Estimation of Radioactivity Release during LOCA using Machine Learning

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1. Introduction

It has been recognized that the Artificial Intelligent (AI) techniques would enhance the nuclear power plant safety and reduce the human errors during abnormal/accident conditions. Especially, the machine learning techniques could be utilized to prepare the real-time operator supports; thus, the accurate prediction of the accident progressions and the consequences could be provided to determine the optimum strategies for preventing or mitigating the abnormal/accident conditions. In light of prediction using machine learning, Ref. [1] and Ref. [2] were utilized Long-Term Shor-Memory (LSTM) algorithm [3] to predict the plant conditions using MAAP5 [4] and MARS-KS [5], respectively.

In this study, as an extension of the previous studies [1,2], the radioactive releases during a severe accident have been estimated by using machine learning algorithm. On top of the plant conditions, the information related to consequences (e.g., environmental impact, public dose) would enable the operator and the technical support committees to make risk-based decisions and initiate the timely emergency programs.

As a simulation code, MELCOR [6] has been used to model SMART (System integrated Modular Advanced ReacTor) [7]. Small Break Loss of Coolant Accident (SBLOCA) with containment leakage has been analyzed and the radioactive gas release has been compared. To construct the training set, the release data with different containment leaks has been collected and the machine learning algorithm, i.e., LSTM, has been applied to construct the prediction model. The prediction accuracy has been analyzed by comparing the actual MELCOR simulation results.

2. Machine Learning Application to Release Rate Estimation

2.1. Accident condition and analysis cases.

Reference accident scenario for the prediction of the radioactive releases is selected as a small break loss of coolant accident (SBLOCA) due to 2 inch (25 mm) Safety Injection Line Break with UCA (Upper Containment Area) damage. The vapor and the aerosol of fission products released to LCA (Lower Containment Area) would be transported to UCA via IRWST and RRT (Radioactive material Removal Tank) and be released to the environment through the damaged UCA. Schematic of the SMART Containment Area is presented in Fig.1. Based on the MELCOR analysis results with various break sizes of the containment building, the machine learning algorithm is applied to predict the radioactive gas quantity for an unknown break size. MELCOR analysis conditions and cases for machine learning training and testing are presented in Table I.

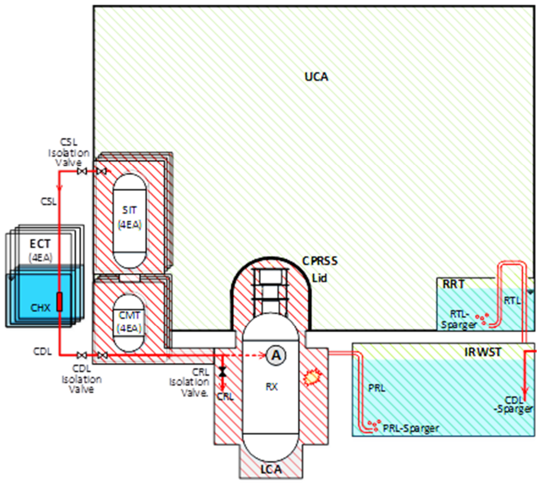

Fig.1. Schematic of the SMART Containment Area

Table I: Analysis condition and cases

Analysis Condition		
• SBLOCA occurs at 0.0 s • Containment Fail Occurs at 0.0 s • Cavity Flooding System(CFS) Available • No Safety System Available		
	Training	Testing
Containment Break Area [m^2]	0.01	0.5
	0.1	
	1.0	
	2.0	

2.2. Variable Selection

The variables related to the release of the radioactive gases are summarized in Table II.

