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Prediction of Severe Accident Entry Time based on Core Exit Temperature Using Explainable Boosting Machine

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1. Introduction

Since the Fukushima Nuclear Power Plants (NPPs) accident, safety have been emphasized in NPPs. NPPs, designed considering design basis accidents, are operated stably to avoid exceeding them. If the design basis accident is exceeded and the reactor core is damaged, it is considered a severe accident. The Core Exit Temperature (CET) is a typical severe accident starting condition, and it is an important factor in presenting the starting condition temperature [1]. If the CET reaches 922K, the corresponding time is regarded as the entry time of the severe accident. As a result, the core cooling function may be lost, core exposure may occur. A severe accident is an accident with a large scale of damage, so it is necessary to prepare for such accident and take quick actions. However, because of the high complexity of various systems, there is a possibility that operators may become confused due to many variables. Therefore, operation support system for reducing human error, such as golden time prediction, is being researched [2].

In this study, prediction of the severe accident entry time was performed in the loss of coolant accident (LOCA) situations. Specifically, the entry time of a severe accident was predicted through CET prediction using artificial intelligence (AI). Through this, operators can recognize the entry time into a severe accident in an emergency situation, and can quickly mitigate the accident based on preemptive action. It can also determine optimal operating conditions and control strategies, and increase the efficiency of NPPs.

Recently, research using AI is being actively conducted to prevent accidents and support operators. However, existing AI models have a trade-off relationship between explainability and accuracy, and the use of black-box models in existing studies limits their application due to limitations in explainability [1].

Therefore, the Explainable Boosting Machine (EBM), which has the potential for explanations, is applied to predict the CET in this study. EBM is a machine learning model that adds explainability to the existing boosting machine method [3]. Also, EBM is a generalized additive model, and as a white-box model, it presents reasons that can be explained to users and provides high interpretability accordingly. In this study, Modular Accident Analysis Program (MAAP) code was used to obtain data for AI learning. The MAAP code is a program that can simulate a virtual severe accident of NPPs, and the user can obtain data about the desired situation [2]. The LOCA scenarios were selected and simulated.

2. Method

This section describes the EBM model employed for predicting the entry time of the severe accident. The EBM represents one of the machine learning algorithms designed to enhance predictive model performance while also ensuring result interpretability. EBM is a tree-based gradient-boosting model. In each tree of the ensemble, individual features are learned sequentially through a round-robin approach, without prioritizing any feature [4]. Throughout this process, a small learning rate is employed to mitigate overfitting. The equation for the EBM model, which represents an advancement over the generalized additive model, can be expressed as Eq. (1).

$$g(E[y]) = \beta_0 + \sum f_j(x_j) \qquad (1)$$

where g is the link function, which adapts the model to various settings. f_j is the feature function, and one feature function is assigned to each feature and receives the value of the corresponding feature x_j as input. Through this, the predicted value, $g(E[y])$, is obtained. In this process, since the values for each feature are added all, it becomes easier to understand the influence of each feature. Furthermore, the non-linear relationship between the predicted value and the features can be easily discerned, contributing to the model's excellent performance. However, there are limitations in expressing the interactions between features in the form of Eq. (1). To overcome this constraint, a pairwise interaction term is introduced to Eq. (1). The equation with the pairwise interaction term added can be expressed as Eq. (2).

$$g(E[y]) = \beta_0 + \sum f_j(x_j) + \sum f_{i,j}(x_i, x_j) \qquad (2)$$

In Eq. (2), the model can include the interaction between each feature. However, there is a problem in that the number of pairwise interactions included increases greatly as the number of features increases.

Therefore, EBM uses the FAST algorithm to prevent the size of the model from increasing due to the rapid increase in the number of pairwise interactions. The FAST algorithm is designed to incorporate only a few important upper level pairwise from among all possible feature pairs in the model. For each combination (x_i, x_j), a few of the most important feature pairs are chosen by introducing a new model used to evaluate them in the modeling process [5]. Through this algorithm, the learning of the final model is completed by focusing on combinations of (x_i, x_j) with strong interactions.

3. Data

Before applying the prediction algorithm, data were acquired through the MAAP code. In this study, simulation was conducted by adjusting the break size at a constant ratio within the range of small LOCA, and data were collected until 10 seconds after the CET reached 922K (approximately 649℃) after the reactor trip. Originally, the CET was calculated by collecting the CETs of the four quadrants, but only one CET was considered in this simulation. A situation in which recirculation is not possible was assumed, and a total of 4 scenario datasets were divided in consideration of the break location and safety system operation. In this study, the safety system means auxiliary feedwater system, containment spray system, high pressure safety injection, and low pressure safety injection. The data were divided into train, validation, and test datasets for each scenario. The specific number of data is shown in Table I.

