Application of Deep Learning Models to Estimate Source Release of NPP Accidents

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Abstract: In the event of NPP (nuclear power plant) accident, estimation of source release should be performed quickly and accurately in order to support the decision of public protection. In case of Fukushima Dai-ichi NPP accident, even though SPEEDI (System for Prediction of Environmental Emergency Dose Information) has been developed and prepared, it was not used to support the decision making of public protection due to the lack of source term information which should be provided from the system. In order to overcome the limitation of existing methods in aspect of quick and accurate source term estimation, deep learning approach using various NPP safety parameters as the learning input and releases of radioactive materials as the learning output is applied in this study. It was tried to search and apply variety of deep learning models such as eQRNN, ANN with pre-assigned function, and Transformer encoder with fully connected layer, in order to find and develop an optimized deep learning model to estimate the source release of NPP accidents.

1. INTRODUCTION

Source term estimation is mandatory procedure to provide the information of the releases of radioactive materials into the environment and quick and accurate estimation is necessary especially in emergency situations such as NPP (nuclear power plant) accident. Decision of public protection can be decided appropriately when reliable data is supported. In case of Fukushima Dai-ichi NPP accident SPEEDI (System for Prediction of Environmental Emergency Dose Information) could not be used to make the decision of public protection [1]. One of the major reasons was that source term information could not be properly provided to calculate public dose. This experience reminded the importance of quick and accurate estimation of source term information.

Though, there can exist high uncertainty in severe accident analyses, it takes a long time to calculate relatively accurate source release using various input data from an NPP and severe accident analysis codes such as MAAP (Modular Accident Analysis Program) or MELCOR. Oppositely, simple source term estimation codes using limited data from an NPP can perform relatively quick estimations but cannot guarantee the accuracy of a calculation. In this study, deep learning approach is employed in order to aim at both speed and accuracy of accident source term estimation.

AtomCARE (Atomic Computerized Technical Advisory System for a Radiological Emergency) assists decision making of public protection in a radiological emergency in Korea. A variety of NPP information is sent to AtomCARE from NPPs. Important NPP parameters related with source release and release rates of radionuclides are adopted as input and output of deep learning, respectively, in this study. MAAP was used to build DB (database) of input and output for learning and testing in accident scenarios. Figure 1 shows deep learning modeling strategy established in a previous work [2].

In another previous work [3], by reviewing NPP parameters, 24 parameters regarded as highly related with accident scenario and source release were selected as learning and testing input. MAAP code can consider 25 kinds of chemical elements and some elements have same release fraction since they have similar chemical characteristics. Radionuclides can be categorized into 12 groups and release fractions of 12 chemical group were selected as learning and testing output. Table 1 and Table 2 present input and output for learning and testing, respectively.

Figure 1: Deep Learning Strategy to Estimate Source Term Release [2]

