Applications of Supervised Machine Learning to Diagnose Reactor Vessel Failure

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1. Introduction

After the Fukushima accident, the importance of the accident management support tool has been emphasized as the importance of managing severe accidents has risen. Accident management support tool (AMST) refers to a program that can help in decision-making for accident mitigation in the event of a severe accident [1]. This AMST consists of three steps, diagnosing an accident, predicting the progression, and making a decision to determine an optimal mitigation strategy. Currently, severe accident analysis codes and databases are commonly used as methods for predicting the progress of accidents. However, the severe accident analysis codes take a long time to calculate, and the database has disadvantages in that it is difficult to predict various accidents beyond the established data. To overcome these challenges, we applied the artificial neural network to quickly predict time-dependent thermal-hydraulic (TH) variables for various accident scenarios [2].

On the other hand, it is also important to predict when a major event such as reactor vessel (RV) failure will occur. This is because the predicted RV failure time can be a major criterion for decision-making. In our previous study, the RV failure time was predicted based on the failure times of various components [3]. However, if the RV failure can be classified based on the TH variables, then the RV failure time can be more accurately predicted by combining the time-dependent TH variable predictor and the RV failure classifier.

In this study, supervised learning machine learning methodology was applied to determine whether RV failure by looking at TH variables in an hourly unit, and based on this, a direction for RV failure prediction will be presented.

2. Methods

2.1 Data production

In order to produce various accident scenarios, a total of 7 component failures and the mitigation strategies from SAMG 1 to 3 were randomly chosen and the accident progressions were calculated from 1 hour to 72 hours using MAAP 5.03 code [4]. The list of failed components is shown in Table I. A total of 10,679 scenarios were produced. The probability of each failure and mitigation strategy occurring within 72 hours was also set to 1/2, so that more diverse accident scenarios can be created. Fig. 1 and Fig. 2 show the frequency according to the number of failed components and the frequency according to the number of mitigation strategies implemented.

Table I Components those can be failed during TLOCCW accident scenario

Component Name
RCP seal LOCA
HPSI
LPSI
CHP
CSS
MDAFW
HX

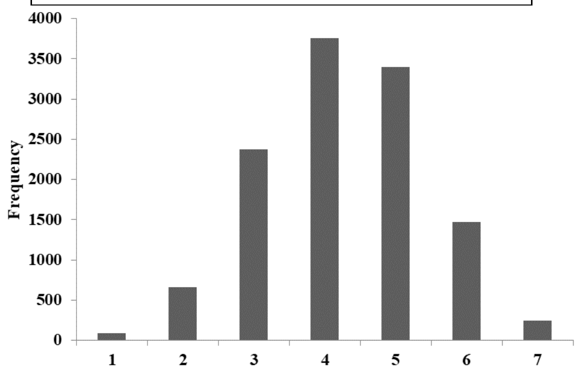

Fig. 1 Frequency according to the number of failed components

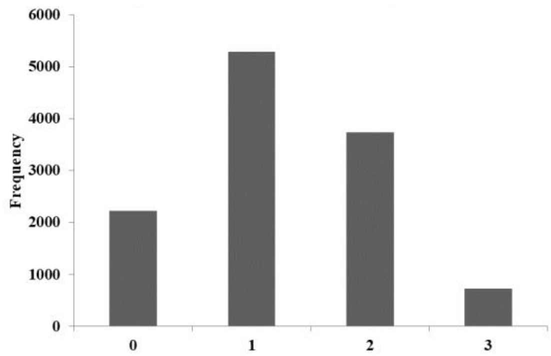

Fig. 2 Frequency according to the number of mitigation strategies

Within 10,679 accidents, the reactor vessel failure time distribution is shown in Fig. 3. It occurs mainly in 20-30 hours, and the case where reactor vessel failure did not occur accounted for 2.8% of the total.

