A data generation system for simulating nuclear thermal-hydraulic model using deep learning

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1. Introduction

Since the deep learning technology is introduced at 2010s, deep learning applications shows remarkable performance in social, industrial, and so on [1-3] The deep learning is representative the data, in other words, deep learning finds the representative equations from data by figuring out relations of data. Thus, obtaining high quality data is key factor of deep learning applications performance.

Many studies are performed to apply deep learning to the nuclear engineering [4, 5]. Though there are many technical hurdles to developing a deep learning model in nuclear engineering, the data acquisition will be a general technical hurdle due to features of nuclear engineering (such as massive facilities and radiation effect). Generally, nuclear engineering is hard to secure real data, particularly in the field related to nuclear accidents. Thus, to obtain data in nuclear engineering, simulation code is well used. In fields related to nuclear accidents, it is used the thermal-hydraulic (TH) codes such as Reactor Excursion and Leak Analysis Program (RELAP), Multi-dimensional Analysis of Reactor Safety (MARS), and Modular Accident Analysis Program (MAAP). Even though TH code could be used, it takes several minutes to hours per a simulation. However, to cover up all accident, it is necessary to numerous code run. Thus, in this study, the data generation system using Nuclear Plant Analyzer (NPA) is developed [ ]. The purpose of this systems is to generate huge amount of data for learning of deep learning applications in a short period. In order to consider various accident scenarios, Emergency Operating Procedure (EOP) is analyzed.

2. Methods

This section describes a summarized description of the NPA code, considered conditions to generate diverse accident scenarios, and parallel processing.

2.1 Nuclear Plant Analyzer (NPA)

NPA is developed that aims to serve the information which needs normal and abnormal operation by predicting and analyzing the operating characteristics of the Korean Standard Nuclear power Plant (KSNP) by the Korea Institute of Nuclear Safety (KINS). In addition, it will perform real-time best-estimate simulations of nuclear power plants with higher quality, fidelity, and accuracy.

The NPA is based on the CENTS code [6] and is composed of a three-dimensional reactor core, nuclear steam supply system, chemical and volume control system, safety injection system, turbine and feedwater system, auxiliary systems, electric system, and various control systems.

Though NPA has various components and systems, the calculation time is within several seconds. Thus, it has a strength which is fast simulation. In this study, parallel computing has been applied for underlying various conditions with the NPA code.

2.2 Analyzing conditions for data generation

In order to generate various accident scenarios, the EOP has been analyzed. EOP has been described the action of an operator during up to core damage after the trip. The accident scenario can be greatly affected depending on performance of the EOP. There is a realistic constraint to analyze all the accident scenarios, only Steam Generator Tube Rupture (SGTR) was selected as a representative accident by existing accident histories. Considerations for selecting a representative procedure stage that can affect the progress of the accident scenario in SGTR are summarized as follows:

- Simplify accident conditions as possible to exclude in case of infringing representative characteristics.
- No consideration for long-term action that is expected to be carried out after 3 hours

The table and figure below show the procedure stage 4.0 of EOP related SGTR, for example.

Table I: stage 4.0 of EOP related to SGTR

Monitoring condition	Monitoring ID
124.5kg/cm^{2}A or less of pressurizer pressure	1
Initiate SIAS	2
Initiate CIAS	3

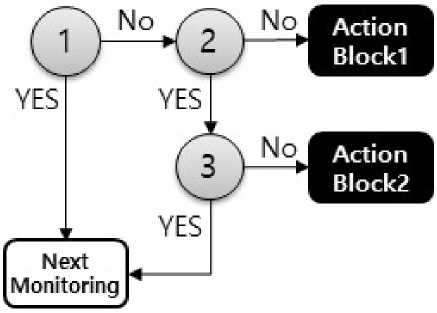

Fig. 1. The monitoring rule and action block from analyzing EOP related to SGTR

Through a total of 12 significant procedures analyzed, 45 monitoring and 34 control rules have been identified. In addition, operator manual actions that could affect the accident progression have been added to the specified monitoring and control rules. In the operator's manual actions, it was considered as a 1) execution time, 2) operator error, and 3) action level. From these considerations have generated a total number of 14,348,907 accident scenarios.

