Transactions of the Korean Nuclear Society Autumn Meeting
Gyeongju, Korea, October 26-27, 2023

Detecting Core Uncovery with Limited Information during Severe Accident Using Machine Learning Methods

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Keywords : severe accident, core uncovery, machine learning, support vector machine

1. Introduction

A severe accident in a nuclear power plant means an accident in which serious core damage occurs beyond a design basis accident. This situation presents a significant risk of radiation release, underscoring the necessity for an effective mitigation strategy. The strategy for mitigation in the event of such a severe accident follows the severe accident management guideline (SAMG). During a severe accident, an appropriate mitigation strategy is determined and applied based on the state of the nuclear power plant. To this end, it is necessary to accurately understand the current state of the nuclear power plant using only instrumentation information that can be checked in the main control room (MCR).

The severe accident entry condition is when the core exit temperature exceeds 1,200 degrees Fahrenheit, and from this point on, taking mitigation strategies to prevent reactor vessel failure becomes the primary goal. To this end, it is important to accurately determine whether core uncovery, a major event that occurs before reactor vessel failure, has occurred. Then, it will be possible to maintain the integrity of the nuclear fuel through external coolant injection. Therefore, a model that can classify whether or not core uncovery has occurred was created based on a machine learning model using only the measurement information that can be seen in MCR.

Currently, machine learning methodologies are widely used as classification and regression models in many fields, and this also applies to the nuclear engineering field. A model for diagnosing the initial event of an accident [1] and a model for diagnosing whether the reactor vessel failure [2] has occurred have been studied. In this study, a model was created to classify core uncovery by using a support vector machine among machine learning models, and its performance was evaluated. The overall research outline is shown in Fig.1.

2. Methodology

This section outlines the process of generating the dataset and constructing a support vector machine model to develop a classification model for core uncovery.

2.1 Dataset Generation

The dataset for this study was derived from the same dataset used to develop a reactor vessel failure diagnosis model in the previous study [2]. Across a span of 72 hours, 10,679 scenarios were computed using the MAAP 5.03 code [3]. For each scenario, seven component failures (High-pressure injection pump, Low-pressure injection pump, Containment spray pump, Charging pump, Motor-driven auxiliary feed water pump, Heat exchanger, Reactor coolant pump seal) and three mitigation strategies (SAMG 1, 2, 3) are randomly applied within 72 hours.

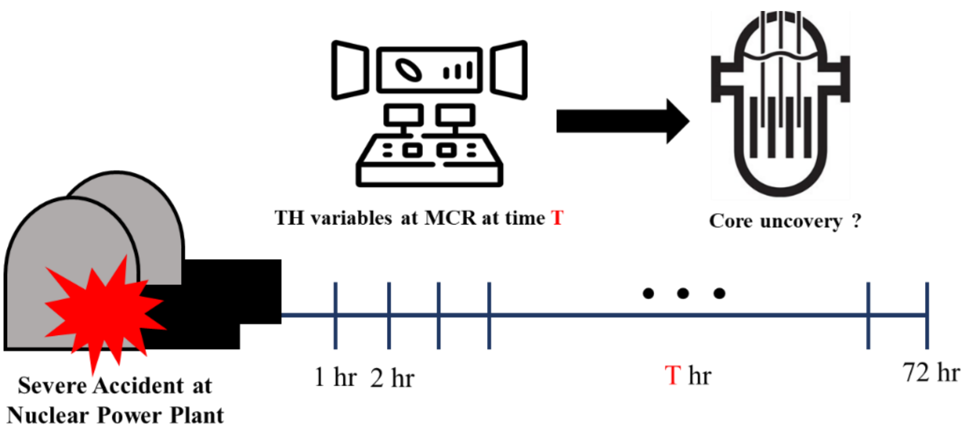


Fig. 1 Research outline of core uncovery detection model

Among these accident scenario calculation results, as shown in Table 1, 6 major thermal-hydraulic variables that can be checked in MCR were selected. By extracting this in 1-hour intervals, the classification model was created that could detect core uncovery at each hour.

Table 1 Major thermo-hydraulic variables can be checked in MCR

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

For a total of 10,679 accident scenarios, the distribution of the six thermal-hydraulic input features is shown in Fig. 2, and the distribution of occurrences for core uncovery is shown in Fig. 3. The majority of these incidents occurred between 8 and 9 hours, overwhelmingly concentrated in that timeframe. This can be attributed to the inherent randomness of accidents (timing of component failure and mitigation strategies) being uniformly sampled from the 0 to 72-hour range, leading to a diminished degree of randomness in the early phases of accidents. By extracting them at 1-hour intervals, a total of 779,567 datasets were created.