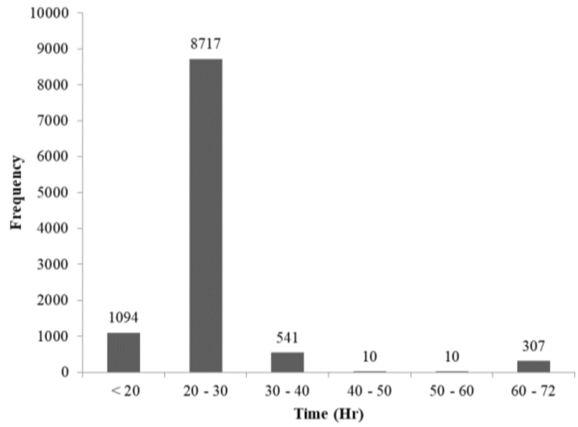

Fig. 3 Frequency according to RV failure time

There are two reactor vessel failure modes, one is the ejection of the instrumental penetration tubes and the other is lower head creep rupture. Both are caused by high temperature and overpressure in the reactor vessel. However, since the calculation in the MAAP code is a complex function that combines various subroutines, it is difficult to determine whether the reactor vessel fails by looking at only the thermodynamic variables. The frequency distribution with respect to the reactor vessel failure mode is shown in Fig. 4.

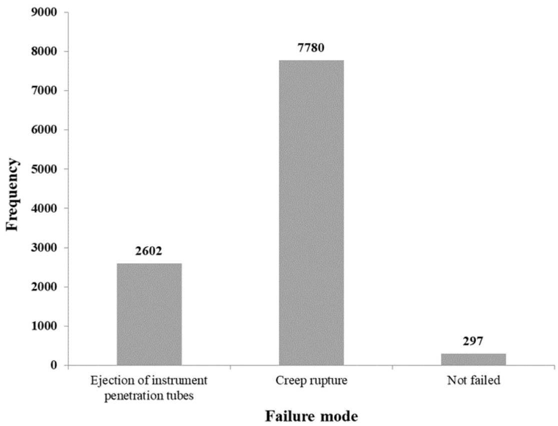

Fig. 4 Frequency according to reactor vessel failure mode

2.2 Input configuration for supervised learning

Through supervised learning, the goal is to check whether it was possible to determine whether the reactor vessel failure can be predicted by looking at only the thermohydraulic variables. For thermohydraulic variables, 7 variables were extracted for each hour from the MAAP calculation data. These variables are shown in Table 2, and the selection criteria were set as major variables that can be monitored in the Main Control Room. Data were generated by mapping these variables and whether or not reactor vessel failure occurred. A total of 779,567 datasets were created by dividing every 10,679 scenarios into a total of 73 datasets from 0 to 72 hours.

Table 2 Thermohydraulic variables for input features

Input features
Primary system pressure
Cold leg temperature
Hot leg temperature
Reactor vessel water level
Steam Generator pressure
Steam Generator water level
Max Core Exit Temperature

2.3 Decision Tree

Decision Tree is a supervised learning methodology that is learned to classify or regress data through multiple criteria divided into yes/no sets based on input features. It was impossible to confirm how artificial neural networks or other supervised learning are trained, but decision trees can verify the criteria used for learning. Because of this advantage, a decision tree methodology was used to confirm the criteria for determining reactor vessel failure. *DecisionTreeClassifier* function of Scikit-learn was used, and as hyperparameters, Gini impurity and max depth of 4 were used [5].

2.4 Random Forest

Random Forest is an ensemble model of decision trees, which can avoid overfitting and obtain more generalized results. However, it is not possible to check the learning process like a decision tree. Instead, feature importance could be checked, so the random forest methodology was also selected. *RandomForestClassifier* function of Scikit-learn was used, and 25 estimators and Gini impurity were used as hyperparameters [5].

