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A Framework for the Applications of a Reduced Order Model to Enhance the Safety of Nuclear Power Plants in Terms of PSA

Kyungho Jin, Hyeonmin Kim, and Jinkyun Park*
Korea Atomic Energy Research Institute, 111, Daedeok-daero 989 beon-gil, Daejeon, Korea, 34057
**Corresponding author: kshpjk@kaeri.re.kr*

1. Introduction

Probabilistic safety assessment (PSA) has been widely used for many decades as a tool for securing the operational safety of nuclear power plants (NPPs). One of the typical benefits expected from the PSA is the identification of accident scenarios resulting in potentially undesirable consequences (e.g., core damage) that can be caused by the combination of both the failures of components and human errors involved in the operation of NPPs. If the catalog of accident scenarios are properly identified, it is expected that a series of countermeasures for strengthening the operational safety of NPPs can be effectively materialized. Nevertheless, many researchers have pointed out a couple of limitations related to the conventional PSA technique. One of the crucial limitations is the static nature of accident scenario identifications that are essential for obtaining more precise and accurate consequences [1]. The meaning of the term static used herein refers to the sequence of mitigations that does not change once determined. This implies that the identification of accident scenarios could have a large uncertainty because of a lack of reality on the progression of accident scenarios (i.e., static scenario identification). In order to resolve this issue, this study suggests an idea for the application of a reduced order model to the operational safety enhancement of NPPs by adopting a deep-learning technique.

2. Limitation of a static scenario identification

In the conventional PSA technique, the identification of accident scenarios largely depends on the analysis of a thermal-hydraulic (TH) code that can simulate the physical responses of an NPP in a specific initiating event such as a steam generator tube rupture (SGTR). As mentioned earlier, since the progression of accident scenarios will be affected by diverse combinations of both component failures and human errors, extensive TH code runs are inevitable for an NPP that is operated by many mechanical components and associated manual actions. Accordingly, it is impossible to analyze the consequence of all kinds of combinations using the TH code. For this reason, in the conventional PSA technique, the number of the TH code runs is reduced by considering several simplification approaches such as grouping similar accident scenarios or assuming conservative criteria with reasonable engineering judgements (e.g., manual actions to be carried out by human operators should be initiated in a specific timing after the reactor trip) [2-4]. This means that the results of the conventional PSA technique should have an uncertainty to some extent [5-6].

3. Reduced Order Model

One promising solution to resolve massive TH code runs is to use the reduced order model (ROM) of a TH code [7-8]. For example, Fig. 1 depicts a typical input for a TH code.

Time	Sequence
0	Reactor trip
100	CV-532 open (automatic)
	PP05 start (automatic)
	CV-514 open (automatic)
1000	PP06 start (manual)
	CV-530 open (manual)
...	...

Configuration change sequence

➔

Time (sec)	CV-530	CV-532	PP05	PP06	CV-514	...
0	Close	0%	Stop	Stop	Close	...
10	Close	0%	Stop	Stop	Close	...
20	Close	0%	Stop	Stop	Close	...
...	Close	0%	Stop	Stop	Close	...
100	Close	100%	Start	Stop	Start	...
...	Close	100%	Start	Stop	Start	...
500	Close	100%	Start	Stop	Start	...
...	Close	100%	Start	Stop	Start	...
1000	Open	100%	Start	Start	Start	...
...	Open	100%	Start	Start	Start	...
10,800	Open	100%	Start	Start	Start	...
...	...	...	...	...	...	...

TH code input

Fig. 1. Typical input for the simulation of a TH code.

If the TH code takes a couple of hours to simulate the trends of key process parameters (e.g., pressurizer pressure and reactor coolant temperature) with respect to the given input, then it is possible to think about the development of a ROM (or surrogate model) of the TH code. In other word, if we are able to create a reliable ROM that provides the results of a TH code within a very short time, it is strongly expect that the catalog of accident scenarios can be soundly obtained even though the explosion of required TH code runs. Indeed, many researchers showed that a deep-learning technique can be used for constructing reliable ROMs [9-12]. Figure 2 depicts the overall scheme to construct a ROM based on the input and output of a TH code.

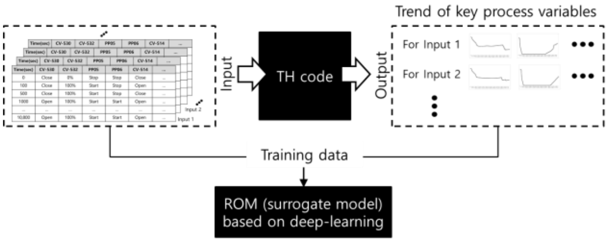

Fig. 2. Overall scheme to construct a ROM based on a TH code.

As can be seen from Fig. 2, the primary role of a ROM is to *emulate* the results of a specific TH code with respect to a series of inputs. If the ROM can generate credible results that are comparable with those of the TH code (e.g., 95% accuracy) within a very short time (e.g., less than 1s), it is possible to explore huge amount of accident scenarios that consist of the combination of diverse component status and manual actions. In other words, the dynamic features in accident progressions can be captured whereas the conventional PSA is limited to static progressions. Figure 3 visually outlines a framework that can be used to effectively search promising accident scenarios that are not discovered in the conventional PSA technique.

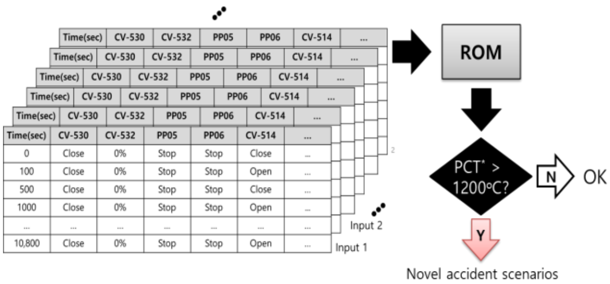

Fig. 3. A framework to explore accident scenarios using a ROM.

3. Conclusions

The framework depicted in Fig. 3 can significantly contribute to the operational safety of NPPs. For example, when an SGTR has occurred, diverse conditions affect the progression of the SGTR. These conditions may include but not limited to: (1) the activation timing of engineered safety features, (2) the response times of human operators who have to manipulate key components, and (3) human errors (e.g., do not open a valve or open a wrong valve). These conditions will be converted into diverse inputs (refer to Fig. 1) and a ROM generates the trends of key process parameters (e.g., peak cladding temperature, PCT) within a very short time. Once these trends are obtained, it is possible to determine the consequence of each condition (or input) based on diverse criteria being used for the conventional PSA technique (e.g., core damage is expected when PCT exceeds 1200ºC).

If this framework is applied to an extremely large number of promising conditions (corresponding to the inputs of a TH code), it is highly anticipated that novel accident scenarios that were not identified in the conventional PSA technique are distinguished with a manageable amount of resources such as time, cost and manpower. When these novel accident scenarios are successfully discovered, the operational safety of NPPs could be evolutionally improved if relevant practical countermeasures can be effectively materialized. Although further studies are indispensable for improving the credibility of ROM results (e.g., the accuracy of key parameter trends compared to those of a TH code), it is evident that this framework is a reasonable approach to evolutionally strengthen the operational safety of NPPs.

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