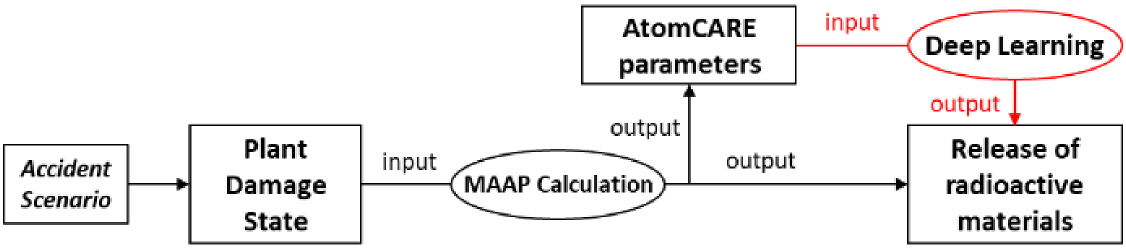


Table 1: Deep Learning Input

No.	Parameter Definition	Unit	MAAP Variable (Original)	MAAP Variable (Print)
1	PRESSURIZER PRESS (WR)	kg/㎠(a)	PPZ	PZR_PRESS
2	PRESSURIZER LEVEL CH X	%	ZWPZ	PZR_LEVEL
3	REACTOR VESSEL WATER LEVEL		ZW_VESSEL	
4	AVG TEMP OF HOT & COLD LEGS	℃	TWRCS	RCS_TEMP
5	COLD LEG 1A MASS FLOW (1)	kg/h	WLOOP(1)	COLD_1A_FLOW
6	COLD LEG 1B MASS FLOW (2)	kg/h	WLOOP(2)	COLD_1B_FLOW
7	COLD LEG 2A MASS FLOW (3)	kg/h	WLOOP(3)	COLD_2A_FLOW
8	COLD LEG 2B MASS FLOW (4)	kg/h	WLOOP(4)	COLD_2B_FLOW
9	SG 1 PRESSURE CH A	kg/㎠(a)	PSGGEN(1)	SG1_PRESS
10	SG 2 PRESSURE CH A	kg/㎠(a)	PSGGEN(2)	SG2_PRESS
11	SG 1 LEVEL (WR)	%	ZWDC2SG(1)	SG1_LEVEL
12	SG 2 LEVEL (WR)	%	ZWDC2SG(2)	SG2_LEVEL
13	MAX REP CORE EXIT TEMP	℃	TGRCS(12)	CORE_EXIT_TEMP
14	HIGHEST CET TEMP - CHANNEL A	℃	TCRHOT	CET_HIGH_TEMP
15	SAFETY INJ TANK PRESS (NR)	kg/㎠(g)	PACUM	SIT_PRESS
16	HPSI PUMP FLOW	L/min	WHPIXX	HPSI_FLOW
17	LPSI PUMP DSCH HEADER FLOW	L/min	WLPI2X	LPSI_FLOW
18	CONTAINMENT SPRAY FLOW	L/min	WSPTA	CSS_FLOW
19	REFUELING WATER TANK LEVEL	%	ZWRWST	RWT_LEVEL
20	CONTAINMENT PRESS CH A (NR)	cmH_2O(g)	PEX0(3)	RB_PRESS
21	CNMT AVERAGE TEMP	℃	TGRB(3)	RB_TEMP
22	CNMT WATER LEVEL CH A	%	ZWRB(2)	RB_LEVEL
23	CNMT RECIRC SUMP LEVEL CH A	%	ZWRB(6)	ESF_SUMP_LEVEL
24	H2 CONCENT. LEVEL(CH.A)	%	NFH2RB(3)	RB_H2_CONC

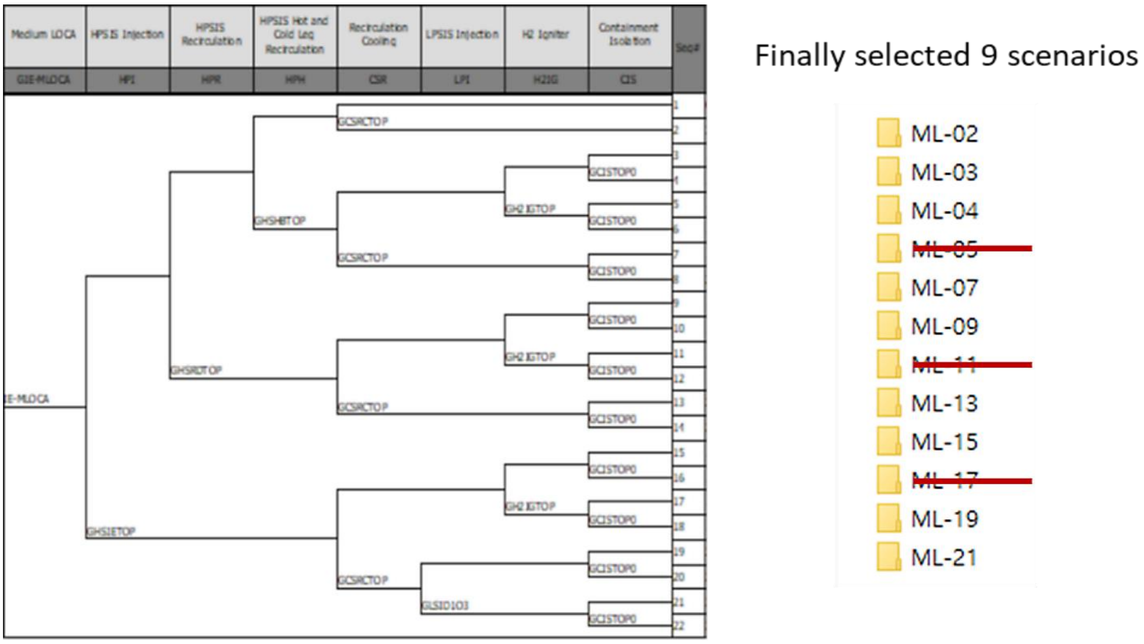
Table 2: Deep Learning Output: Release Fraction