3. Results and Discussion

20% of the entire dataset was classified as a test set, and a confusion matrix was created to check the performance of the classifier through 10 k-fold validation. Table 3 Confusion matrix of Decision TreeTable 3 and Table 4 shows the confusion matrix of decision tree and random forest.

Table 3 Confusion matrix of Decision Tree

Real \ Predict	Not fail	Fail
Not fail	205,980	602
Fail	2686	414,385

Table 4 Confusion matrix of Random Forest

Real \ Predict	Not fail	Fail
Not fail	206505	63
Fail	58	417027

Assuming that not fail is negative and fail is positive in the confusion matrix, the elements of the confusion matrix can be viewed as true negative (TN), false positive (FP), false negative (FN), and true positive (TP). Accuracy, precision, and sensitivity can be calculated from the confusion matrix above, and the formula is as follows. Table 5 shows the values of these indicators. In cross-validation of train set, random forest shows overwhelmingly good performance.

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Table 5 Values of indicators for classifier

	Accuracy	**Precision**	**Sensitivity**
Decision Tree	0.9947	0.9985	0.9936
Random Forest	0.9998	0.9998	0.9999

As can be seen in Table 6, if the accuracy of the test set is compared, it can be seen that both sides show similarly good classification performance.

Table 6 Prediction accuracy for test set

	Accuracy
Decision Tree	0.9944
Random Forest	0.9938

As shown in Fig. 5, the classification criteria could be confirmed through the decision tree model. It can be seen that the root node, which is the most basic node, shows that the most important feature is the primary pressure. Next, cold leg temperature was used for the criteria.

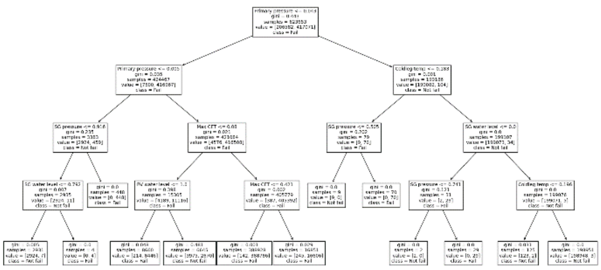

Fig. 5 Plot of decision tree

Fig. 6 shows the plot of the input features importance generated through the random forest model. The most important feature is also primary pressure, followed by temperature-related features which are hot leg temperature, core exit temperature, and cold leg temperature.

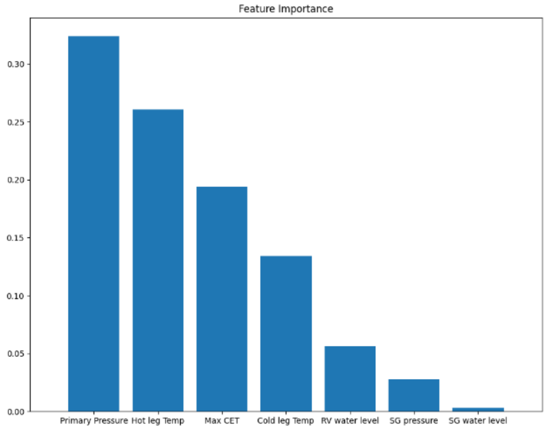

Fig. 6 Plot of input feature importance

4. Summary and Further Study

Using the decision tree and random forest algorithms, which are supervised machine learning models, the results are obtained that it is possible to reliably distinguish the reactor vessel failure by more than 99% with thermohydraulic variables. From this result, two methods can be considered for formulating a criterion for decision-making based reactor vessel failure time.

One way to do this is using a function *predict_proba* in the decision tree. It can show each probability in the determination of reactor vessel failure or not. Therefore, the more likely it is to be classified as reactor vessel failure, the closer it will be to reactor vessel failure incident. Another method is to combine it with another artificial neural network model [2] that predicts 7 thermohydraulic variables and checks when it is determined that reactor vessel failure has occurred through iterative prediction calculations. These methods will be applied in further studies.

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