Development of a Real-time Interactive Nuclear Power Plant Accident Simulation Using Supervised Learning

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1. Introduction

Since the 2011 Fukushima nuclear accident, number of studies on the severe accident is increasing. These studies are being conducted with the aim of collecting information to verify the existing strategy for mitigating severe accidents and establish a new strategy for mitigating severe accidents. For example, a study was conducted to verify whether the RCS decompression strategy is effective in mitigating severe accidents through the MELCOR code [1]. The decompression strategy was a measure that could be implemented 5 minutes after entering the Severe Accident Management Guideline (SAMG). SAMG is entered when the reactor core exit temperature exceeds 992K. The study showed that the core temperature can be lowered temporarily. As shown in Fig.1, the decompression strategy using Atmosphere Dump Valve (ADV) in the secondary side and Safety Decompression System (SDS) on the pressurizer can delay the progress of accident.

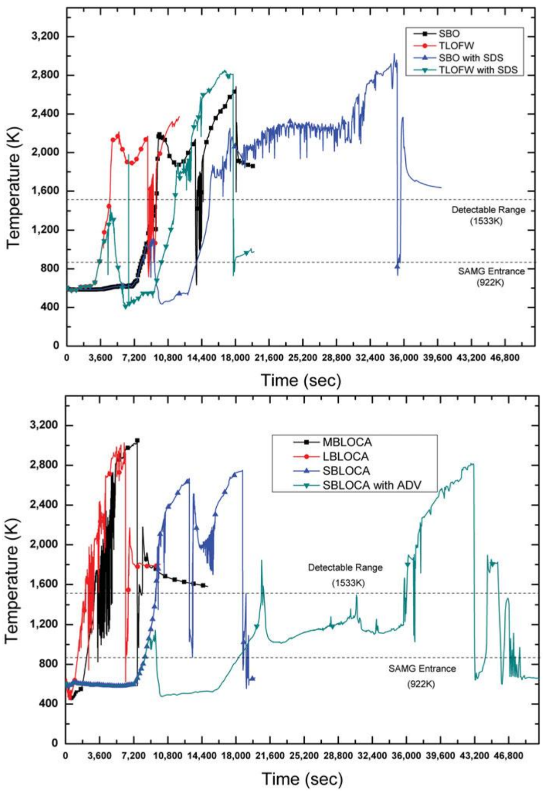


Figure 1 Core exit temperature in SBO, TLOFW (top) and LOCA (bottom) [1]

Current accident analysis is being performed by using an event tree developed from the probabilistic safety assessment (PSA). However, PSA has already determined the accident scenario and deterministically evaluates core damage, containment integrity, and leakage of fission products, so it is not possible to know the difference in the accident process depending on when the equipment fails. In order to efficiently mitigate consequences in severe accident, a study is needed to find the most efficient point when safety measures engage

The existing code calculates the subsequent progress after setting the accident scenario in advance. However, through this method, substantial amount of prior work is required to learn the time of device failure during an accident. In order to change the timing of device failure, a new input is created and a new calculation process is required based on this. As device failure and implementation of mitigation strategies continue to change, a lot of computational resources and time to simulate nuclear power plant accidents are required.

In order to overcome these limitations, this study attempts to explore the possibility of developing a nuclear accident simulation capable of real-time interaction by using supervised learning method. There is already a study showing that the prediction of nuclear power plant thermal-hydraulic parameters under a transient state is possible with the supervised learning [2]. The above study generated data from WWER-1000 preoperational data, data from RELAP5 and ATHLET codes.

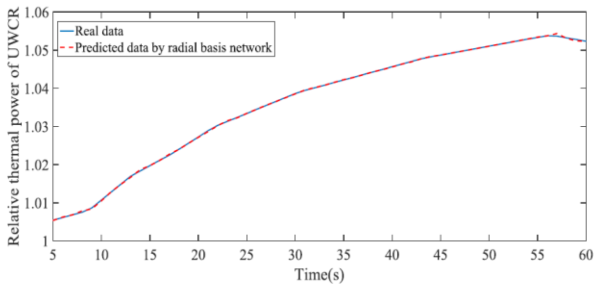


Figure 2 Prediction of relative thermal power of UWCR by RBN [2]

In this study, an interactive nuclear power plant accident simulation capable of generating double failure accident of RCP seal and HPI is developed. The developed simulation tool allows users to actively fail HPI during simulation. The simulation is developed by using supervised learning algorithm to the data generated from MAAP 5.0.3. This accident scenario corresponds to the initial stage of the LOCCW PSA event tree, and through this, it will be possible to simulate how the accident process changes depending on the failure time of HPI.

