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Development of a Robust Machine Learning Model for Detecting Major Events During Severe Accidents in Nuclear Power Plant

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1. Introduction

Severe accidents can occur where the fuel melts and core damage occurs as seen in the Fukushima accident. However, even though the consequence is severe it is not frequent, and thus there is no abundant accident data, or large-scale experimental data. Due to these limitations, considerable uncertainties exist for predicting the severe accident progression and phenomena.

During severe accidents, to mitigate the consequence, it is essential to select the optimal mitigation strategy based on the severe accident management guideline (SAMG). This requires an accurate observation of the status of nuclear power plant during the accident. However, the likelihood of instrument errors during such situations can make it challenging to precisely determine the status of plant. Therefore, a model that can assess the status of plant despite instrument error values may be necessary.

Under severe accidents, determining whether core uncovery has occurred at early stage is a critical decision criterion. If core uncovery happened, it becomes urgent to inject water into the reactor coolant system (RCS) as the fuel may melt. Additionally, reactor pressure vessel (RPV) failure represents another significant event during severe accidents. If RPV failure occurs, the mitigation strategy goal shifts towards maintaining containment integrity. Consequently, a robust major event detection model that can indicate whether core uncovery or RPV failure has occurred, even with instrumentation error, is required.

To develop such an event detection model, machine learning methodologies are proposed in this paper and are utilized. These methodologies are well-suited for classifying the data. Also, if the model is once trained, it allows very rapid computations, and convenient to apply to accident situation. In the previous study, the authors developed a machine learning model based on the random forest to determine the occurrence of RPV failure using thermal-hydraulic (TH) data with 1-hour interval [1], and a machine learning model based on support vector machines to detect the occurrence of core uncovery with fifteen-minute interval [2]. Building on this experience, the research aims to advance further by developing a model capable of accurately detecting the occurrence of accidents, even in the presence of instrumentation errors.

2. Methodology

2.1 Dataset Generation

The foundational dataset used in this research is the same as that utilized in the previous studies [1, 2]. In short, the dataset consists of scenarios totaling 10,679, in which accident scenarios are generated by assuming random failures of 7 different components at random time, and the random implementation of 3 mitigation strategies (SAMG 1, 2, 3) at random time until 72 hours after accident occurs. These scenarios were computed using the MAAP 5.03 [3] severe accident analysis code.

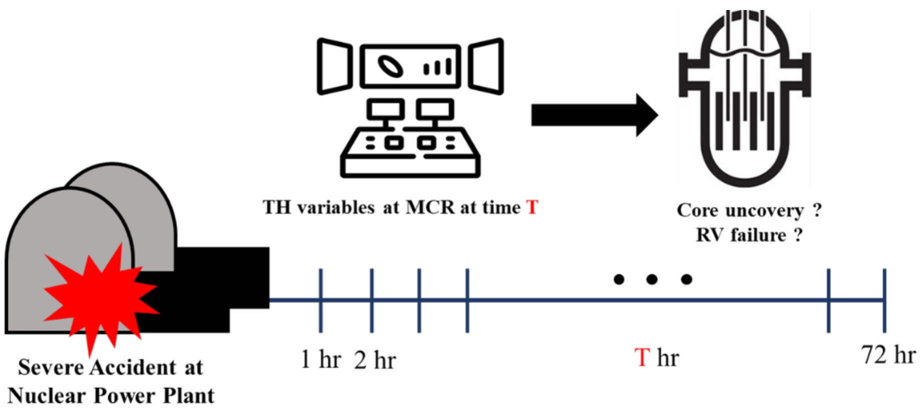

Fig. 1 Research outline of major event detection model

From this, a total of 5 TH variables were selected for the accident detection. These variables were chosen based on their observability from the main control room (MCR) and are detailed in Table 1.

