A Framework for the Dynamic Extension and Fast Progression Analysis of Accident Scenarios Using a Deep Learning Technique

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1. Introduction

Since the deep impression of Alpha-Go in March 2016, it is evident that the use of diverse deep learning techniques is an irreversible trend in many industries [1-7]. Although the underlying concepts of deep learning techniques are not different from those of machine learning techniques, the deep learning techniques have become very popular because of novel algorithms due to the increase of computing power [8]. Typical examples of novel algorithms would be convolution neural networks (CNNs), generative adversarial networks (GANs), variational autoencoder (VAEs), and recurrent neural networks (RNNs) such as a long short-term memory (LSTM) cell and gated recurrent unit (GRU) cell.

One of the key benefits expecting from these deep learning techniques is that it is possible to create an emulation system that can synchronize the repose (or behavior) of a target system. This expectation is known as *Universal Approximation Theorem (UAT)* [9]. The meaning of UAT is that, in theory, any kinds of functions can be properly modeled by the combination of networks. In this regard, this paper proposes the framework of a fast extension and progression analysis that would be effective for reducing the uncertainty of probabilistic safety assessment (PSA) results in nuclear power plants (NPPs).

2. Introduction to PSA technique

A PSA technique has been used for many decades to estimate the risk of NPPs. Without loss of generality, the PSA technique denotes: "The method or approach (1) provides a quantitative assessment of the identified risk in terms of scenarios that result in undesired consequences (e.g., core damage or a large early release) and their frequencies, and (2) is comprised of specific technical elements in performing the quantification [10]." This means that the crucial part of the PSA technique is to identify, as realistic as possible, plausible accident scenarios with associated frequencies that can cause undesired consequences (e.g., core damage or large early release frequency).

The problem is that, however, the number of accident scenarios will drastically increase for a complicated system that comprises of many systems or components, such as NPPs. Consequently, it is inevitable to run a tremendous number of a thermal-hydraulic (TH) code that specifies the consequence of each accident scenario. As a result, as depicted in Fig. 1, the number of accident scenarios to be considered in the PSA technique is not sufficient, which include the limited evolution of process variables, automated actions, and human actions [11, 12]. In addition, due to this problem, many people have criticized the uncertainty of PSA results for many decades.

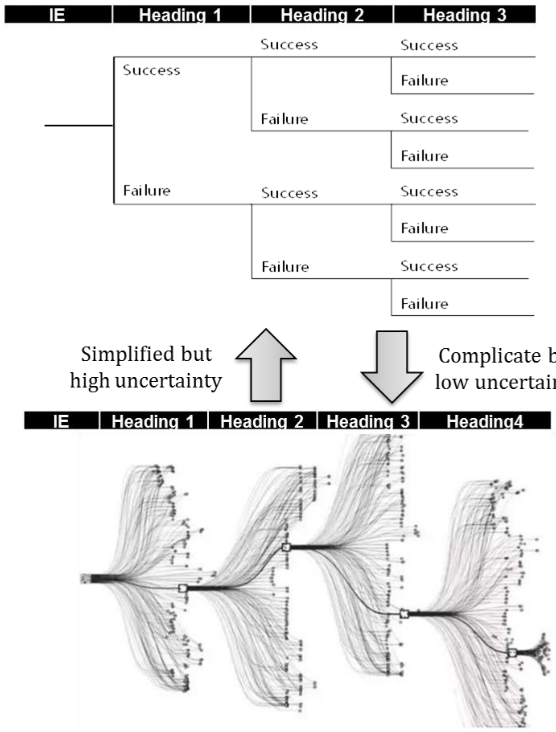

Figure 1. Uncertainty source of PSA results [13]

One promising solution for resolving this problem is to enlarge the number of accident scenarios through the combination of three important techniques: (1) diagnose PSA initiating event, (2) dynamic scenario extension, and (3) fast analysis of scenario progression.

3. Framework to reduce the uncertainty of PSA results

As mentioned in the previous section, in order to reduce the uncertainty of PSA results, it is indispensable to identify accident scenarios as many as possible. In this regard, this study proposed a framework as shown in Fig. 2.