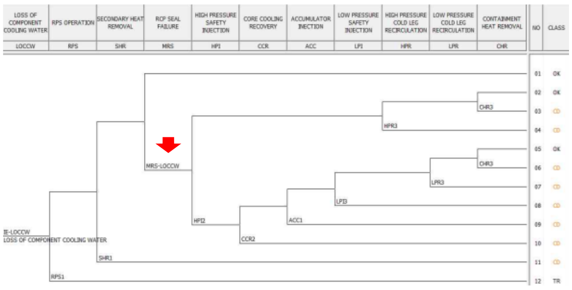


Figure 3 PSA Event Tree in LOCCW Accident

2. Methodology

The authors intend to replace MAAP simulations with artificial neural networks (ANN). Using MAAP data, information about nuclear power plant physical values at a specific point in time and subsequent points in time is generated and processed in input-answer format. Artificial neural networks are trained based on these data and can predict values at a specific point in time based on physical data at a specific point in time. Through this, if only the data at the initial point of the accident is given, it will be possible to create an artificial neural network that predicts values during the whole accident process.

Table 1. Physical values used in ANN

Physical value
Pressure of the primary side
Maximum core temperature
Boiled-up water level from bottom of RPV
Pressure of annular compartment
Maximum core exit temperature
Collapsed water level in the S/G downcomer
Accumulator pressure
Flow rate in Break

	TIME	PPS	PEX0(2)	MCR	TCRHOT	MH2CR1	MH2CBT	Failure	
	SECONDS	PA	PA	KG	K	KG	KG	RCP	HPI
Input	3600	9.42E+06	1.38E+05	1.37E+05	5.96E+02	0.00E+00	0.00E+00	1	0
Answer	7200	1.46E+07	2.29E+05	1.37E+05	9.94E+02	4.14E-01	0.00E+00	None	None

Figure 4. Sample structure of training data

The configuration of ANN will be multi-layer. As shown in Figure 5, the input layer contains information of the physical values and the information of component failure. The output layer contains information of physical values of nuclear power plant. As the output of ANN contains only physical value, user can intervene accident progress while stimulating with ANN.

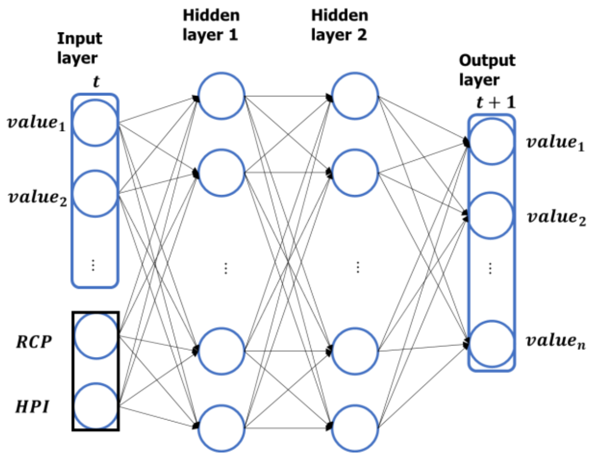
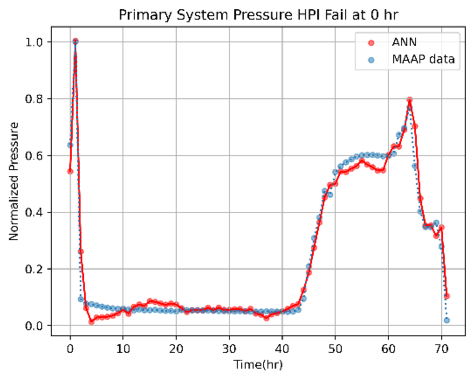


Figure 5. Configuration of accident stimulation ANN

5256 data sets are generated with MAAP 5.0.3. The data is collected for first 72 hours after the accident. The continuous data is sampled every one-hour interval, so that ANN can be predicting the physical values after one hour. The failure of RCP is the initial condition at 0 hour and the failure of HPI is randomly selected. Among the data sets, 70% of data set is used for training and 30% of data is used for overall accuracy test.

3.Results & Discussions

The prediction of ANN shows 87% of accuracy in the overall accuracy test. Following figures are prediction of primary system pressure and core exit temperature and original MAAP data. Typically, figures were drawn for failure before operation (HPI failure at 0 hour), failure during operation (HPI failure at 10 hour), and failure after completion of HPI (HPI failure at 20 hour).