Table 1 Selected thermal-hydraulic variables

Input features
Primary system pressure
Cold leg temperature
Hot leg temperature
Steam Generator pressure
Steam Generator water level

The selected thermal-hydraulic variables were extracted with 15-minute interval from 0 to 72 hours. As a result, a total of 3,054,194 data points were generated, which were divided into 80% for the training set and 20% for the test set. Based on this generated data, a dataset with inserted data errors was also generated. This involved errors in 10% of a variable that is important for the classification. As shown in equation (1), the error values were replaced to the mean value of the entire dataset. This approach was referring to the previous research work that demonstrated the capability to diagnose initial accident events even in the presence of data errors [4].

$$x_{error} = \overline{x} \tag{1}$$

2.2 Random Forest

The Random Forest model is a type of machine learning model that acts as an ensemble of decision tree models. A decision tree model functions like the branches of a tree, establishing classification criteria and segmenting data into categories based on yes/no responses to learn these criteria. Random Forest combines multiple decision trees to create a more generalized model, thereby preventing overfitting and smoothing out the classification criteria. Hence, the Random Forest model was chosen because, as an ensemble model, it can be more robust against data errors compared to individual decision trees, making it particularly suitable for applications where data inaccuracies may be present.

Leveraging these advantages, Random Forest models were employed to construct event detection models. These are classification models that input five TH variables at 15-minute intervals and classify the occurrence of an event as either 0 (no event) or 1 (event occurred). Separate models were developed for both core uncovery and RPV failure detection.

2.3 Performance Metrics

The performance of data classification models is commonly assessed using a confusion matrix. A confusion matrix allows for a straightforward comparison between the actual and predicted classifications of data. Each cell within the matrix represents True Positives, True Negatives, False Positives, and False Negatives. This distribution is detailed in Table 2.

As shown in equation (2) to (5), Using the elements of the confusion matrix, four key performance metrics can be calculated. First, accuracy represents the proportion of correctly predicted instances out of the total. Precision indicates the ratio of correctly predicted events out of all predictions made following an event's occurrence. Recall reflects the proportion of correctly predicted instances out of the actual occurrences of the event in the dataset. The F1 score, considering the imbalance in data distribution, is an overall performance metric that calculates the harmonic mean of Precision and Recall.

Table 2 Confusion Matrix

Actual \ Predict	0 (Before event)	1 (After event)
0 (Before event)	True Negative (TN)	False Positive (FP)
1 (After event)	False Negative (FN)	True Positive (TP)

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision+Recall}} \tag{5}$$

3. Results

3.1 Major event detection model without data error

Before training models on datasets with errors, models for detecting core uncovery and RPV failure were initially trained based on a dataset without errors using a Random Forest approach. These models were developed using scikit-learn [5], with the number of decision trees (n_estimators) set to 50. The confusion matrises for the trained core uncovery model and the RPV failure model are presented in Tables 3 and 4, respectively.

Table 3 Confusion matrix of RPV failure model

Actual \ Predict	Before RPV failure	After RPV failure
Before RPV failure	199138	377
After RPV failure	82	411242

Table 4 Confusion matrix of core uncovery model

Real \ Predict	Before Uncovery	After Uncovery
Before Uncovery	82601	125
After Uncovery	51	528062

Based on the confusion matrices, the calculated performance metrics are shown in Table 5, demonstrating exceptionally high performance with all metrics exceeding 99.9%. This indicates the models' robustness and accuracy in detecting core uncovery and RPV failure under conditions without data errors.

Table 5 Performance of the event detection model

Score	RPV failure model	Core uncovery model
Accuracy	0.9992	0.9997
Precision	0.9991	0.9998
Recall	0.9998	0.9999
F1 score	0.9994	0.9998

One of the advantages of the Random Forest model is its ability to identify feature importance. The results, presented in Table 6, reveal that in both models, the primary pressure holds over 50% of the importance, indicating its significant role in the models' classification processes. Consequently, for generating the dataset with errors, emphasis was placed on the primary pressure variable to maximize the impact of the errors. As previously mentioned, this was achieved by substituting 10% of the data for the primary pressure variable with its average value to introduce errors.

