Production of Deep Learning Data Base for Accident Source Term Estimation

Sung-yeop Kim *, Soo-Yong Park
Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daejeon, 34057, Republic of Korea
**Corresponding author: sungyeop@kaeri.re.kr*

1. Introduction

Estimation of accident source term is an important procedure to protect public in the event of NPP (nuclear power plant) accident. By the Korean law of radiation protection [1], in case of a radiation emergency, population in the PAZ (precautionary action zone) is evacuated precautionary to prevent deterministic health effects and population in the UPZ (urgent protective action planning zone) is determined to evacuate by radiation monitoring or dose assessment using a computational code in order to reduce stochastic health effects. When performing a dose assessment, providing a source term information quickly and accurately is vital as the starting point of radiological consequence analysis.

The definition of source term is information about a release of radioactive materials to the environment in the event of an accident. Information of source term includes magnitude of release and manner of release. Magnitude of release means amount of release and manner of release contains starting time of release, duration of release, height of release, energy of release, particle size distribution of release, and etc. Frequency of a release is also an important factor, when performing a PSA (probabilistic safety assessment).

When Fukushima Daiichi accident happened, SPEEDI (System for Prediction of Environmental Emergency Dose Information) failed to estimate accident source term and could not be utilized to assist the decision of public protection [2]. From the experience of Fukushima Daiichi accident, importance of a system to provide accurate and quick source term estimation was highly increased.

In a recent study performed by KAERI (Korea Atomic Energy Research Institute), deep learning approach is employed to perform a rapid and accurate source term estimation and overcome the limitation of the current source term estimation technics. In order to conduct deep learning, generation of DB (data base) for learning and validation is a mandatory procedure. In order to build DB, selecting important input & output parameters and selecting important scenarios are also necessary. In this study, as the previous steps to develop a deep learning model, the ways and procedures are introduced such as how important input and out parameters for learning are selected, how representative severe accident scenarios were selected, and how DB was generated.

Overall strategy of deep learning modeling to estimate accident source term is introduced in Yoon et al., 2021 [3].

2. Methods and Results

The major objective of this study is predicting an accident source term quickly and accurately from information provided by AtomCARE (Atomic Computerized Technical Advisory System for a Radiological Emergency). Therefore, learning and validation DB should be produced in order to achieve the main objective of the study.

2.1 Selection of Major Input and Output

After reviewing various parameters which can be obtained from the AtomCARE [4], 25 parameters were chosen as learning inputs highly related with source releases. Then, these parameters were mapped with corresponding MAAP (Modular Accident Analysis Program) parameters, since DB are established by performing severe accident analyses using MAAP5 code in this study. As the order of an AtomCARE parameter is not always same with that of corresponding MAAP parameter, it is necessary to match them by treating the print of MAAP output. Selected parameters as deep learning input are as follow:

- Pressure in pressurizer
- Collapsed water level in pressurizer
- Collapsed water level in Rx-vessel
- Temperature of water in loop 1 hot leg
- Water mass flow in cold leg 1A
- Water mass flow in cold leg 1B
- Water mass flow in cold leg 2A
- Water mass flow in cold leg 2B
- Pressure in the S/G 1
- Pressure in the S/G 2
- Collapsed water level in the S/G 1
- Collapsed water level in the S/G 2
- Temperature of gas in loop 1 upper plenum
- Hottest core node temperature
- Pressure in accumulator
- High pressure injection system flowrate
- Low pressure injection system flowrate
- Containment spray system flowrate
- Water level in refueling water storage tank
- Pressure in containment building compartment #3
- Temperature of gas in containment building compartment #3
- Collapsed water level in containment building compartment #2

- Collapsed water level in containment building compartment #6
- Mole fraction of H2 in containment building compartment #3

A release of radioactive materials can be directly expressed as release amount by mass (g) or radioactivity (Bq). Another way to express the amount of release is the release fraction multiplied by core inventory. Release fraction can be a more general choice as the output for deep learning because a core inventory can vary by burnup and other conditions and release amount is dependent on the core inventory. Accordingly, release fraction of 22 elements in Table I was chosen as the output of deep learning.

Table I: Release Fraction of Selected Elements

MAAP Variables and Corresponding Elements [5]			
FMRELEL(1)	Xe	FMRELEL(12)	Mo
FMRELEL(2)	Kr	FMRELEL(13)	Tc
FMRELEL(3)	I	FMRELEL(14)	Ru
FMRELEL(4)	Rb	FMRELEL(15)	Sb
FMRELEL(5)	Cs	FMRELEL(16)	Te
FMRELEL(6)	Sr	FMRELEL(17)	Ce
FMRELEL(7)	Ba	FMRELEL(18)	Pr
FMRELEL(8)	Y	FMRELEL(19)	Nd
FMRELEL(9)	La	FMRELEL(20)	Sm
FMRELEL(10)	Zr	FMRELEL(21)	Np
FMRELEL(11)	Nb	FMRELEL(22)	Pu

2.2 Selection of Accident Scenario

Phenomena of severe accidents, such as pressure boundary break, DCH (direct containment heating), MCCI (molten core concrete interaction), steam generation, and hydrogen generation progress totally different with RCS (Reactor Cooling System) pressure. Therefore, LOCA (loss of coolant accident) representing low RCS pressure and transient representing high RCS pressure were selected as representative accident scenarios. By referring to the contribution to the CDF (core damage frequency) of a reference PWR (pressurized water reactor), MLOCA (medium LOCA) and TLOCCW (total loss of component cooling water) were chosen as representative initiating event for LOCA and transient, respectively.

