Development of a method for the fast progression of accident scenarios using deep learning techniques

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1. Introduction

A Probabilistic Safety Assessment (PSA) has been used to estimate the risk of Nuclear Power Plants (NPPs). For more accurate analysis, the PSA analysis should be performed, as realistic as possible. 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. The Fig. 1 shows the effect on uncertainty source of PSA results. To obtain equivalent results as the bottom of Fig 1, it is inevitable to run a tremendous number of a thermal-hydraulic (TH) code that specifies the consequences of each accident scenario. To handle this problem, as previous study, a framework for the dynamic extension and fast progression analysis of accident scenario was suggested [1]. In this paper, a deep learning based generative model for replacing a specific TH code is explained, which plays a critical role for implementing the fast progression analysis of accident scenario.

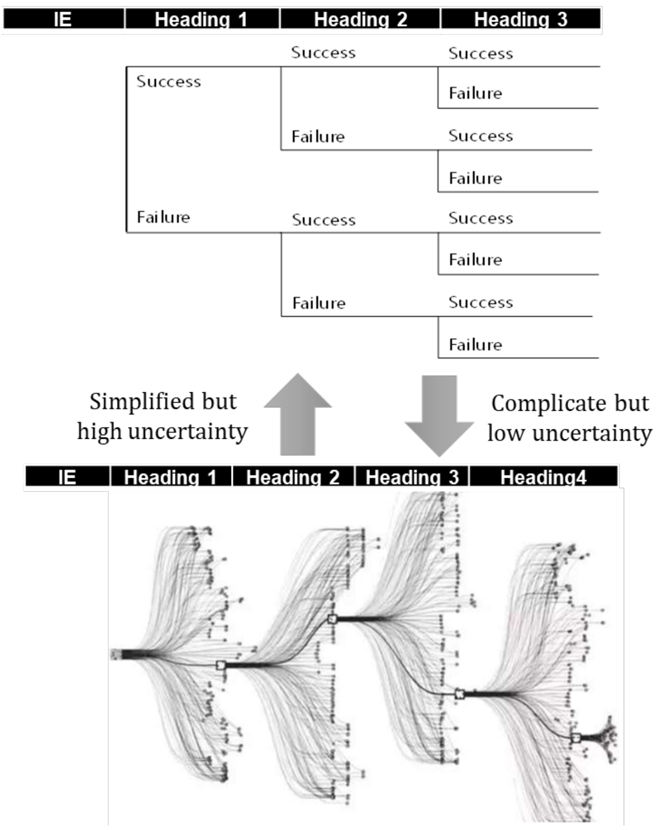

Figure 1. Uncertainty source of PSA results [2]

The deep learning techniques have become very popular because of novel algorithms due to the increase of computing power [3]. Thus, it is evident that the use of diverse deep learning techniques is an irreversible trend in many industries [4-10]. 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.

2. Deep learning model for synchronizing TH results

To develop fast progression system, the generative model is considered because it will be able to generate an accident scenario by using specific condition. The generative model is one of the applications of deep learning, recently, it shows remarkable performance in deep learning such as auto-encoder, Variational auto-encoder (VAE), Convolutional Neural Network (RNN), and Generative Adversarial Network (GAN). There are many deep learning models have been studied for image generation or image inpainting, however, the generating time series data (especially accident scenario data) relatively less researched.

The structure of the developed deep learning model is conditional auto-encoder (CAE) as illustrated in Fig. 2. The CAE is kind of auto-encoder which consists of encoder and decoder. The encoder compresses the data to reduce dimension (latent space in Fig. 2), and the decoder generates the original data. Thus, if we have an appropriate generative model, the original data can be obtained by only using latent space and decoder. With this characteristic of auto-encoder, the CAE can be calculated the original data what we want to train decoder with conditional input.

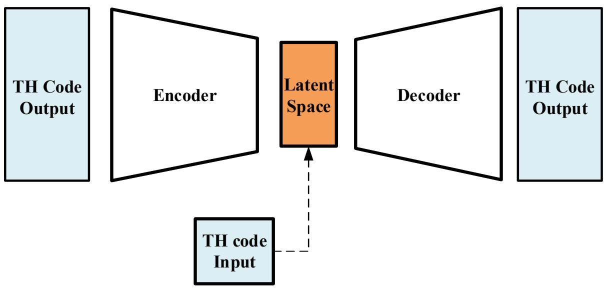

Figure 2. The schematic diagram of the developed deep learning model

As illustrated Fig. 2, developed model has TH code output (primary side pressure, primary side temperature, reactor power, etc.) as model input. The latent space is generated through encoder, then, the decoder generates TH code output. However, in case of just only using latent space, the TH code output does not include what we want to know. Thus, conditional input which is TH code input in case of our developed model is added to latent space, then, adequate result is generated from using latent space and conditional input.

