Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 18-19, 2023

Verification of the Approach to Estimate Accident Source Term Using Deep Learning

Sung-yeop Kim [a*], Soo-Yong Park [a], Yun Young Choi [b]
[a]*Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daejeon, 34057, Republic of Korea*
[b]*National Institute for Mathematical Science, Yuseong-daero 1689-70, Yuseong-gu, Daejeon, 34047, Republic of Korea*
[*]*Corresponding author: sungyeop@kaeri.re.kr*

1. Introduction

The need to improve source term estimation technology in the event of nuclear power plant accident has been steadily emphasized. An innovative source term estimation method using deep learning was developed and introduced in the previous studies [1, 2]. In the initial stage, deep learning modeling strategy [3] was established and learning data base (DB) [4, 5] was constructed by a large number of calculations using MAAP5 [6] severe accident analysis code. In order to investigate feasibility, scenarios representing low- and high-pressure conditions of reactor coolant system (RCS) of OPR 1000 have been selected. Medium-break loss of coolant accident (MLOCA) scenario, which represents low-pressure condition, consists of 9 sub-scenarios by plant damage state event tree (PDS ET). In the same way, total loss of component cooling water (TLOCCW) scenario, which represents high-pressure condition, is comprised of 3 sub-scenarios. 24 safety parameters of nuclear power plant that are highly related with accident source term were selected as learning input by expert judgement:

- PRESSURIZER PRESS (WR)
- PRESSURIZER LEVEL CH X
- REACTOR VESSEL WATER LEVEL
- AVG TEMP OF HOT & COLD LEGS
- COLD LEG 1A MASS FLOW (1)
- COLD LEG 1B MASS FLOW (2)
- COLD LEG 2A MASS FLOW (3)
- COLD LEG 2B MASS FLOW (4)
- SG 1 PRESSURE CH A
- SG 2 PRESSURE CH A
- SG 1 LEVEL (WR)
- SG 2 LEVEL (WR)
- MAX REP CORE EXIT TEMP
- HIGHEST CET TEMP - CHANNEL A
- SAFETY INJ TANK PRESS (NR)
- HPSI PUMP FLOW
- LPSI PUMP DSCH HEADER FLOW
- CONTAINMENT SPRAY FLOW
- REFUELING WATER TANK LEVEL
- CONTAINMENT PRESS CH A (NR)
- CNMT AVERAGE TEMP
- CNMT WATER LEVEL CH A
- CNMT RECIRC SUMP LEVEL CH A
- H2 CONCENT. LEVEL(CH.A)

Release fractions of three major elements (Xe, Cs, and I) were set as deep learning output [2].

300 MAAP calculations for each scenario considering uncertainties relevant with break size, operator action time, and code itself were conducted and constructed the learning DB [4, 5].

A global deep learning model which can be used to diagnose severe accident [7, 8] and estimate source term [1, 2] was developed. Diagnosis of severe accident means classification of 12 sub-scenarios. Developed deep learning model is employing Transformer encoder [9, 10], fully connected layer, and AdamP optimizer [11, 12] as depicted in Fig. 1. It has been confirmed that the classification accuracy of the model is above 95% when 20,000-sec (about 5.56 hr) data after the accident initiation is obtained from a nuclear power plant. 99% classification accuracy is guaranteed when 30,000-sec (about 8.33 hr) data is received. And accuracy was verified once more by conducting blind test [7, 8].