No.	Representative Element	Group Elements	MAAP Variable
1	**Xe**	Kr	FMRELEL(1)
2	**I**		FMRELEL(3)
3	**Cs**	Rb	FMRELEL(5)
4	**Sr**		FMRELEL(6)
5	**Ba**		FMRELEL(7)
6	**La**	Y, Zr, Nb, Pr, Nd, Sm	FMRELEL(9)
7	**Mo**	Tc	FMRELEL(12)
8	**Ru**		FMRELEL(14)
9	**Sb**		FMRELEL(15)
10	**Te**		FMRELEL(16)
11	**Ce**	Np	FMRELEL(17)
12	**Pu**		FMRELEL(22)

2. Application of Deep Learning Models

This study focuses on MLOCA (medium break loss of coolant accident) scenario of OPR-1000 and 9 sub-scenarios are considered by following PDS ET (plant damage state event tree). 12 sub-scenarios that cover above 99.99% of frequency were selected from PDS ET as depicted in Figure 2. However, 3 sub-scenarios relevant with hydrogen ignitor were finally excluded, because operation of hydrogen ignitor is conducted in long-term phase. Using long-time data including long-term-phase data diminishes the meaning of prediction or estimation.

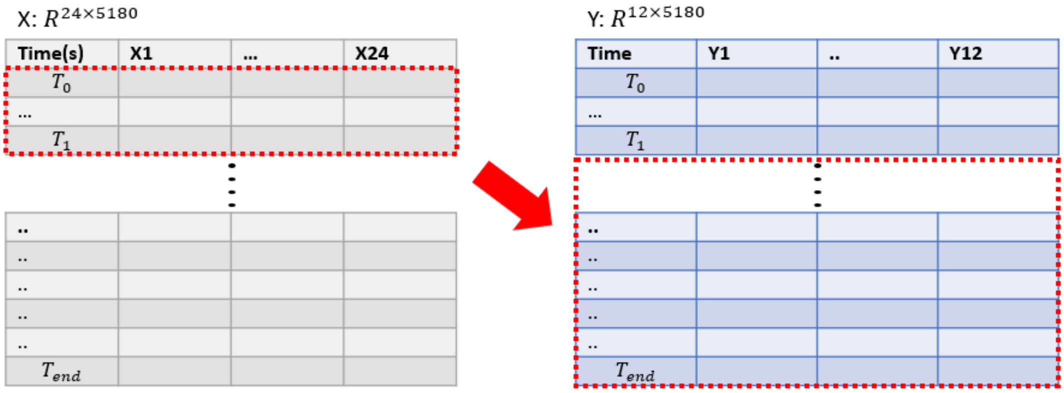
Figure 2: Selection of Sub-scenarios based on PDS ET



Deep learning DB was established by a large number of runs of MAAP code [3]. Learning and testing were conducted for each sub-scenario using an identical deep learning model. Various deep learning models were applicated to find the fittest model to solve the problem.

Data structure of both input and output is 72 hours-time-series data. There exist 5,180 time steps and each time step is 50 seconds. This study tried to estimate subsequent source releases by using early parameters of NPP state information from the accident initiation as depicted in Figure 3. 300 time steps (15,000 seconds) were used in the first trial, then it was extended to 600 time steps (30,000 seconds) for better estimation.

Figure 3: Estimation of Subsequent Source Releases by Using Early NPP Parameters



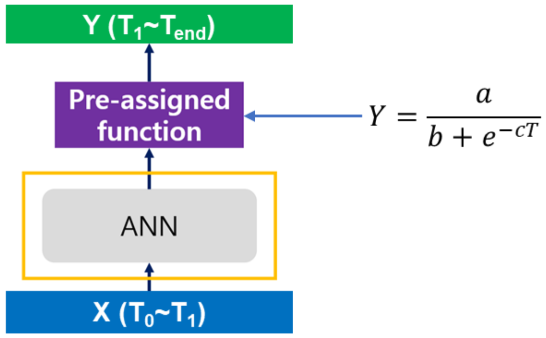
2.1. eQRNN

KAERI (Korea Atomic Energy Research Institute) developed a deep learning model named eQRNN (ensemble Quantile Recurrent Neural Network) [4] in order to predict plant behavior such as temperature or pressure when signals are actuated at certain time. It was confirmed that eQRNN is inappropriate to solve the problem in this study, because eQRNN needs on/off or open/close format as input parameters [2].