2.3 Establishment of Data Base for Deep Learning

For MLOCA scenario, as shown in Fig. 1, 22 branch scenarios were categorized by the operation of safety systems and 12 branch scenarios were selected which are covering 99.99% of CDF (Core Damage Frequency).

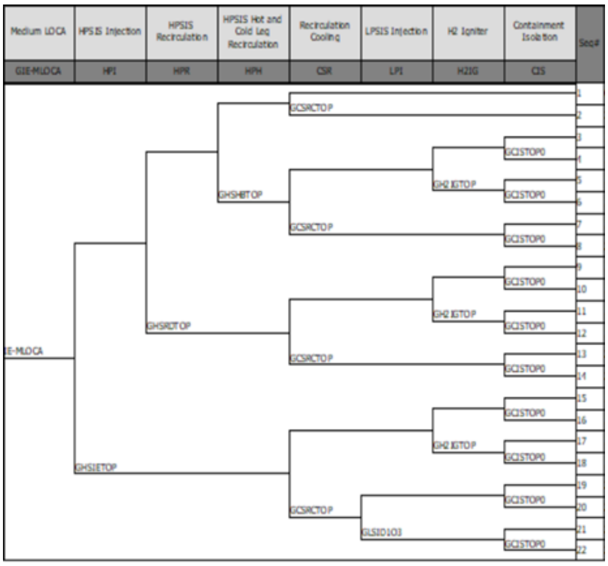

Fig. 1. Event Tree of Safety System Operation in MLOCA Scenario

For those 12 detailed scenarios, a large numbers of sampling cases were produced by break size and other uncertain variables of MAAP code. These sampling cases were defined as analysis cases and input DB and output DB were produced by performing MAAP5 analyses for each analysis case.

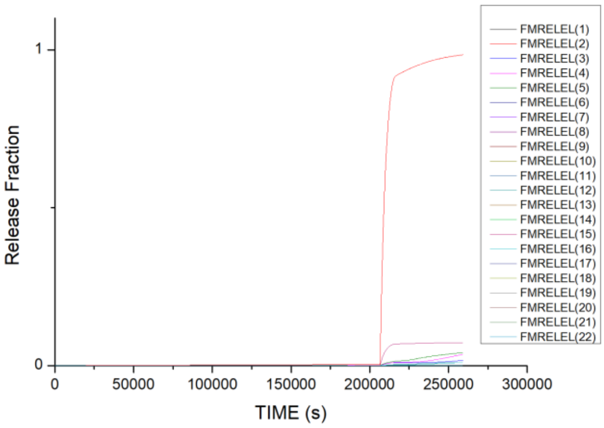

Fig. 2. Example of Deep Learning Output Data (Linear Scale)

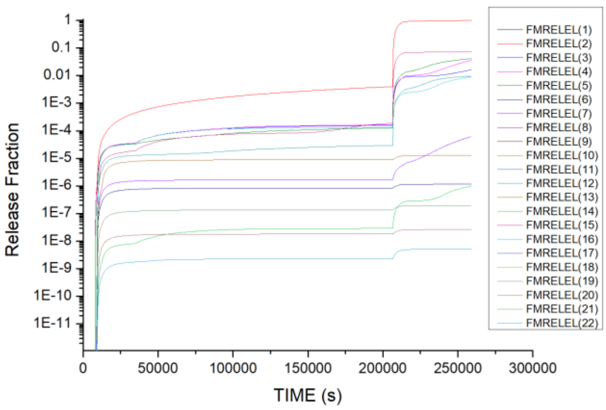

Fig. 3. Example of Deep Learning Output Data (Log Scale)

Fig. 2 and Fig. 3 show the examples of output data for deep learning depicted in linear scale and log scale, respectively. A large amount of learning and validation DB was established to develop a deep learning model to estimate accident source term.

3. Conclusions

In order to develop a quick and accurate source term estimation method, deep learning technic was employed in a recent research of KAERI. In order to produce a learning and validation DB, important variables were selected as input and output of DB and representative severe accident scenarios were also chosen. Finally, deep learning DB was built as a previous step to develop a deep learning model.

4. Further Work

DB is possibly updated by the feedback during developing a deep learning model.

Acknowledgements

This work was supported by a Korea Foundation of Nuclear Safety (KOFONS) grant funded by the Korean government (NSSC: Nuclear Safety and Security Commission) (No. 1805018).

REFERENCES

[1] NSSC, Article 20-2 (Establishment of Radiation Emergency Planning Zones), Act on Physical Protection and Radiological Emergency, Act No. 16574, Nuclear Safety and Security Commission, Aug. 27, 2019.
[2] NRA, About the Operation of SPEEDI in an Emergency Situation (緊急時迅速放射能影響予測ネットワークシステム(SPEEDI)の運用について), Japan Nuclear Regulation Authority, 2014. 10. 8.
[3] J. Y. Yoon, K. O. Song, K. H. Jin, S. Y. Kim, Deep Learning Modeling Strategy to Estimate Accident Source Term, Transactions of the Korean Nuclear Society Autumn Meeting, October 21-22, 2021, Changwon, Korea.
[4] KINS, Functionality Advancement of AtomCARE, KINS/GR-509, Vol.2, Korea Institute of Nuclear Safety, 2013
[5] EPRI, Modular Accident Analysis Program – MAAP5 v5.05 for Windows, Electric Power Research Institute, 2019.