Table I: LOCA scenario classification

No.	Scenario	Safety system operation	Number of data (train/validation/test)
1	Cold-leg LOCA	On	80/20/17
2		Off	80/20/16
3	Hot-leg LOCA	On	80/20/17
4		Off	80/20/17

As for the input variables applied to model development, the top 6 variables were selected from the feature importance graph provided by the EBM model for each scenario. Fig. 1 shows the feature importance results using the EBM model. In addition, the input variables used for each scenario are shown in Table II.

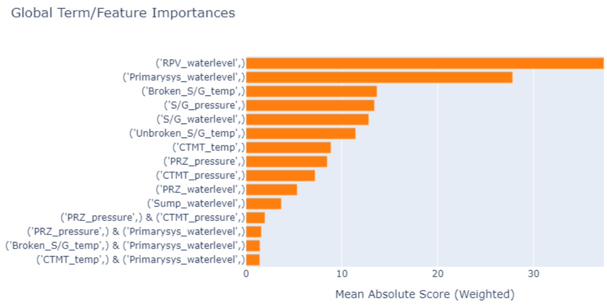

Fig. 1. Feature importance in cold-leg, safety system-off LOCA scenario.

Table II: Input variables for each scenario

No.	Scenario	Safety system operation	Input variables
1	Cold-leg LOCA	On	Pressurizer pressure, Reactor pressure vessel H_2 mole fraction, Primary system water level, Refueling water storage tank water level, Broken steam generator temp, Containment temp
2		Off	Primary system water level, Broken steam generator temp, Reactor pressure vessel water level, Unbroken steam generator temp, Steam generator water level, Steam generator pressure
3	Hot-leg LOCA	On	Pressurizer pressure, Primary system water level, Reactor pressure vessel water level, Pressurizer water level, Steam generator pressure, Containment temp
4		Off	Pressurizer pressure, Primary system water level, Refueling water storage tank water level, Steam generator water level, Containment pressure, Containment temp

4. Result

In this study, the severe accident entry time was predicted based on the CET. A total of 4 scenarios were utilized involving break location and safety system operation, and the model predicted after 10 minutes. The prediction was performed using EBM, with the CET specified as the dependent variable. Root mean squared error (RMSE) and R-squared (R^2) were used as evaluation metrics of the model. The equations of the evaluation metrics are shown in Eqs. (3) and (4).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\Sigma(y - y_{pred})^2}{n}} \qquad (3)$$

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} = 1 - \frac{\Sigma(y - y_{pred})^2}{\Sigma(y - y_{mean})^2} \qquad (4)$$

In the equations, y represents the actual value, y_{pred} represents the predicted value of the model, and y_{mean} is the average of the actual values. The lower RMSE value and the R^2 value closer to 1 indicate better prediction performance. Figs. 2 to 5 show the CET prediction results for the test dataset from each of the 4 scenarios.

As a result, the CET reached 922K at 5860 seconds after the reactor trip when the safety system was operated in the cold-leg LOCA scenario. On the other hand, when the safety system was not operated, the CET reached this threshold at 2377 seconds after the reactor trip. Additionally, in the hot-leg LOCA scenario, if the safety system was operated, the CET reaches 922K after 3858 seconds, whereas if the safety system was not operated, it is reached after 1066 seconds. The figures show that the prediction after 10 minutes performed well. Table III represents the performance metrics of the predictive model for each scenario. It shows that the RMSE are within 9 and R^2 are all 0.99.

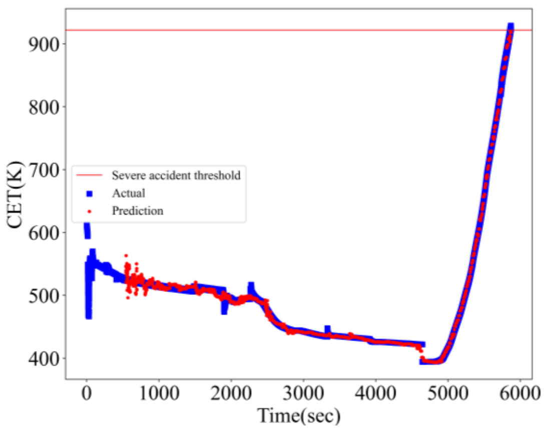

Fig. 2. Prediction results for cold-leg, safety system-on LOCA scenario.

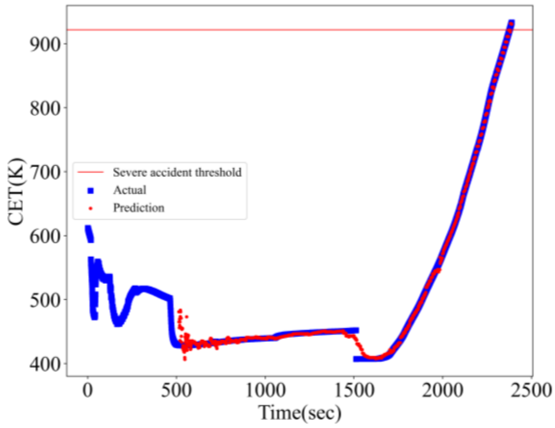

Fig. 3. Prediction results for cold-leg, safety system-off LOCA scenario.