Table II: Selected variable for machine learning

No.	Selected Variable
1	Core Level
2	RCS Pressure
3	RCS Temperature
4	Cavity Level
5	IRWST Level
6	RRT Level
7	Lower Containment Area (LCA) Pressure
8	Upper Containment Area (UCA) Pressure
9	Lower Containment Area (LCA) Temperature
10	Upper Containment Area (UCA) Temperature
11	Xenon Released Quantity
12	Cesium Released Quantity

If SBLOCA occurs, the core level is getting lower, and fuel is uncovered. And then fuel is melt down, the fuel-containing material is discharged to the outside of the Reactor Pressure Vessel (RPV). The core level (1) determines the time of entry into the severe accident. RCS pressure (2) and temperature (3) are related to corium ejection rate. The water levels of IRWST (5) and RRT (6) are included to consider the removal of the radioactive gases and aerosols flowing from LCA to UCA through scrubbing at IRWST and RRT. In addition, if the core outlet temperature exceeds 650 °C, Cavity Flooding System (CFS) is activated after 30 minutes to fill the cavity with coolant from IRWST. RCS Temperature (3), Cavity level (4), IRWST level (5) are related variables for cavity filling that can reduce the water soluble radioactive gas. Containment pressure (7,8) and temperature (9,10) is an important variable that determines the release of the radioactive gas release rate.

2.3. Machine Learning using LSTM

LSTM is a unique type of recurrent neural network (RNN) capable of learning long-term dependencies, which is useful for certain types of prediction that require the network to retain information over longer time periods.

The analysis conditions for LSTM machine learning are as follows. Simulation time of each accident case is 300,000 seconds and time step is 1,000 sec. The data of 300 rows are used for each accident analysis case. Number of epochs and batch size are set as 30 and 5, respectively. One epoch is when an entire dataset is passed forward and backward through the neural network only once. Batch size means divided dataset into number of batches or sets or parts. Machine learning is conducted with 1,800 ($300/5 \times 30$) iterations per accident case as shown in Fig.2.

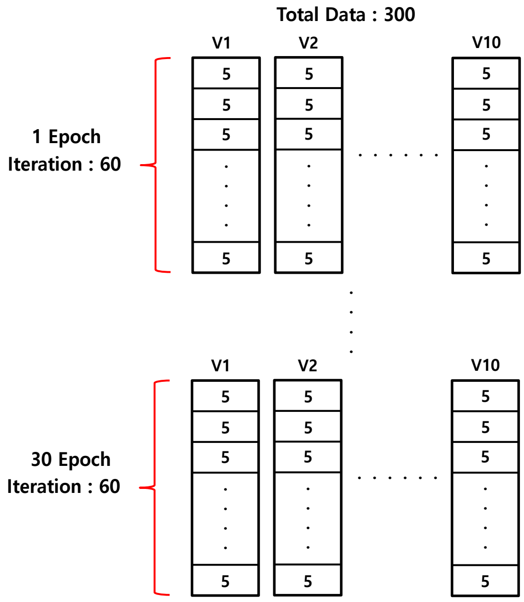

Fig.2. Schematic of machine learning

3. Numerical Results

Based on the SBLOCA analysis results for various damage sizes using MELCOR, the radioactive gas released quantity of Xenon and Cesium are predicted using machine learning.

Fig.3 and Fig.4 present the training data of the Xenon release and the prediction result of the Xenon release, respectively. The quantity of the Xenon release is larger as the break size increases (Fig.3), and the prediction result by machine learning is similar to the simulated data (Fig.4). At the end of the simulation time (300,000s), the prediction accuracy is evaluated as 97.7%.

Fig.5 presents the prediction results of the break area of the containment based on the Xenon released quantity data and the accuracy is evaluated as 97.0%.