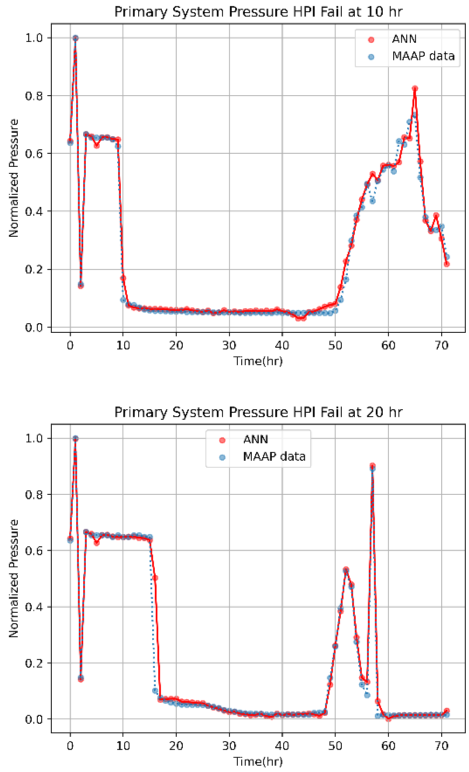
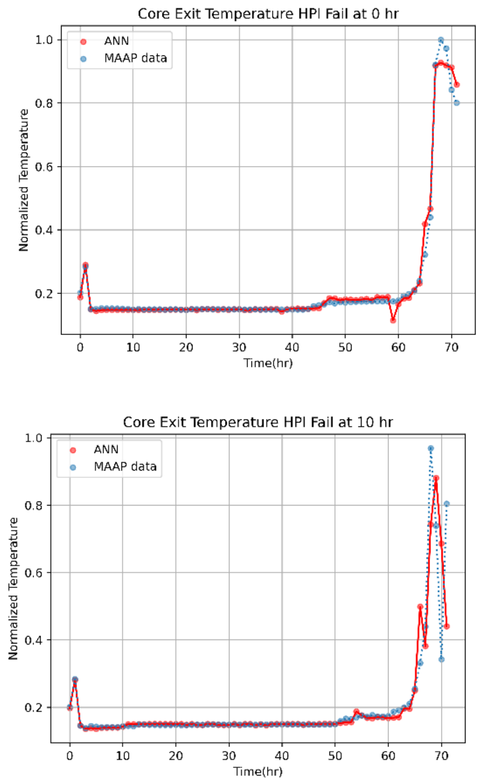


Figure 6. Primary system pressure HPI fails at 0hr (top), at 10hr(middle), at 20hr (bottom)



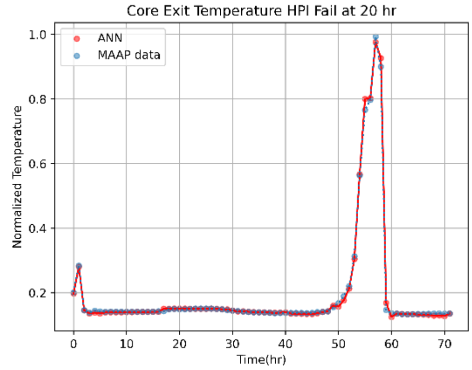


Figure 7. Core exit temperature HPI fails at 0hr (top), at 10hr(middle), at 20hr (bottom)

4. Conclusions and Future Works

It is shown that the artificial neural network generally predicted MAAP data for the selected severe accident very well. It is noted that since data for ANN learning is sampled with 1-hour interval, when the thermal-hydraulic conditions vary greatly ANN cannot predict sufficiently.

These results are obtained from multi-layer perceptron using supervised learning algorithm. It is expected that more accurate predictions can be made by using other supervised learning techniques such as RNN and LSTM, or by reducing the interval of training data.

ACKNLOGEMENT

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REFERENCES

[1] Lee, Seongnyeon, et al. "Validation of RCS depressurization strategy and core coolability map for independent scenarios of SBLOCA, SBO, and TLOFW." Journal of Nuclear Science and Technology 51.2 (2014): 181-195.

[2] Moshkbar-Bakhshayesh, Khalil. "Comparative study of application of different supervised learning methods in forecasting future states of NPPs operating parameters." Annals of Nuclear Energy 132 (2019): 87-99.