2.2. ANN with Pre-assigned Function: ANN + Sigmoid Function

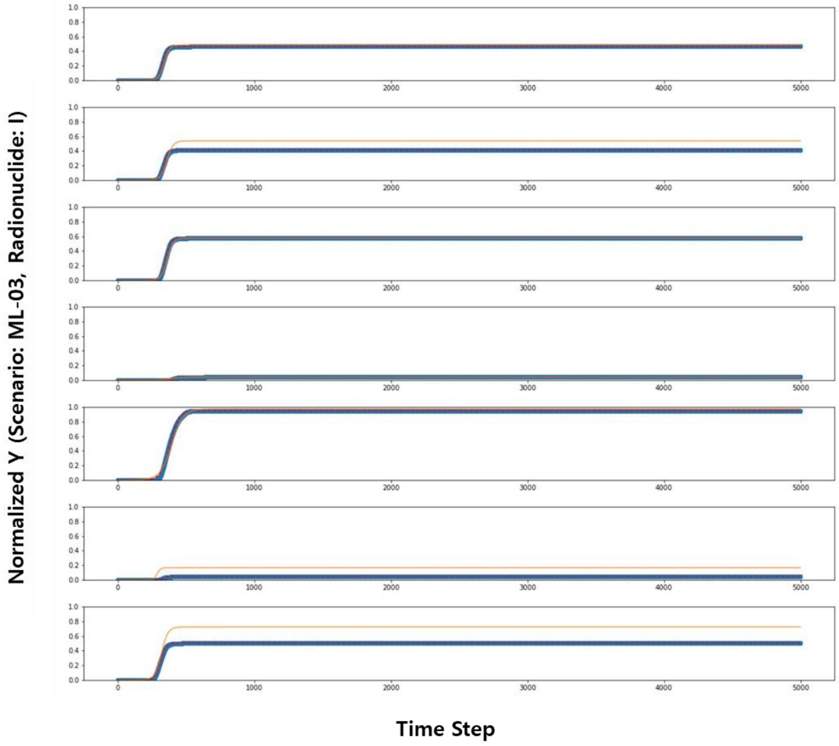
ANN (artificial neural network) was used with the assumption that release fraction has sigmoid function. ANN estimate 3 parameters (a, b, c) of sigmoid function from input data $X(T_0 \sim T_1)$ and sigmoid function calculates $Y(T_1 \sim T_{end})$.

Figure 4: ANN with Pre-assigned Function



It was found that this model predicts the starting points of releases and the slopes of increasing release fractions well as shown in Figure 5. However, this model has limitations that it is poor to predict saturation timing and amount. In addition, some radionuclides do not have release fractions shaping sigmoid function in some scenarios.

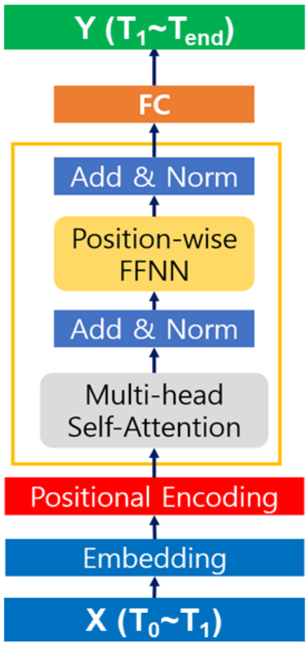
Figure 5: Example Results of Pre-assigned Function NN: Various Samples in Scenario ML-03



2.3. TF-EFC (Transformer: Encoder + Fully Connected Layer)

Transformer, one of the up-to-date analysis and prediction models, was employed. In order to avoid the limitation of the assumption of sigmoid function and to generalize the shape of release, the pre-assigned function is excluded in this model. Only the encoder of the transformer was used to efficiently perform time series prediction on a fixed time domain.

Figure 6: Transformer Encoder + Fully Connected Layer



As described in Figure 7 and Figure 8, TF-EFC model predict major radionuclides such as iodine (I) and cesium (Cs) relatively accurately in the scenario ML-04, ML-05, and ML-09 that release sources relatively early. It should be noted that not every time step is printed in the figures of this section, therefore, time step in X-axis is different with the time step of Figure 5. In every figure, final time step means 72 hours. Y-axis means release fraction normalized to the maximum release fraction of the maximum releasing sample. Red solid line means true value and black dotted line means predicted value.

Figure 7: Example Results of TF-EFC for Iodine: ML-05 Scenario (Left) and ML-09 Scenario (Right)

