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Prediction of Remaining Trip Time in Nuclear Power Plants Based on Artificial Intelligence

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1. Introduction

In nuclear power plants (NPPs), abnormal states may occur for various reasons. In the abnormal states, the operators perform state diagnosis and mitigation action according to established procedures to restore the integrity of the NPPs. Mistakes or failures in operator actions can further deteriorate the state of the NPPs. If the state of the NPPs continues to deteriorate, it may lead to a shutdown of the reactor by the safety systems. In this study, an unplanned reactor shutdown is defined as a trip. A general reactor shutdown is carried out over a long period of time by a planned procedure. The occurrence of the trip may cause the failure of many facilities constituting the NPPs and may cause economic losses due to the shutdown of the NPPs. Therefore, the tasks of operators in abnormal states can be very burdensome.

Accordingly, many researchers have been conducting research on operator support systems using artificial intelligence (AI) [1, 2]. The operator support system aims to assist operators in their decision-making and tasks through various functions, which include anomaly detection, diagnosis, and prediction.

In this paper, we propose an algorithm to predict the remaining trip time (RTT) as a part of the operator support system function, which provides information on the remaining time until the trip when an abnormal state occurs. The algorithm incorporates a diagnosis function that identifies scenarios for abnormal states of NPPs. RTT prediction is then performed for the diagnosed scenario, utilizing the concept of remaining useful life prediction. The diagnosis and RTT prediction functions are implemented using a light gradient boosting machine (LightGBM) method.

The proposed algorithm enables the development and utilization of the RTT prediction model for each scenario, and it is expected to demonstrate high performance. The high performance RTT prediction information is expected to support operators in planning operations and carrying out safe mitigation actions during abnormal states of NPPs.

2. Light Gradient Boosting Machine

In this study, LightGBM, which shows good performance in various fields as an AI method, was used. LightGBM is a tree-based learning algorithm that uses a gradient boosting machine framework [3]. The conventional gradient boosting machine requires calculating all feature instances for all features to estimate the information gain of all possible tree split points. Consequently, there is a problem that learning takes a long time. To improve the above problems, LightGBM utilizes two techniques: gradient-based one side sampling (GOSS) and exclusive feature bundling (EFB). GOSS selects instance with large gradients as fixed, while randomly excludes instances with small gradients. In other words, GOSS enhances learning efficiency by sampling data based on the gradients. EFB is a technique to reduce feature size by grouping mutually exclusive features. Therefore, EFB can reduce the complexity of the model and shorten the learning time. Additionally, the LightGBM uses a leaf-wise tree segmentation method, which segments the tree into leaf units more efficiently than the conventional level-wise method. This can improve learning speed and reduce memory usage. Fig. 1 shows the structure of level-wise and leaf-wise methods.

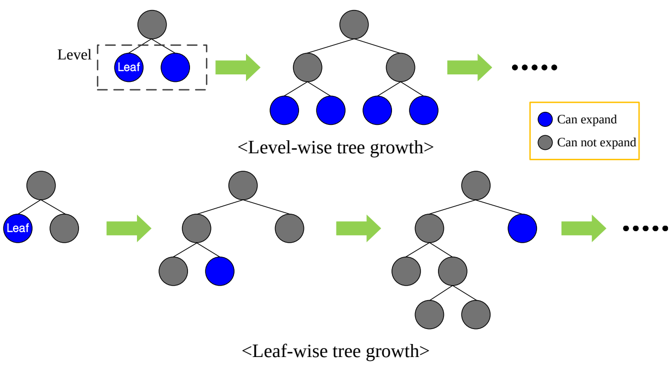

Fig. 1. The structure of level-wise and leaf-wise tree methods [4].

3. Data Processing

3.1 Data Collection

In this study, the training and test data for diagnosis and RTT prediction models were collected using the compact nuclear simulator (CNS). The CNS was developed by the Korea Atomic Energy Research Institute for the purpose of system education referring to the design of Westinghouse-993Mwe Kori NPP units 3 and 4 [5]. In the CNS, abnormal scenarios can be simulated by injecting various malfunctions. In this study, data were collected for 8 abnormal scenarios regarding instrument error, equipment abnormalities, and pipe leakage, as well as normal data. Additionally, data were collected up to the point where no action was taken by the user and the trip occurred. The scenario information of the collected data is shown in Table I.

Table I: Collected Scenario List

No.	Scenario name
0	Normal
Instrument error	
1	Pressurizer pressure channel failure (High)
2	Pressurizer level channel failure (Low)
3	Steam generator level channel failure (High)
Abnormalities in equipment	
4	Pressurizer PORV opening
5	Pressurizer safety valve failure
6	Pressurizer spray valve failed opening
Pipe leakage	
7	Leakage from CVCS to CCW
8	Steam generator u-tube leakage
※ CVCS: Chemical and volume control system ※ CCW: Component cooling water system ※ PORV: Pressurizer power-operated relief valve	

3.2 Data Pre-Processing

In AI learning, variable selection is one of the important tasks. If there are many unnecessary variables, the impact of each variable may not be reflected properly during the AI learning process. This can complicate AI learning and potentially lead to a decline in performance. Accordingly, in this study, 152 variables were selected and utilized from among 2,222 variables in the CNS data.