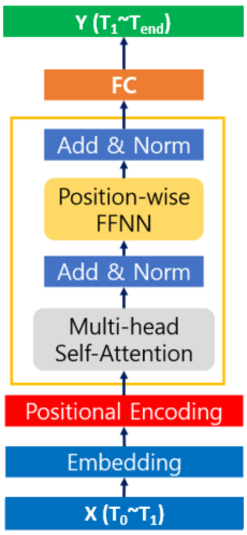
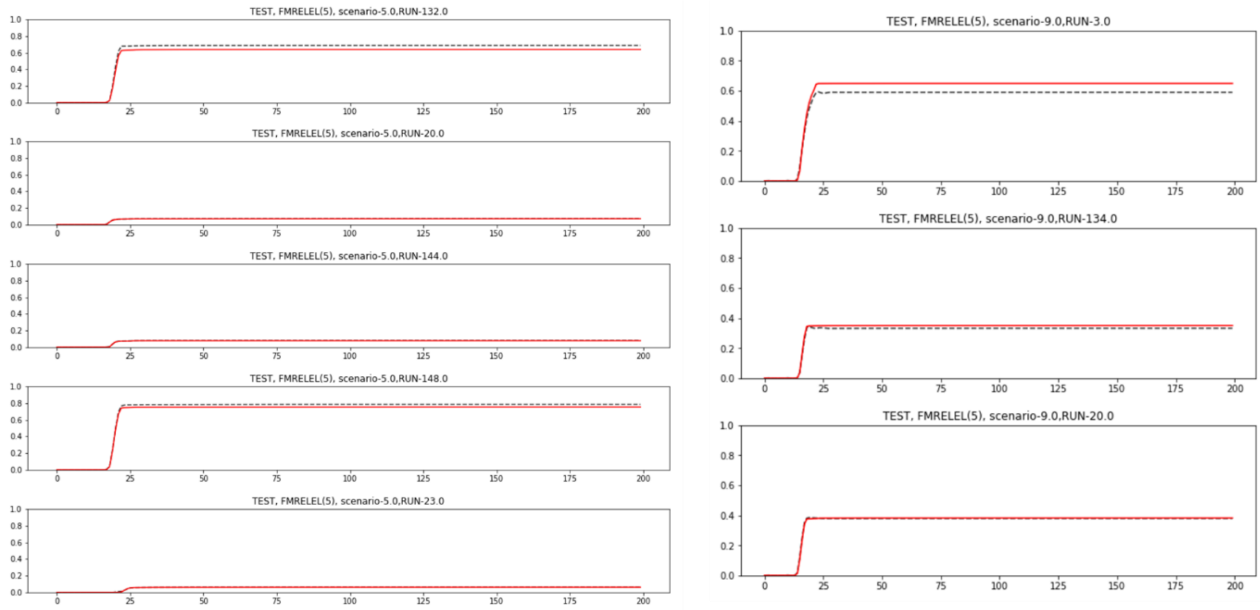


Fig. 1. Structure of the Deep Learning Model for source term estimation

The deep learning model shows decent source term prediction results for most 12 sub-scenarios. Example results of source term prediction for cesium, when 30,000-sec (about 8.33 hr) NPP data is received, are presented in Fig. 2 [1, 2]. Similar to the severe accident diagnosis, it is necessary to verify the results derived from the deep learning model for the purpose of source term estimation. Verification of the deep learning model to estimate accident source term was carried out and introduced in this study.



Y-axis: Normalized release fraction to maximum release fraction / X-axis: 72 hours expressed as 200 time steps
Fig. 2. Example Results of Source Term prediction for Cesium: ML-05 Scenario (Left) and ML-09 Scenario (Right) [1, 2]

2. Methods and Results

In order to verify the developed deep learning model, DB comprising 100 MAAP calculations for each sub-scenario was established separately [2]. For the verification DB, sampling to develop MAAP input considers only the uncertainties derived from the code. The uncertainties related with break size and operator action time were excluded since they incur wide band of results. Those uncertainties are considered only to establish learning and testing DB when the deep learning model was developed. In other words, verification DB shows narrower band than learning and testing DB [4, 5]. Therefore, if predicted source term exists in the band of verification DB, developed deep learning model can be evaluated as estimating accident source terms appropriately.

Fig. 3 and Fig. 4 show the examples of the verification results for several sub-scenarios. Gray line shows 100 uncertainty analysis results and their band. Blue and red line mean true value and predicted value, respectively. As described in the figures, it can be confirmed that most predicted values locate in the uncertainty band, though not every line precisely follows real value.

3. Conclusion

In order to overcome the limitation of existing methods and improve the accuracy and speed of severe accident diagnosis and source term estimation, an approach employing deep learning has been developed.

Not only development of an approach but also verification of the approach is very important and essential. In the previous study [7, 8] verification of severe accident diagnosis using developed deep learning model has been performed. In this study, verification of source term estimation using the deep learning model was conducted and appropriateness of using deep learning model was evaluated. It was confirmed that the source term prediction result using developed deep learning model exist in the uncertainty band for most scenarios considered in this study.

4. Limitations and Further Work

Only two representative scenarios that are MLOCA and TLOCCW were considered in this study, in order to confirm the feasibility of the approach. A framework and approach adopting deep learning has been developed and verified for representative scenarios in the previous studies. It is expected to be extended to all initiating event of OPR100 and other reactor types in subsequent studies.

In this study, input data length received from a nuclear power plant was fixed at 30,000 seconds. It is planned to develop a adaptive model which improves the accuracy as the data reception time increases.

It is necessary to check the feasibility of installing the approach to AtomCARE [13] as an option of source term estimation system (STES)

Acknowledgements

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT: Ministry of Science, ICT) (No. RS-2022-00144405).