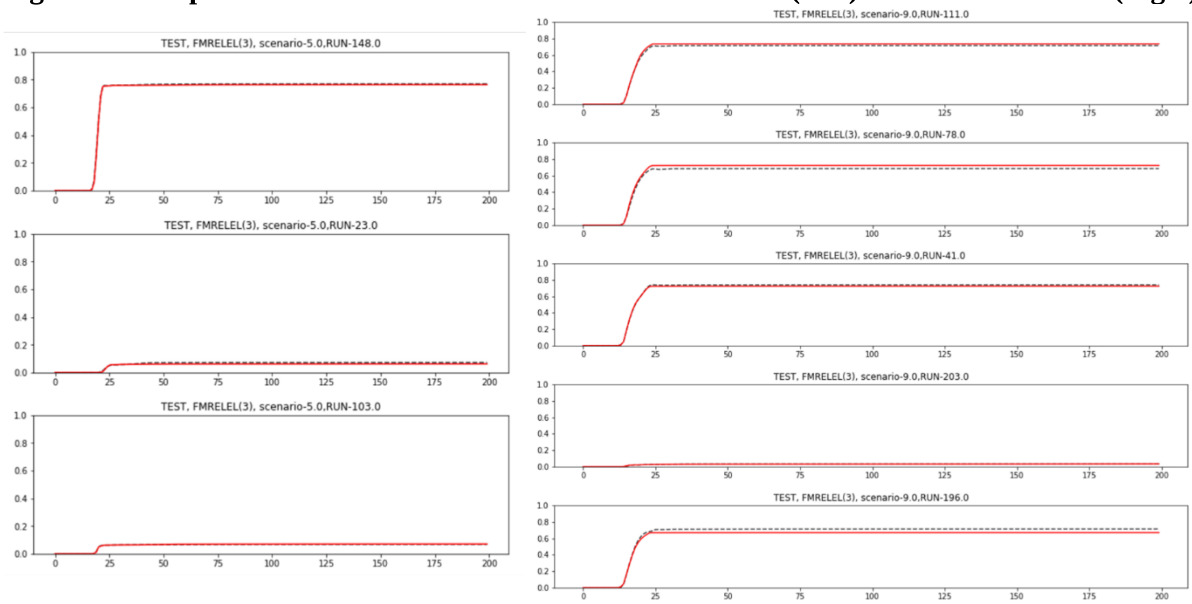
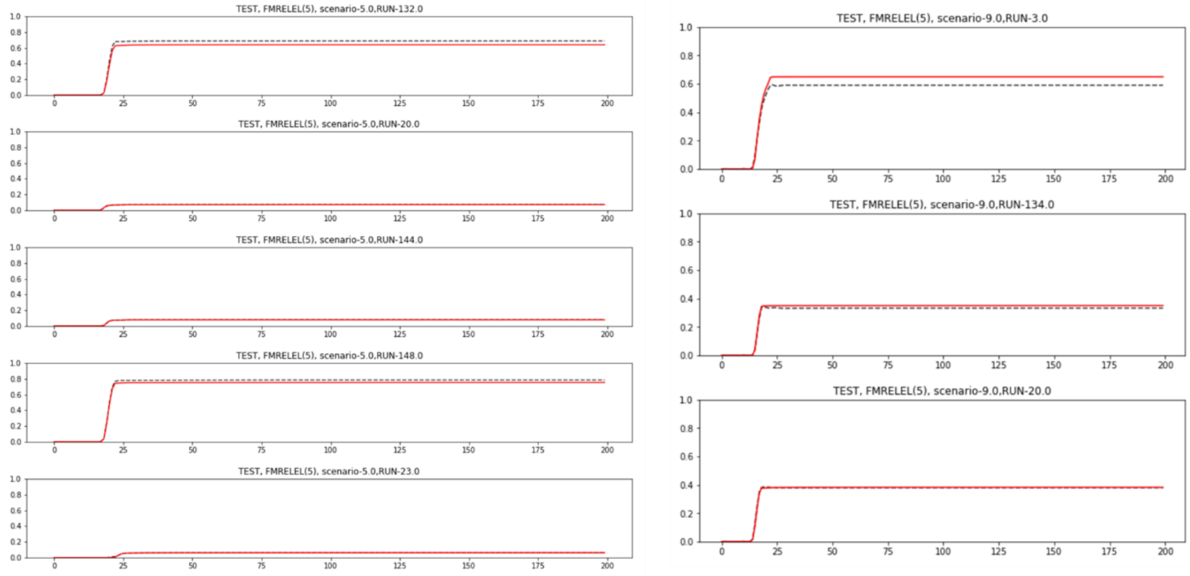


Figure 8: Example Results of TF-EFC for Cesium: ML-05 Scenario (Left) and ML-09 Scenario (Right)



TF-EFC predicts the releases of xenon (Xe) and molybdenum (Mo) in ML-05 scenario well as shown in Figure 9. However, TF-EFC does not predict accurately the releases of strontium (Sr), antimoni (Sb), and ceriem (Ce) as depicted in Figure 10.