4. Implementation of RTT Prediction Algorithm

4.1 RTT Prediction Algorithm

The RTT prediction model was developed for each scenario to achieve high performance prediction. To utilize the individually developed prediction model for each scenario, the diagnosis function must be preceded. So, in this study, an RTT prediction algorithm that utilizes the diagnosis function was developed. The algorithm is divided into data pre-processing, abnormal scenario diagnosis function, and RTT prediction function. Through the diagnosis function, the abnormal scenario of the NPPs is determined, and the corresponding RTT model is utilized. If the diagnosis result indicates the normal state, the RTT value is fixed in 1,800 seconds through post-processing. This is because the collected data are the data in which the trip occurred within 1,800 seconds. Fig. 2 shows the schematic diagram of the algorithm used for RTT prediction.

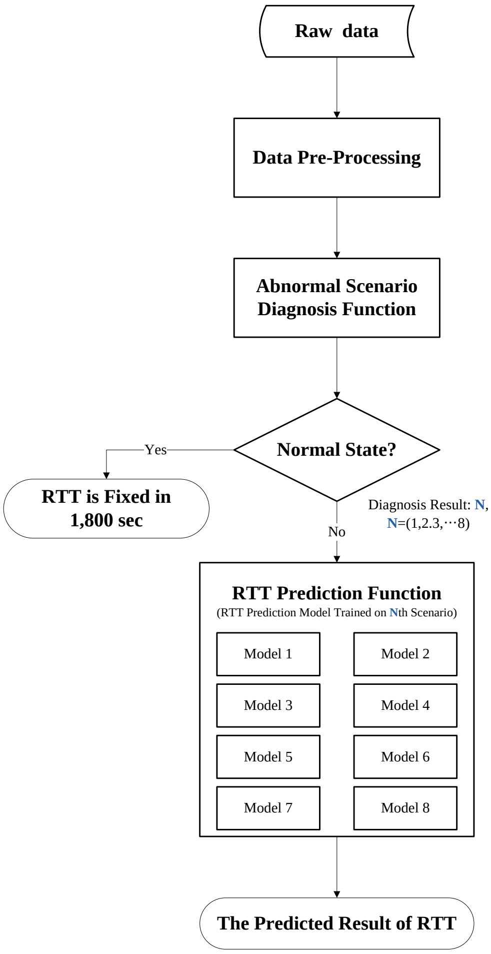

Fig. 2. Schematic diagram of the RTT prediction algorithm.

4.2 Diagnosis Function Result

The diagnosis function is evaluated using the test data. Evaluation includes accuracy score calculation and confusion matrix schematization. The confusion matrix provides a comparison between AI's predicted results and actual true answers. This allows for the identification of areas where the AI's learning may be insufficient. Fig. 3 shows the confusion matrix of the diagnosis model test result. As a result of the performance evaluation, it was confirmed that the accuracy score was 100% for all scenarios. The accuracy score is calculated by the Eq. (1).

$$\text{Accuracy score} = \frac{\text{number of correctly predicted data}}{\text{number of total data}} \quad (1)$$

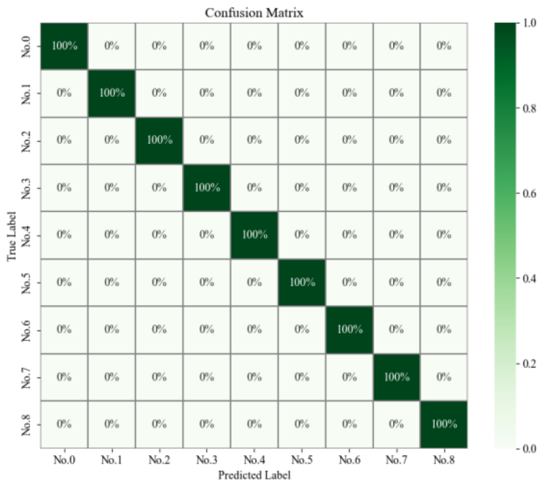

Fig. 3. Confusion matrix representing test result of diagnosis function.

4.3 RTT Prediction Function Result

LightGBM has numerous hyperparameters and can be optimized by tuning them. In this study, optimization was performed by adjusting the learning rate, maximum depth (max depth), and number of leaves (num leaves) among the hyperparameters, and early stopping technology was used. The performance of the optimized models was evaluated using the root mean squared error (RMSE). Eq. (2) represents the expression for calculating RMSE. Additionally, Table II shows the hyperparameter information and RMSE scores of the RTT prediction model developed for each scenario.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^{i}_{actual} - y^{i}_{pred})^{2}} \tag{2}$$

where, y_{actual} and y_{pred} are actual and predicted values, respectively. N is the total number of datasets.