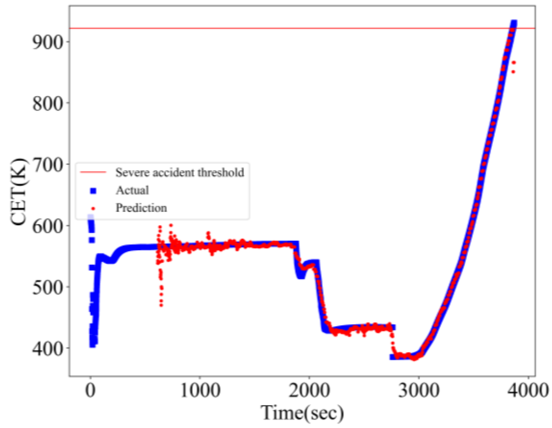

Fig. 4. Prediction results for hot-leg, safety system-on LOCA scenario.

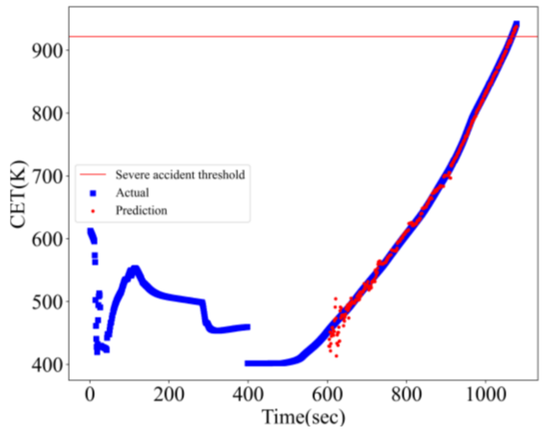

Fig. 5 Prediction results for hot-leg, safety system-off LOCA scenario.

The biggest reason for using EBM for prediction is its explainability. Since EBM performs a prediction and at the same time explains why the predicted value was derived, the reliability of the predicted value is improved. EBM explains the reason for the prediction by presenting the contribution of each variable to the predicted value.

Table III: Prediction performance of EBM model

Scenario	Safety system operation	RMSE	R^2
Cold-leg LOCA	On	4.65	0.99
	Off	5.81	0.99
Hot-leg LOCA	On	8.36	0.99
	Off	6.51	0.99

Fig. 6 shows the contribution of each variable that made the model derive the predicted value in the cold-leg, safety system-off scenario. Figure 7 shows the contribution of the variables in the hot-leg, safety system-off scenario. Through Figs. 6 and 7, the variables in Table II and the interaction of each variable have positive and negative contributions. In the case of cold-leg, safety system-off scenario and hot-leg, safety system-off scenario, primary system water level and reactor pressure vessel water level had the largest contribution.

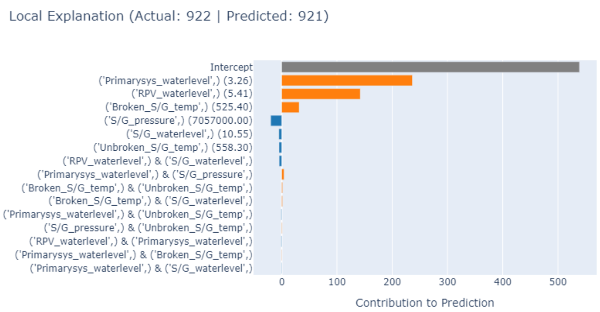

Fig. 6. Contribution of variables to predicted values in the cold-leg, safety system-off LOCA scenario.

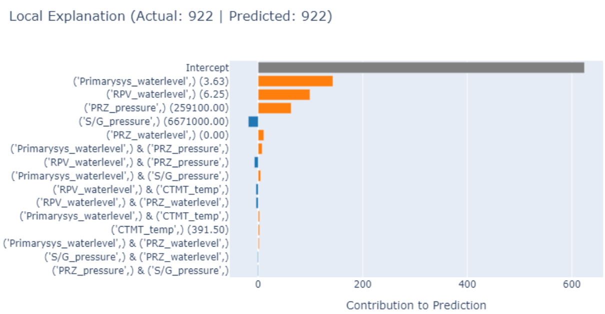

Fig. 7. Contribution of variables to predicted values in the hot-leg, safety system-off LOCA scenario.

5. Conclusions

In this study, the entry time of a severe accident was predicted through CET prediction using EBM. The study results indicate that EBM exhibits high prediction performance. In addition, EBM not only provides the predicted value but also explains the basis for the prediction through explainability. This enhances the reliability of the model. Moreover, it facilitates the identification of input variables that significantly influence the dependent variable. The study shows that EBM successfully predicts the CET while providing an explanation of variables. It is expected to be beneficial for supporting operators, including prediction and early warning systems, in NPPs.

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