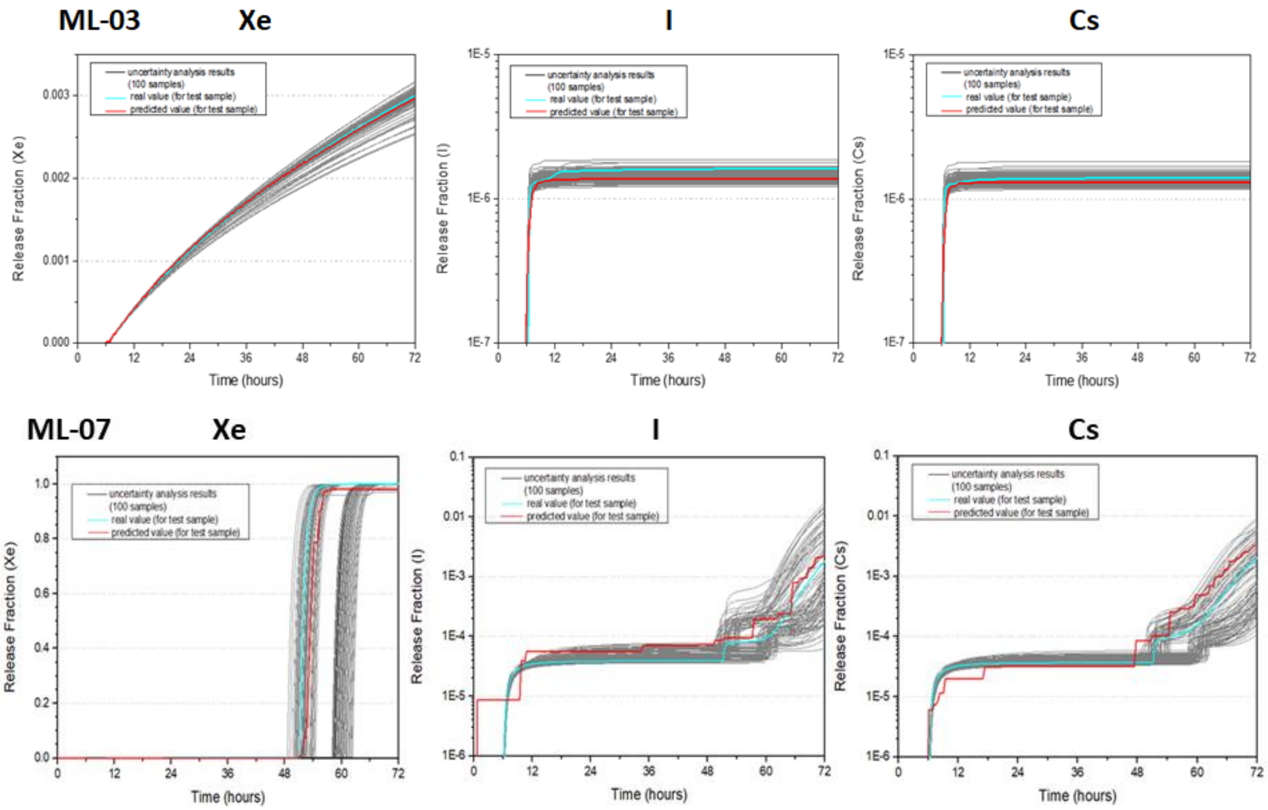


Fig. 3. Examples of the verification results for MLOCA scenario

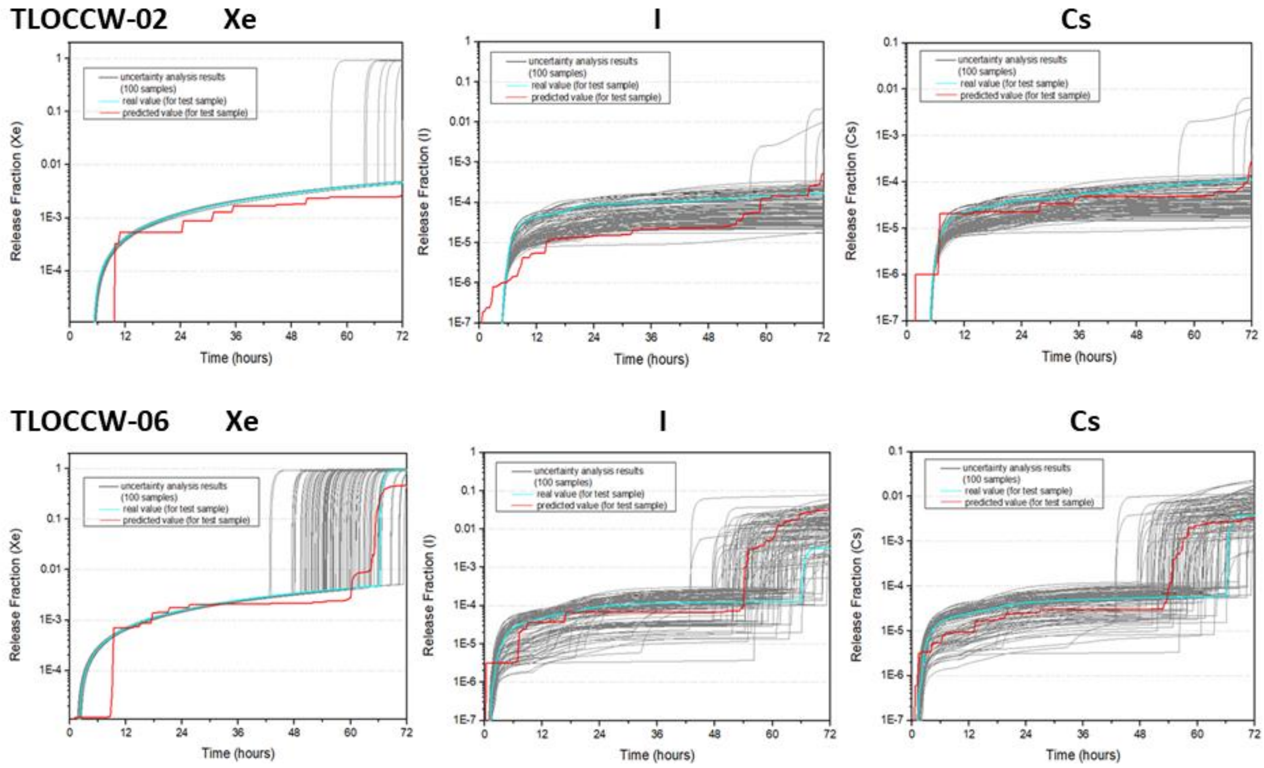


Fig. 4. Examples of the verification results for TLOCCW scenario

REFERENCES

[1] S.Y. Kim, Y.Y. Choi, and S.Y. Park, Application of Deep Learning Models to Estimate Source Release of NPP Accidents, Probabilistic Safety Assessment and Management 16, Honolulu, Hawaii, June 26-July 1, 2022.
[2] S.Y. Kim, S.Y. Park, and H.K. Shin, Development of a Deep Learning Model for Nuclear Power Plant Accident Source Term Estimation, NSTAR-22RS42-313, KAERI/TR-9301/2022, 2022.
[3] J.Y. Yoon, K.O. Song, K.H. Jin, and 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] S.Y. Kim and S.Y. Park, Production of Deep Learning Data Base for Accident Source Term Estimation, Transactions of the Korean Nuclear Society Autumn Meeting, Changwon, Korea, October 21-22, 2021.
[5] S.Y. Kim, S.Y. Park, J.Y. Yoon, K.O. Song, and K.H. Jin, Construction of Severe Accident Analysis DB for Deep Learning of Source Term Estimation, NSTAR-21RS42-395, 2021.