Table II: RTT Prediction Model Information for Each Developed Scenario

Scenario No.	Learning Rate	Max Depth	Num Leaves	RMSE
1	0.01	5	25	0.0025
2	0.02	7	49	0.0077
3	0.01	5	25	0.0056
4	0.02	4	14	0.2369
5	0.01	6	36	0.0194
6	0.03	7	49	0.2658
7	0.01	4	16	0.0856
8	0.02	7	49	0.0328

Additionally, for performance comparison, the RMSE score of the model trained across all the above scenarios (i.e., scenarios from no.1 to no.8) was calculated. The RMSE was calculated as 0.3049 when the learning rate, max depth, and num leaves were 0.01, 5, and 25, respectively. This confirms that the prediction models developed for each scenario showed high performance.

4.4 Experiment

The pressurizer safety valve failure scenario (i.e., scenario number 5) data were used as a test experiment for the RTT prediction algorithm. For this data, a malfunction signal (e.g., pressurizer safety valve failure signal) at 30 seconds, and the trip occurs at 222 seconds. It means that the first 30 seconds are normal states, and then abnormal states. Fig. 4 shows the diagnosis result of the diagnosis, demonstrating successful diagnosis directly to scenario 5 when a malfunction is injected. Fig. 5 shows the results of the RTT prediction algorithm. In the figure, the orange dotted line indicates the malfunction injection time, the blue line represents the predicted RTT, and the red line represents the actual RTT. The blue box shows an enlarged view of the prediction result after the malfunction was injected. As a result of the experiment, all RTT prediction values exhibited high prediction performance within a 5% error margin.

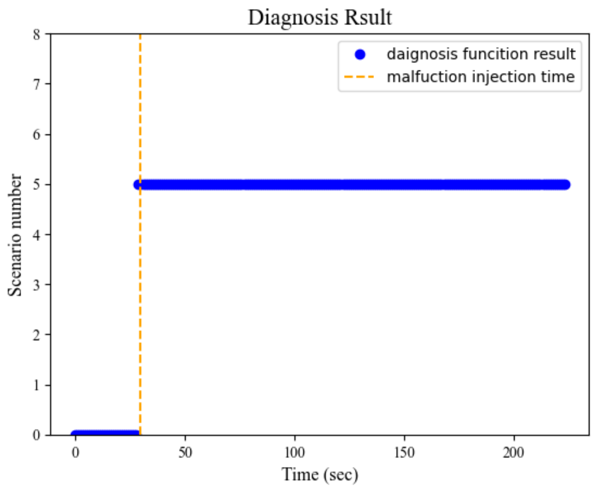

Fig. 4. Diagnosis result in pressurizer safety valve failure scenario.

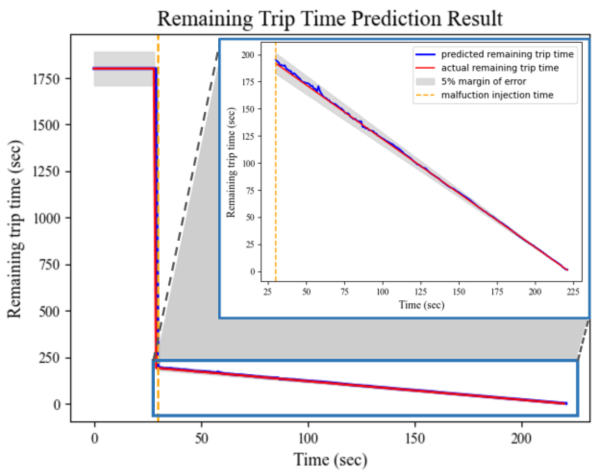

Fig. 5. Prediction result of remaining trip time in pressurizer

safety valve failure scenario.

5. Conclusions

In this study, we proposed the algorithm to predict the remaining trip time (RTT) as part of the operator support system function in NPPs. The algorithm consists of the diagnosis function and prediction function, and the LightGBM method was used. The diagnosis function provides the current scenario state of the NPPs. The prediction models have been developed individually for each scenario, and accordingly, the prediction function uses a model of the diagnosed scenario among the developed prediction models. The single prediction model developed individually for each scenario is simpler than a model trained on all scenarios and allows for high performance predictions. Additionally, as the results of test and experiment, the diagnosis function showed 100% accuracy, and the prediction function also shows RTT prediction within 5% margin of error.

However, in this study, relatively simple diagnosis and prediction were performed for 8 distinct abnormal scenarios with clear characteristics. In future work, we plan to collect a more diverse set of abnormal scenario data. In addition, we plan to perform RTT prediction by collecting data that includes user actions. It is expected that the RTT value will increase when appropriate actions are taken and, conversely, the RTT value will decrease when incorrect actions are taken. As a result, the predicted RTT values represent the state of the NPPs and are expected to be helpful for the mitigation task.

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