

# Consideration for applying machine learning in uncertainty analysis method of severe accident

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## 1. Introduction

The analysis of severe accident is usually performed based on the results of the probabilistic safety assessment. The integral-level code can be used to understand expected phenomena during the progress of severe accident, and the mechanical analysis code can be used for detailed modeling of a specific physical phenomena.

The safety review guideline for accident management program from KINS (Korea Institute of Nuclear Safety) suggests that the ability of simulation codes and methodologies used in the best-estimate analysis of severe accident should be appropriately presented, and the uncertainty of that should be estimated [1].

To assess the uncertainty of a particular phenomenon as accurately as possible, an analysis should be performed which involved all the related parameters. In this case, however, an enormous number of simulations are required. Due to the limitation of cost and time, it is impossible so that the minimized parameters based on sensitivity analysis are used in the current method.

Recently, machine learning gets attention as the most proper method of understanding and arranging multi-dimensional data. Since the input and output data including various parameters are a kind of data pair, there is a possibility to apply machine learning in the uncertainty analysis method.

In this study, the current uncertainty analysis method, categories of the machine learning, and the possible way to apply the machine learning for improving the method were considered.

## 2. Current method for uncertainty analysis

The USNRC (US Nuclear Regulatory Commission) proposed the CSAU (Code Scaling, Applicability and Uncertainty) method as a methodology for quantifying uncertainty based on the results of various studies. The CSAU process is divided into 3 elements and 14 steps as shown in Figure 1 [2].

In the process of the first element, the main components of the objective phenomenon are specified. The basic parameters related to the phenomena are determined considering the scenario and the plant type through the PIRT (Identify and Rank Phenomena) in the step 3. Based on the parameters, the proper simulation code is selected by considering the model and correlations for the analysis.

After determination of the simulation code, the accuracy of the code is verified in the process of the second element. The accuracy can be quantified by the comparison between the experiment data and the benchmark result.

Finally, sensitivity and uncertainty analysis are performed in the process of the third element. The input variables corresponding to the boundary conditions are selected based on the results of the sequence analysis. In the case of the input variables related to the physical modeling, the values are determined based on the code manual and/or the benchmark result. After that, the sensitivity analysis is performed to evaluate the importance of variables. Based on the result of the sensitivity analysis, the uncertainty parameters and the ranges of the parameters are selected. Using a sampling method such as Latin-Hyper-Cube, the sequences are determined based on the values of the uncertainty parameters, then all sequences are calculated. The difference between the experimental and the calculation result is indicated as a bias, and the final value is determined by reflecting the bias in the specific confidence level of the calculation result.

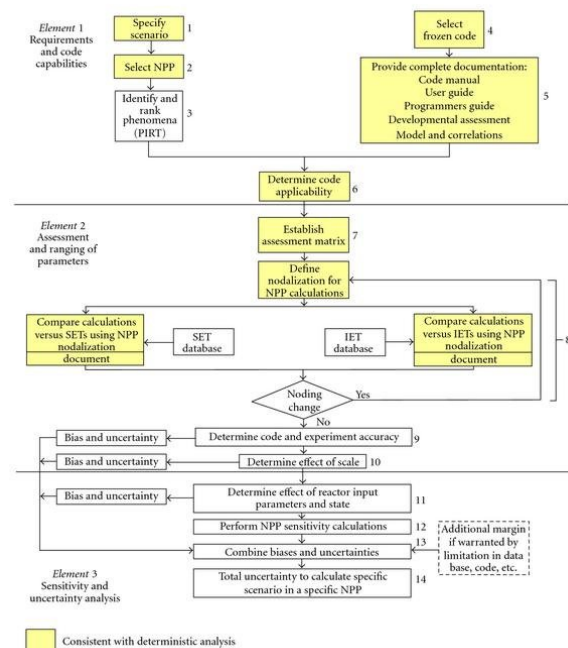


Fig. 1. The CSAU methodology framework

## 3. Application of machine learning

Machine learning is a kind of AI (Artificial Intelligence) to improve its skills and decision-making ability with basic data. The machine learning helps to find the pattern in a large amount of data so that proper prediction about the unknown result can be possible based on the model. The accuracy of the prediction can be increased based on the model update with additional data. However, there is a possibility of the model distortion because the system can understand the pattern of the data in wrong way, so the uncertainty of this method should be controlled properly.

There are three representative categories of machine learning; supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is used to a problem that involves both input and output pairs, which is called training sets. The model performs mapping between input and output pairs as shown in figure 2. There are two main algorithms in supervised learning; regression, and classification. Unsupervised learning is used when the data does not involve the clear input and output pairs. Instead constructing a fit model, the system extracts relationship in data compared to supervised learning. Clustering is an algorithm in unsupervised learning. Reinforcement learning is that the system learns the best approach using trial and error method. If there is a set of goals which can be achieved in a specific environment, the system progresses to get the optimized way for the objective based on the feedbacks. Deep learning using neural network is an example of the reinforcement learning.

Among these machine learning categories, supervised learning is considered to be suitable for application to the uncertainty analysis method of the severe accident because input and output of the sequence analysis can be defined as a training set. In the current uncertainty analysis method, the important parameters are only considered based on the results of the sensitivity analysis. If all parameters are considered in the analysis, the enormous number of simulations from the sampling should be required. Because of the limitation of cost and time, it is impossible to perform. But if the model between input and output can be constructed by the machine learning, the required number of simulations can be decreased. In other words, only with a limited number of simulations, the output can be predicted without additional simulations. Therefore, it is expected that the uncertainty analysis can be performed with all related parameters of the specific simulation code based on the plant type and the scenario for the objective phenomenon when the machine learning is applied in the method.

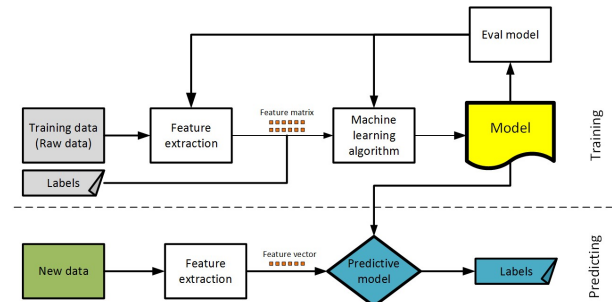


Fig. 2. A flowchart of a supervised machine learning model

#### 4. Conclusions

In this study, a simple conceptual approach to apply the machine learning in the uncertainty analysis method of severe accident was performed. Supervised learning method was considered for improving the uncertainty analysis method among three representative categories of machine learning based on the assumption that input and result of the simulation can be considered as a training data set. By applying the machine learning in the uncertainty analysis method, cost and time can be saved. It is expected that the method will be especially useful for a new type reactors that has more uncertainty than the original type reactors. However, uncertainty in the model constructed by the machine learning also should be quantified.

Detailed application process, and the uncertainty analysis for a sample severe accident phenomenon will be provided in further study. Other possible ways to apply the machine learning also can be discussed later.

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