Figure 9: Example Results of TF-EFC for ML-05 Scenario: Xenon (Left) and Molybdenum (Right)

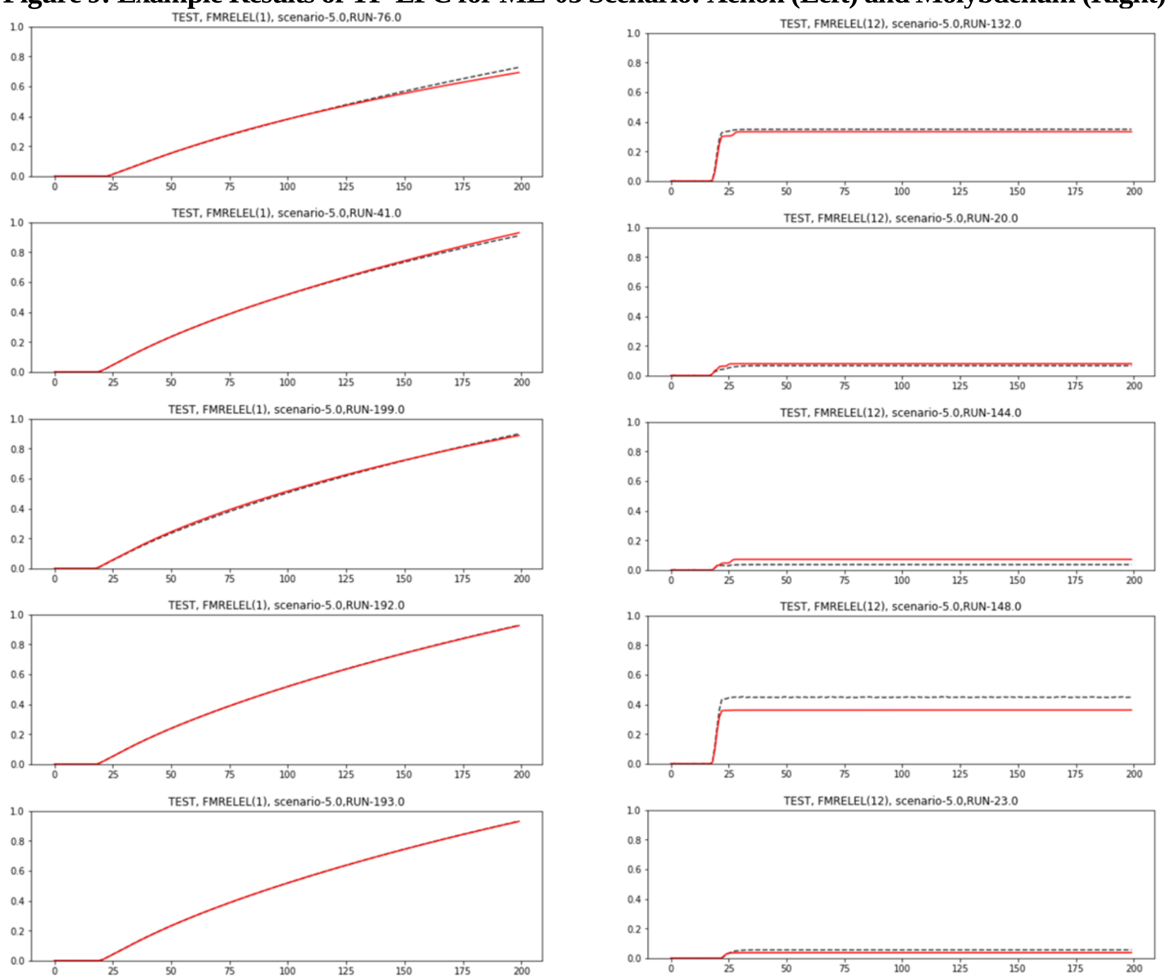


**Figure 10: Example Results of TF-EFC for ML-05 Scenario:
Strontium (Left), Antimoni (Middle), and Ceriem (Right)**

