Deep Learning Modeling Strategy and a Feasibility Study to Estimate Accident Source Term

Jae Young Yoon *, Ki Won Song, Kyungho Jin, Sung-yeop Kim

Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daejon, Republic of Korea
** Corresponding author :jyyoon@kaeri. re. kr*

1. Introduction

After Fukushima accident, estimation of the amount of radioactivity release has become certainly decisive in the early stage of the public protection management. Radioactivity effect estimation system SPEEDI (System for Prediction of Environmental Emergency Dose Information) was not properly utilized for decision making of public protection management, and failed to provide accurate source term information.

Source term estimation at accident management level depends generally on SAMG (Severe Accident Management Guideline), which doesn't manage each accident scenario, but take care of the plant condition. So, this paper suggests a strategy for fast and accurate prediction of accident scenario and source term from plant and environment information.

2. Strategy on Deep Learning Modeling

This study introduces the technique to supply the information regarding severe accident scenario and source term by using deep learning method. A database about radioactivity release was generated from MAAP (Modular Accident Analysis Program) code by using plant parameters[l]. This paper tried to apply a pre-developed deep learning model, which is called as eQRNN (ensemble Quantile Recurrent Neural Network) [2], to the source term estimation process. This study was carried out in procedure below. Detailed methods and selection criteria are expressed in Kim and Park [1].

1. To select important parameters of state information
2. To select representative severe accident scenarios
3. To generate database about AtomCARE* parameters, MAAP input parameters (input) and release of radioactive materials (output)
4. To train the regression model (eQRNN in this study) using the input/output data
5. To review applicability of eQRNN model.

**AtomCARE (Atomic Computerized technical Advisory system for a Radiological Emergency) is an accident response system operated by KINS.*

Figure 1 schematizes the deep learning strategy to estimate accident source term. Firstly, plant damage state (PDS) is determined depending on accident scenario. MAAP input parameters have their unique distribution based on the accident progress probability [3]. MAAP calculation based on PDS is carried out to generate selected AtomCARE parameters and source term which are input and output variables of deep learning respectively. Next section presents feasibility test result by using eQRNN regression model, and reviews its applicability.

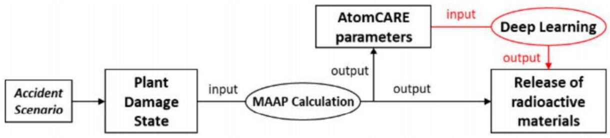

Fig. 1. Deep learning strategy to estimate source term release

3. Example Feasibility Study

In this section, a feasibility study was carried out to estimate accident source term using the eQRNN. For simplicity, the construction of the training data to be developed in step 1-3 of Sec.2 is omitted in this paper.

The eQRNN has been developed to predict plant behavior such as pressure or temperature, when some signals are actuated at specific time automatically or manually [2]. For example, the pressurizer pressure is predicted during the accident scenario after one hour through eQRNN, when charging valve open at ti and pressurizer heater is turned on at t2. The eQRNN requires the discrete input, which could be zero/one (e.g., on/off) and 0/25/50/75/100 (e.g., a degree of valve open), according to a type of input parameters.

In this study, we tried to make eQRNN predict the source term during the MLOCA (Medium Loss of Coolant Accident) accident scenario after one hour using the information of AtomCARE data or MAAP input data which are considered as input parameters. The basic structure of eQRNN which is based on bi-directional LSTM (Long Short Term Memory) model is shown in Table I.

Table I: Structure of eQRNN

Structure	Bi-directional LSTM
Activation function	LeakyReLU
Optimizer	Adam
Cost function	Mean Squared Error

After reviewing the applicability of AtomCARE data, it was confirmed that variables of AtomCARE data is not proper to be considered as an input of eQRNN because the type of input is different between the

AtomCARE data and the input of eQRNN. The AtomCARE collects the plant information such as pressurizer pressure, reactor vessel water level and containment hydrogen concentration continuously, and therefore the AtomCARE data is continuous time-variant. On the other hand, the input of eQRNN is constant regardless of time.