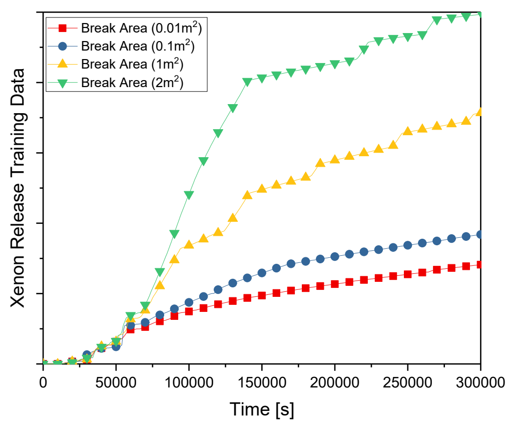

Fig.3. Xenon release training data

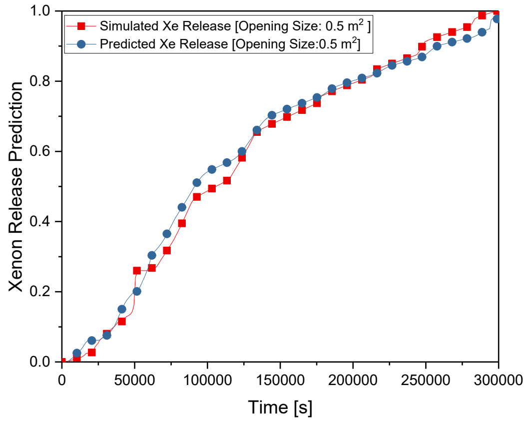

Fig.4. Prediction of the Xenon release

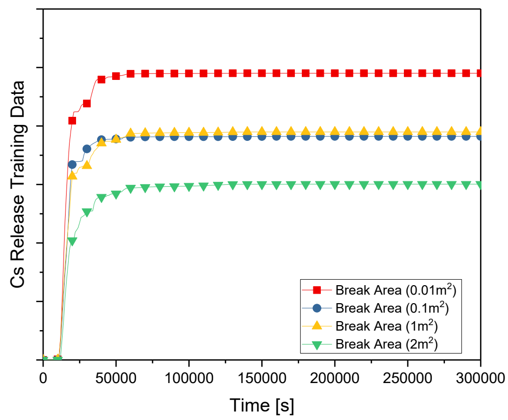

Fig.6. Cesium release training data

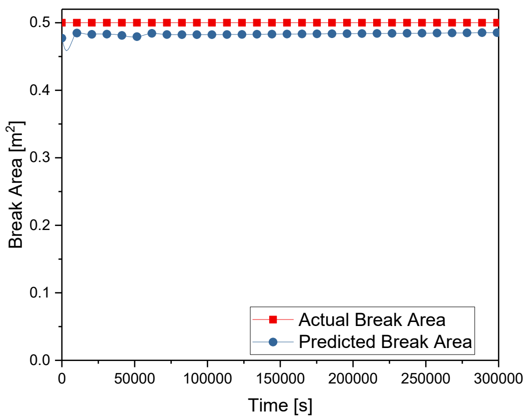

Fig.5. Prediction of the break area

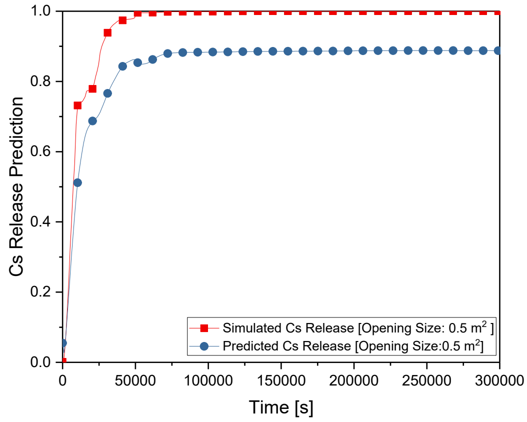

Fig.7. Prediction of the Cesium release

Fig.6 and Fig.7 present the training data of the Cesium release and the result of the Cesium release prediction, respectively. As a result of the MELCOR, the size of the break area and the quantity of the Cesium released is not proportional (Fig.6), and the machine learning prediction accuracy is 88%.

During the release of the radioactive aerosols from LCA to UCA through IRWST and RRT, almost all of Cesium is dissolved by water in reactor cavity, IRWST, and RRT. Therefore the small amount of Cesium enters into UCA in an aerosol state. And the Cesium in the containment building is also settled down within a short time, and only a small amount of Cesium is released to the outside of the reactor building. In addition, the pressure of the containment building does not increase with a large break area, and the amount of release may decrease. It has been noticed that the prediction like Cesium requires more input variables due to its complex settling/dissolving and releasing mechanism.

4. Conclusions

The applicability of the machine learning to estimate the radioactive gas release has been examined. Training set has been constructed by using MELCOR simulations and LSTM has been utilized to build the prediction model. It has been concluded that the prediction accuracy would be acceptable for emergency decision making. However, it has been found that the further work should be conducted for Cesium due to its complex settling/dissolving mechanism in releasing.

The estimation results could be used as a source term input to atmospheric dispersion/dose calculation and determine the emergency countermeasure like public evacuation. As the consequences would be estimated earlier, the consequences to environment and public could be reduced or prevented.

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