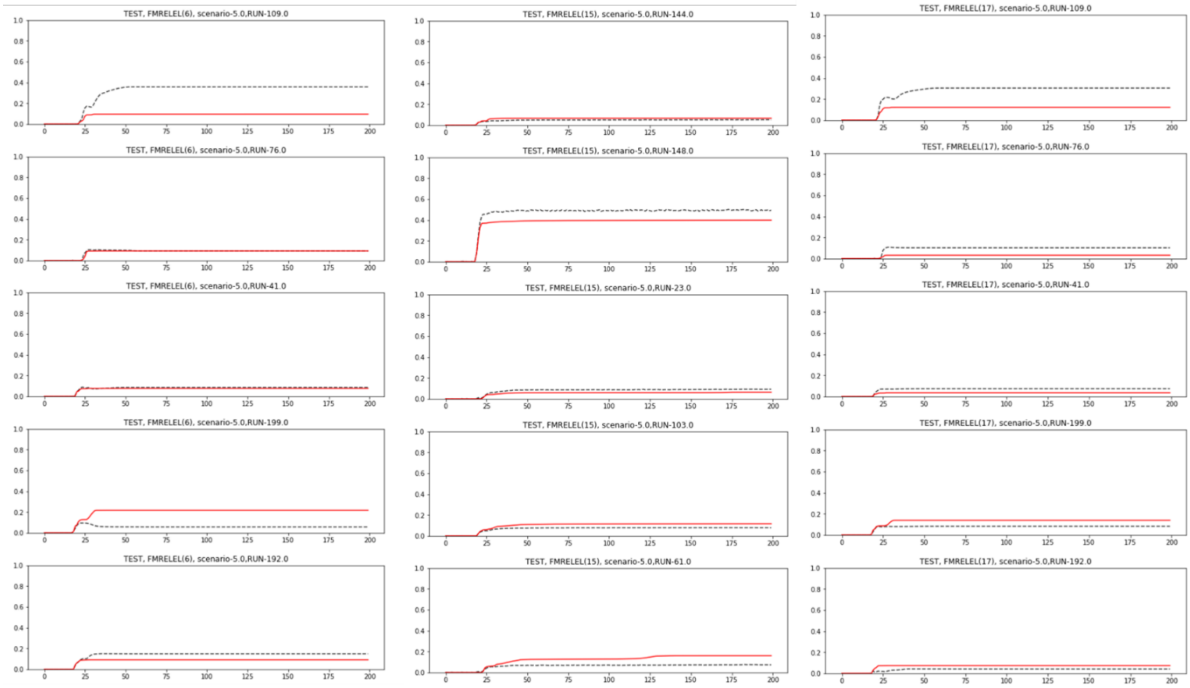
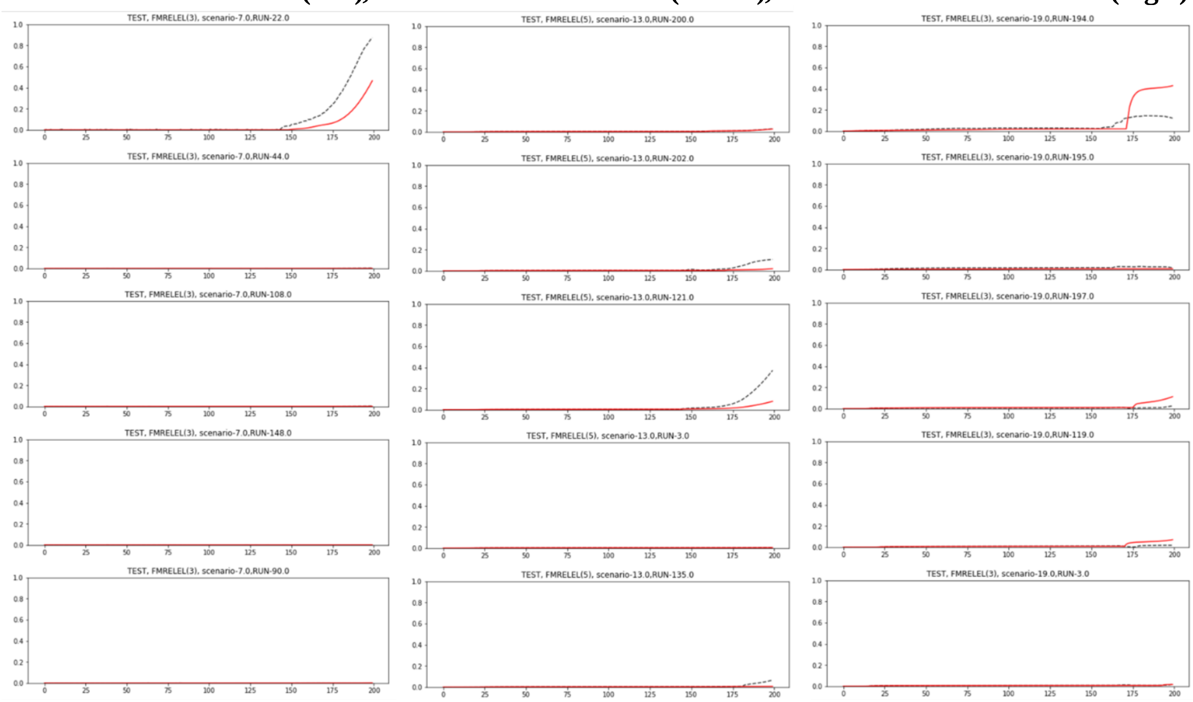


Figure 11 shows the scenarios in which prediction accuracy of major radionuclides such as I and Cs decreases. Those scenarios represent the scenario in which release starts relatively late.

