2.8E+06	**2.0E+05**

5. Conclusions

In this study, preliminary modeling for predicting electronic component RUL was performed with the goal of developing a failure prediction model for the RPS. It involves a series of processes including selecting artificial intelligence methods for RUL prediction, data processing, and selecting input variables. Because RPS failure data are currently being collected, open-source data was used in preliminary modeling to develop a failure prediction model. The open-source data utilized in this study are the IGBT accelerated aging dataset provided by NASA.

RUL prediction for IGBT was performed using the LSTM with MC dropout method. In the case of input variables, environmental variables that can be obtained from actual NPPs, such as aging time, temperature, and voltage, were selected. In addition, the mean values and exponential moving average values for environmental variables were used. The prediction models were developed for 3 input variable groups. The performance of the prediction model developed using mean and exponential moving average values as additional input variables was superior to that of the model utilizing only environmental variables as input. Therefore, when developing a failure prediction model using RPS failure data in the future, we plan to use mean and exponential moving average values along with environmental variables as input variables. Additionally, we plan to apply more diverse dropout rates to compensate for the lower prediction performance as the failure time approaches.

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