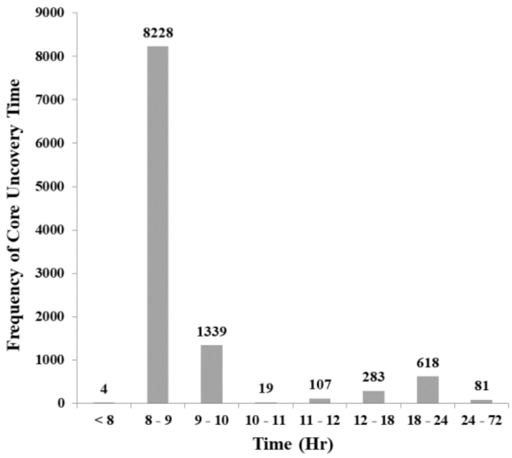
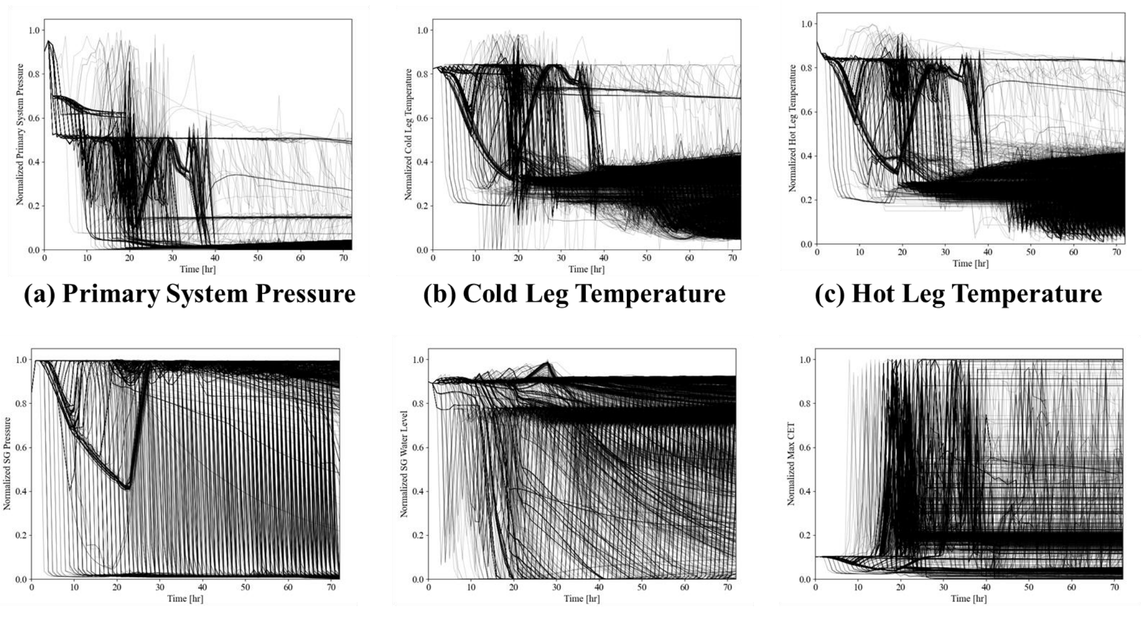


Fig. 3 Frequency according to core uncovery time

2.2 Support Vector Machine

Support vector machine (SVM) is a supervised learning methodology that classifies data by calculating hyperplanes that classify two types of datasets. The hyperplane calculation method calculates the margin between the hyperplane and the support vector to find the hyperplane that maximizes the margin. When the hyperplane of nonlinear data needs to be obtained, the hyperplane is found by converting the data to a higher dimension using the kernel function. There are various types of these kernels, such as RBF, Linear, Polynomial,



(a) Primary System Pressure **(b) Cold Leg Temperature** **(c) Hot Leg Temperature**

(d) SG Pressure **(e) SG Water Level** **(f) Max CET**

Fig. 2 Distribution of 6 thermal-hydraulic input variables in the dataset and Sigmoid. In this study, a support vector machine model with RBF kernel in scikit-learn was used.

$$\text{RBF kernel : } K(x_i, x_j) = \exp\left(-\frac{\|x_1 - x_2\|^2}{2\sigma^2}\right)$$

As shown in Fig.4, a support vector machine model was trained to classify the six selected thermal-hydraulic variables before and after core uncovery.

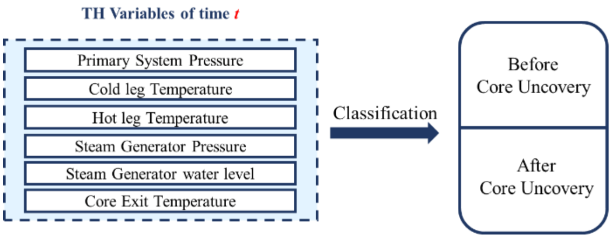


Fig. 4 Structure of core uncovery classifier model

3. Results

70% of the total dataset was set as training set and 30% as test set. As a result of checking the classification performance using the test set for the learned model, the confusion matrix shown in Table 2 was obtained.

Table 2 Confusion matrix of support vector machine

Predict / Real	Before Uncovery	After Uncovery
Before Uncovery	31322	387
After Uncovery	112	194596

In Table 2, if 'before uncovery' is regarded as negative and 'after uncovery' as positive, the accuracy, precision, sensitivity values can be calculated from the below equations for each term of the true negative (TN), false negative (FN), true positive (TP), and false positive (FP). As shown in Table 3, obtained value for this metric is approximately 0.998, indicating a notably high level.

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

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

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

Table 3 Values of indicators for support vector machine

	Accuracy	**Precision**	**Sensitivity**
Support vector machine	0.9978	0.9980	0.9994

4. Summary and Conclusions

In order to prevent reactor vessel failure in a severe accident, a machine learning-based model was created to detect core uncovery. The support vector machine model trained through the dataset created using the MAAP 5.03 program showed a very high accuracy of 0.998. If this is combined with a severe accident progress prediction model [5], it seems possible to predict the core uncovery time.

ACKNLOGEMENT

This work was supported by KOREA HYDRO & NUCLEAR POWER CO., LTD (No. 2020-Tech-01).

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