[6] EPRI, Modular Accident Analysis Program – MAAP5 v5.05 for Windows, Electric Power Research Institute, 2019.
[7] S.Y. Kim, S.Y. Park, and H.K. Shin, Development of a Deep Learning Model for Nuclear Power Plant Severe Accident Diagnosis, NSTAR-22RS42-311, KAERI/TR-9300/2022, 2022.
[8] S.Y. Kim, Y.Y. Choi, S.Y. Park, O.K. Kwon, and H.K. Shin, Nuclear Power Plant Severe Accident Diagnosis Using Deep Learning Approach, Journal of the Korea Industrial Information Systems Research, Vol.27, No.6, pp. 95-103. 2022.
[9] C. Chen, Q. Fan, and R. Panda, CrossViT: Cross-Attention Multi-Scale Vision Transformer for Image Classification, Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pp. 357-366, 2021.
[10] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, Ł. Kaiser, and I. Polosukhin, Attention is All You Need, Advances in Neural Information Processing Systems 30, 2017.
[11] D. Kingma and J. Ba, Adam: A Method for Stochastic Optimization, arXiv:1412.6980v9, 2017.
[12] B. Heo, S. Chun, S. Oh, D. Han, S. Yun, G. Kim, Y. Uh, and J. Ha, Adamp: Slowing Down the Slowdown for Momentum Optimizers on Scale-invariant Weights, arXiv:2006.08217, 2020.