Table 6 Feature importance of the model

RPV failure model		Core uncovery model	
Primary Pressure	0.5215	Primary Pressure	0.6227
Hot leg T	0.2981	Cold leg T	0.1819
Cold leg T	0.1311	SG water level	0.0850
SG pressure	0.0394	Hot leg T	0.0842
SG water level	0.0099	SG pressure	0.0263

3.2 Major event detection model with data error

Using datasets that include errors in 10% of the Primary Pressure variables, models for detecting core uncovery and RPV failure were developed. The outcomes of these models, reflected through their confusion matrices, can be seen in Tables 7 and 8.

Table 7 Confusion matrix of RPV failure model (with error)

Actual \ Predict	Before RPV failure	After RPV failure
Before RPV failure	199099	416
After RPV failure	102	411222

Table 8 Confusion matrix of core uncovery model (with error)

Real \ Predict	Before Uncovery	After Uncovery
Before Uncovery	82564	162
After Uncovery	48	528065

Upon examining the confusion matrix results, it can be observed that there is no significant difference in accuracy between models trained on datasets without errors and those trained on datasets with errors. However, an important analytical criterion would also be to evaluate how much the accuracy decreases when models trained on datasets without errors are tested on datasets with errors. The outcomes of testing the models on datasets containing errors can be found in Table 9 and 10.

Table 9 Performance of the RPV failure model with error dataset

Score	Original RPV failure model	RPV failure model with error
Accuracy	0.9353	0.9992
Precision	0.9990	0.9990
Recall	0.9048	0.9998
F1 score	0.9496	0.9994

Table 10 Performance of the Core uncovery model with error dataset

Score	Original Core uncovery model	Core uncovery model with error
Accuracy	0.9865	0.9997
Precision	0.9848	0.9997
Recall	0.9998	0.9999
F1 score	0.9923	0.9998

When tested with datasets containing errors, models trained on datasets with errors demonstrated high performance, with all metrics exceeding 99.9%, similar to those trained on error-free datasets. However, models trained on error-free datasets showed a slight decrease in performance when tested with datasets containing errors, yet still maintained a high level of performance. These results indicate that to develop models capable of accurately detecting accidents in real-world scenarios, where instrumentation errors may occur, it is beneficial to include some level of error in the training datasets as well. This approach provides valuable insights into preparing models for the inherent uncertainties present in actual operational environments, ensuring they remain effective in accurately detecting critical events under less-than-ideal conditions.

4. Summary and Conclusions

This research aimed to develop robust machine learning models for detecting core uncovery and RPV failure events in nuclear power plants, leveraging Random Forest algorithms. The study began with the development and validation of models using an error-free dataset, resulting in highly accurate event detection with performance metrics exceeding 99.9%.

Further exploration involved training models on datasets with artificially inserted errors in variables, specifically Primary Pressure, to assess the impact on model performance. This approach was motivated by the real-world scenario where sensor inaccuracies or failures can compromise data integrity.

Testing models trained on error-free datasets with error-containing datasets revealed a slight performance degradation, yet the accuracy remained impressively high, above 93%. Conversely, models trained with error-inclusive datasets and tested likewise maintained their high-performance threshold.

These findings underscore the significance of incorporating data errors into the training process to mirror operational challenges faced in nuclear power plant management. It highlights the Random Forest model's capability to offer reliable, accurate predictions even in the presence of data inaccuracies, ensuring that the detection of severe accidents like core uncovery and RPV failure remains effective under various conditions.

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REFERENCES

[1] Yeonha Lee et al., "Applications of Supervised Machine Learning to Diagnose Reactor Vessel," Transactions of the Korean Nuclear Society Autumn Meeting (2022).
[2] Yeonha Lee et al., "Detecting Core Uncovery with Limited Information during Severe Accident Using Machine Learning Methods," Transactions of the Korean Nuclear Society Autumn Meeting (2023).
[3] EPRI, “Modular Accident Analysis Program (MAAP5) Version 5.03 – Windows,” Fauske & Associates, Inc, August 2014.
[4] Li, Jiangkuan, and Meng Lin. "Research on robustness of five typical data-driven fault diagnosis models for nuclear power plants." Annals of Nuclear Energy 165 (2022): 108639.
[5] Pedregosa et al., “Scikit-learn: Machine Learning in Python,” JMLR, Vol. 12, pp. 2825-2830 (2011).