2.3 Parallel processing

The parallel processing used Multiprocessing which is a library of Python 3. The hardware for parallel processing consists of 256 cores. Within a massive data generation system, NPA calculation is executed. After that, post-processing for deep learning is also performed and sent to a data server. Post-processing consists of determining fail/success based on the event tree, replacing for Nan and infinite value, and converting the NumPy array.

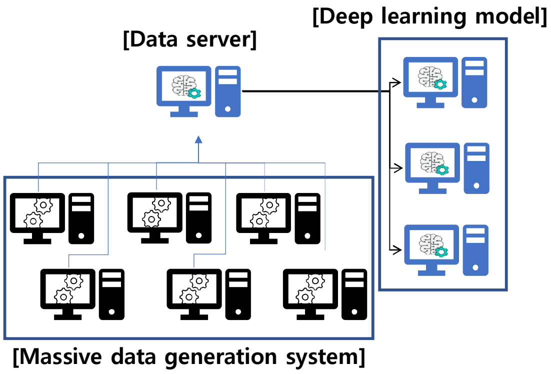

Fig. 2. The schematic diagram for data generation system by adopting parallel processing

3. Results and Conclusions

Fig. 3. shows the NPA results considering various conditions based on analyzing EOP. Thanks to parallel processing, the calculation speed has been reduced within 30 days for 14,348,907 accident scenarios.

In this study, a system for generating huge amounts of data for training of deep learning model has been developed. The generated data by the developed system will be provided as a trained deep learning model. A trained deep learning model will be helped to enhance model performance in other applications by using the transfer learning technique.

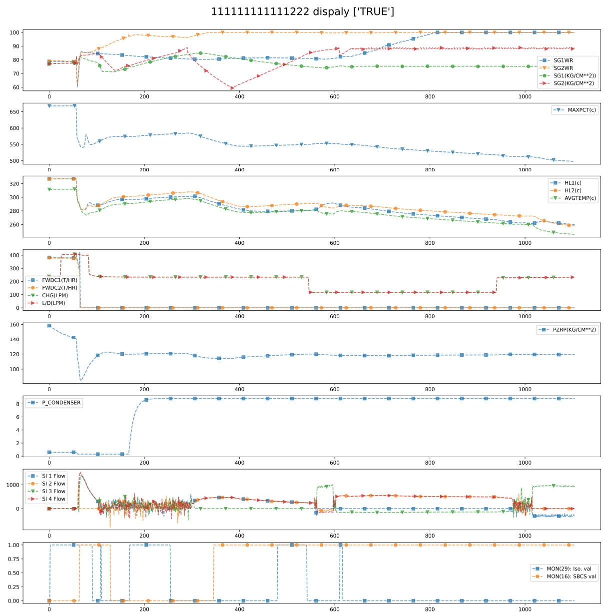

Fig. 3. The NPA results considering various conditions based on analyzing EOP

Acknowledgements

This work was supported by a Nuclear Research & Development Program grant from the National Research Foundation of Korea (NRF), funded by the Korean government, Ministry of Science and ICT (Grant Code: NRF-2019M2C9A1055906).

REFERENCES

[1] A.M. Abbas, "Social network analysis using deep learning: applications and schemes." Social Network Analysis and Mining, 11.1 (2021): 1-21.
[2] C. Shorten, T.M. Khoshgoftaar, B. Furht, "Deep Learning applications for COVID-19." Journal of big Data, 8.1 (2021): 1-54.
[3] S. Sengupta, S. Basak, P. Saikia, S. Paul, et al., "A review of deep learning with special emphasis on architectures, applications and recent trends." Knowledge-Based Systems, 194 (2020): 105596.
[4] H. Kim, J. Cho, and J. Park, "Application of a deep learning technique to the development of a fast accident scenario identifier." IEEE Access, 8 (2020): 177363-177373.
[5] S. Ryu, et al., "Probabilistic deep learning model as a tool for supporting the fast simulation of a thermal–hydraulic code." Expert Systems with Applications 200 (2022): 116966.
[6] ABB Power Plant Controls, “Technical Manual for the Nuclear Plant Analyzer CENTS Models Rev. 1,” ABB Power Plant Controls, 1994