Secondly, the values of MAAP input parameters consist of zero or one at specific time which means on/off or open/close, and therefore it seems to be applicable to the input of eQRNN. However, some MAAP parameters changed from zero to one repeatedly, for example, the MSSV (Main Steam Safety Valve) opens and closes according to system pressure. Therefore, the MAAP parameters are not also regarded to be appropriate as the input of eQRNN. Figure 2 and 3 show an example of AtomCARE data and MAAP input data respectively. Table II shows comparisons between eQRNN, AtomCARE, and MAAP input.

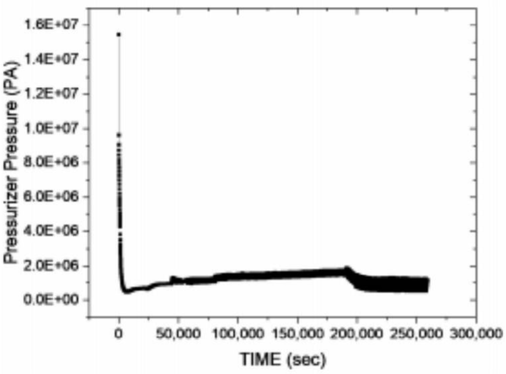

Fig. 2. Pressurizer pressure obtained from AtomCARE data

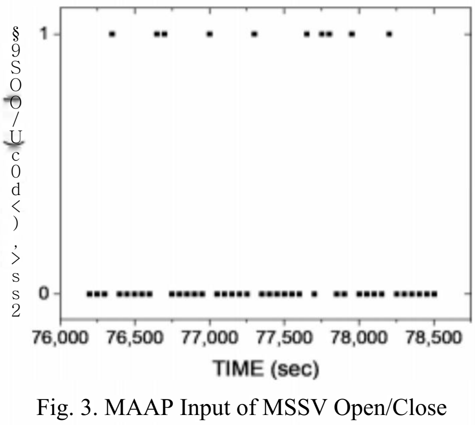

Fig. 3. MAAP Input of MSSV Open/Close

Table II: Comparisons between methods

	eQRNN	Atom CARE	MAAP Input
Number of Input variables	16	36	58
Type of Input	Constant regardless of time	Continu OUS time-variant	Discontin uous time-variant

4. Conclusions

The strategy to estimate accident source term is developed through deep learning and it consists of five steps: 1. To select major parameters of state information, 2. To select representative severe accident scenarios, 3. To generate database about AtomCARE parameter, MAAP input parameters (input) and source release (output), 4. To train the regression model using the input/output data, 5. To review applicability of a deep learning model. This study focuses on step 4 and 5. It was evaluated whether the source term obtained from MAAP results could be estimated through the eQRNN deep learning model with the AtomCARE data or MAAP input data considered as training data of eQRNN. As a results, the eQRNN model is not applicable to estimate source term, because the AtomCARE data is continuous time-variant and the MAAP input data is discontinuous time-variant, whereas the input of eQRNN is constant regardless of time.

5. Future Work

From the feasibility study, the deep learning model, eQRNN is not applicable to estimate source release. In order to use the AtomCARE data or MAAP input data, the otheranother deep learning model is needed to be employed or developed. The input of a new model will be continuous or discontinuous time-variant and the output of a new model also will be continuous time-variant. It is planned to search and develop an appropriate deep learning model for fast and accurate estimation of source term information from the plant state data.

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] 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, October 21 - 22, 2021, Changwon, Korea.

[2] Seunghyoung Ryu, Hyeonmin Kim, Seunggeun Kim, Kyungho Jin, Jaehyun Cho and Jinkyun Park, Probabilistic deep learning based fast running model of thermal-hydraulic code, Transactions of the Korean Nuclear Society Autumn Meeting, October 21-22, 2021, Changwon, Korea.

[3] Park, S. Y. and K. I. Ahn. "Phenomenological uncertainty analysis of containment building pressure load caused by severe accident sequences. Annals of Nuclear Energy 69 (2014): 205-211.