**Figure 11: Example Results of TF-EFC:
Iodine in ML-07 Scenario (Left), Cesium in ML-13 scenario (Middle), and Iodine in ML-19 Scenario (Right)**



From the results shown in above figures, TF-EFC model predicts relatively accurately major radionuclides in early release scenario. However, prediction accuracy decreases for the late release scenarios. It is regarded that accuracy can be enhanced when time duration of learning data from accident initiation increases from current status which is 600 time steps (30,000 seconds).

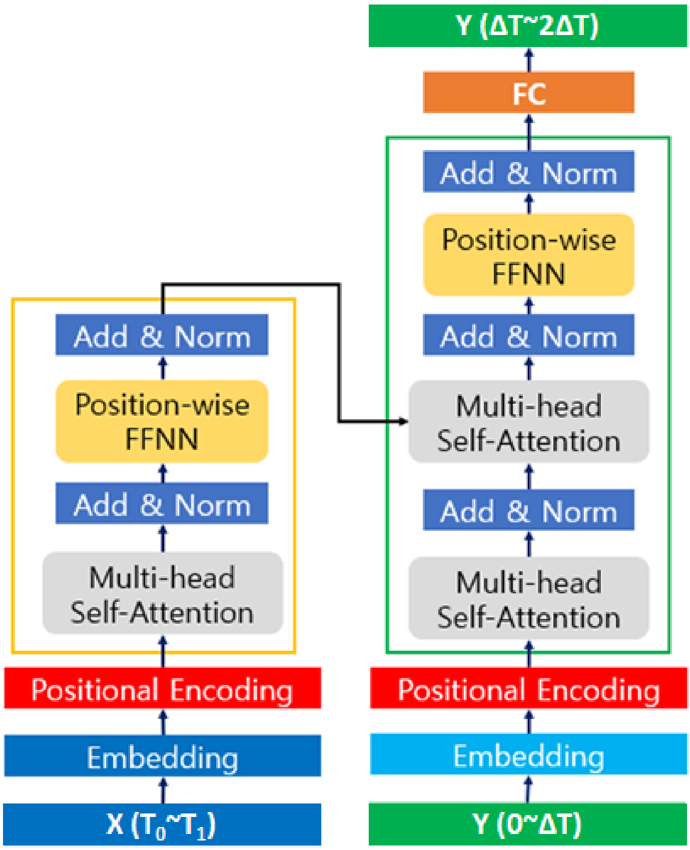
3. CONCLUSION

A variety of deep learning models such as eQRNN, ANN with pre-assigned sigmoid function, and TF-EFC were reviewed and applied to estimate source releases of NPP accidents. TF-EFC model is regarded as an appropriate model to predict source release. However, it still has limitations to predict some radionuclides such as Sr, Sb, and Ce. In addition, accuracy decreases for the scenarios in whch radionuclides release relatively late. In order to overcome existing limitations, both updating TF-EFC model and employing another model such as adaptive model are in progress.

4. LIMITATIONS AND FURTHER WORK

Time duration of input data from the accident initiation is fixed for the current deep learning models. It is expected that self-updating deep learning model using updated input data can be developed. In this adaptive model, accuracy of source term estimation is expected to be enhanced by using longer input data as time goes by from the accident initiation. Multi-horizon transformer can be a candidate. Although transformer is a prominent model for time series prediction, it has a limitation in the long sequence time-series forecasting. Therefore, transfer model can be modified for multi-horizon forecasting to decrease the time-series length of single-step prediction. It has the advantage of the adaptive approach, which can provide results with any number of time step data without past information and increase the accuracy with time data near the target.

Figure 6: Concept of Multi-horizon Transformer



It is possible that data from a nuclear power plant to AtomCARE system is incomplete with missing data due to unexpected circumstances in an accident situation. This study is not considering the case that missing data exists. Development of a deep learning model which can detect and supplement the missing data can be a necessary further study.

Only MLOCA scenario was focused on this study as the scenario representing low pressure condition. When development of deep learning model for MLOCA is finished, it will be applied and tested in TLOCCW (total loss of component cooling water) scenario as well, which represents low pressure condition. MLOCA and TLOCCW were selected, since it was found that these scnearios have the highest CDF (core damage frequency) for low and high pressure conditions respectively, from the Level 1 PSA results of OPR-1000. Finally, this approach can be extended to every scenario, after confirming the applicability of the approach to the representative scenarios.

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

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