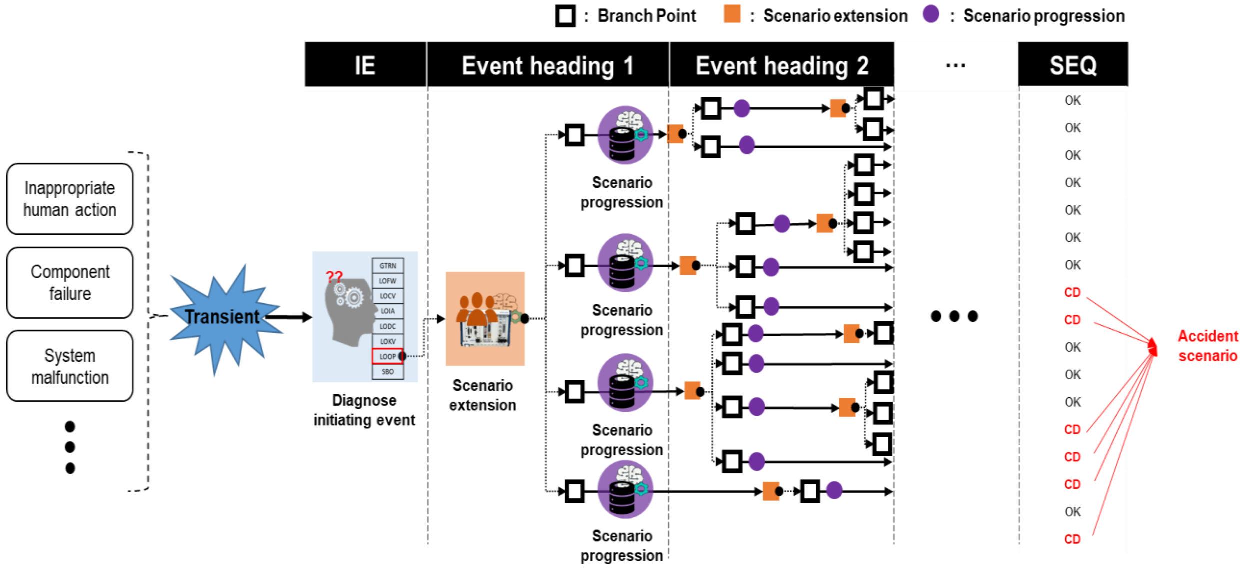

Figure 2. Framework to reduce the uncertainty of PSA results (IE: initiating event)

As can be seen from Fig. 2, the first step to identify the catalog of accident scenarios is the diagnose of PSA initiating events which could be originated from diverse causes such as inappropriate human actions, component failures, and system malfunctions. Once the initiating event is properly diagnosed, the next step is to dynamically generate plausible scenarios based on the branch conditions of each event heading. For example, let us consider the content of an arbitrary event heading such as 'Initiate cooldown reactor coolant system (RCS).' In this case, the time variability of the RCS cooldown initiation will be varied with respect to the nature of human operators (e.g., fast operators vs. slow operators) or the existence of human error (e.g., wrong manipulation). In addition, if human operators have to monitor several process parameters (e.g., pressure or temperature) in order to determine whether or not the initiation of RCS cooldown is necessary, then the time variability of the RCS cooldown initiation becomes more broad due to the trend of the associated parameters (e.g., fast vs. slow decrease of RCS pressure).

The last step to identify the catalog of accident scenarios is the fast progress analysis of all scenarios which are dynamically generated branch point in the second step. Generally, this step was done by the run of a precise TH code such as RELAP (Reactor Excursion and Leak Analysis Program) or MARS (Multi-dimensional Analysis of Reactor Safety). Unfortunately, as already mentioned in Section 1, each run of these TH codes takes too much time ranging from several hours to a day. This means that a technique that allows us to analyze the progress of each scenario within a short time period is the key to identify the catalog of accident scenarios.

4. Conclusion

As stated at the end of Section 3, the fast analysis of scenario progression is crucial for implementing the framework shown in Fig. 2 which can contribute to the uncertainty reduction of PSA results. In this regard, it is very interesting to emphasize that an RNN be a good resolution because Park and Yoon [13] and Park [14] demonstrated that a LSTM network can soundly provide the results of a specific TH code. Although there are many issues remain, which are critical for actual implementation of the framework depicted in Fig.2, it is expected that this framework would be a good starting point to enhance the quality of PSA results by reducing the underlying uncertainty of the PSA technique.

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