3. Results

In order to validate deep learning model, the rapid cooldown operation in a small loss-of-coolant accident (SLOCA) in the APR-1400 NPPs was applied. TH analyses for the RCS rapid cooldown operation in SLOCA of the APR-1400 were performed with MARS (Multi-Dimensional Analysis of Reactor Safety)-KS code. Monte Carlo sampling and multiple TH simulations were performed utilizing MOSAIQUE code. The break sizes of SLOCA are 0.5, 1.0, 1.5 and 2.0 inch. Table 1 summarized variable distribution results as conditional input (TH code input in Fig. 2).

Table I: Variable distribution summary

Variable	Distribution
MSADV initial open time (seconds)	Lognormal Ln(X)~N(41, 0.38542)
RCS cooling fate (K/h)	Weibull (10.2, 0.019531)
Duration of available safety injection (seconds)	Fail-to-start (98%): 0.0s Fail-to-run(2%): p(t) p(t) = 1.61E-9*Exp(-1.61E-9*t)
RCS trip time (seconds)	Lognormal Ln(x)~N(13, 0.38542)

The length of simulation data is different depending on break size of SLOCA. However, the input length of developed model is same at all cases, hence, simulation length was equally truncated. The input data was normalized by min-max-scaler and split by train, validation, and test. The sizes of each samples are 6404, 160, and 1441. Total data size is 8005. The CAE has the encoder and the decoder. The encoder and the decoder have symmetrical structure. In this paper, the encoder structure has 3 layers that consist of different number of nodes (10, 95, 190, and 380). The more detailed explanation of suggested model is summarized in Table 2. The Xavier initialization method was applied. After the completion of data generation, moving average was performed with 20 windows.

Table II. summary of deep learning model

Parameter	Value
Activation function	Relu
Optimizer (epsilon)	Adam (0.1)
Learning rate	0.00005
Cost function	Mean Squared Error
Epoch	50,000
Batch size	10

The Fig. 3 and 4 show the results of developed model. The blue line indicates true values from MARS, and, the orange line indicates prediction. The average accuracy is 0.45% and standard deviation is 0.51%.

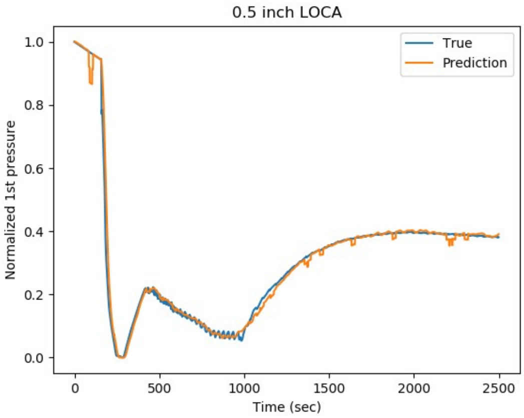

Figure 3. The results of 0.5 inch LOCA

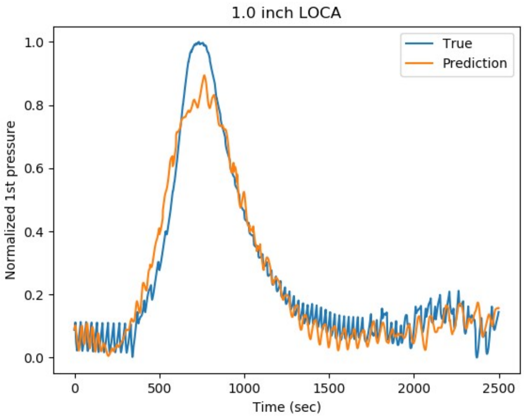

Figure 4. The results of 1.0 inch LOCA

4. Conclusion

In this paper, a deep learning based generative model for replacing a specific TH code was developed. The developed model follows trend of accident scenarios with high accuracy. In addition, the calculation speed is 0.01 seconds for one simulation. Using this technique, the PSA model can seek more realistic results and less uncertainty results because of considering more sequences.

For the further study, fixed length problem will be solved. The fixed length problem means the auto-encoder has always same length for all cases, however, the accident scenarios have not same time sequences.

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