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Preliminary Prediction of Core Exit Temperature for Severe Accident using Machine Learning

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1. Introduction

During a severe accident, there is a possibility that operators will not take appropriate mitigation action because operators are exposed to excessive information about plant conditions and have limited time to make decisions. Therefore, great efforts are being made to develop an accident coping strategies and facilities to prevent entry into a severe accident.

The core exit temperature (CET) is typically used to a criterion for determining the entry of a severe accident in domestic and abroad nuclear power plants (NPPs). If CET can be predicted, the operators will be more effectively coping to the accident because it is possible to secure response time until the entry of a severe accident. However, in an urgent accident situation, CET prediction through computer code analysis takes a lot of time, and it is also difficult for experts to judge due to complex plant conditions.

Recently, the importance of the 4th industrial revolution technology such as an artificial intelligence (AI) is emerging, and AI technology is also introduction in various fields of NPPs. The purpose of this study is to predict CET, which determines the entry of a severe accident using machine learning, a representative AI technique. For machine learning, training data to reach a severe accident is required for various accident scenarios. The training data was obtained from the severe accident analysis using MAAP5 [1] code for the OPR-1000.

In this study, long short-term memory (LSTM) [2] methodology has been applied. LSTM is an artificial recurrent neural network (RNN) architecture used in the field of machine learning. Unlike standard feed-forward neural networks, LSTM has feed-back connections. It can also treat learning long-term dependencies, which is useful for certain types of prediction that require the network to retain information over longer time periods.

2. Training Variables Selection

The target variable, CET, is one of thermal hydraulic behavior inside the reactor pressure vessel (RPV). Basically the thermal hydraulic behavior of a RPV is determined from the mass and energy balance. Table 1 and 2 represent variables of MAAP code for maintaining the mass and energy balance of the global primary system.

Table 1. Primary System Mass Balance [1]

1	Total Initial Water Mass, evaluated at time zero
1.1	Initial water mass : MWPST0
1.2	Initial steam mass : MSTPS0
2	Integrated Water Mass Addition
2.1	Engineered safeguard injection : MESFPS
3	Integrated Water Mass Loss
3.1	Letdown & relief flows : MLETPS
3.2	Break flows : MBRKPS
3.3	Steam loss to zirconium and steel oxidation : MZRRXN

Table 2. Primary System Energy Balance [1]

1	Total Initial Energy, evaluated at time zero
1.1	Initial water energy : UFLPSO
1.2	Initial core energy : UCRNO
1.3	Initial structure energy : UCSO
1.4	Initial corium energy : UCMPSO
2	Integrated Energy Addition
2.1	Decay energy inputs : UDECPS
2.2	Fission produce decay energy : UFPDEC
2.3	Zirconium and steel oxidation energy : UZRH20
2.4	Engineered safeguard system sources : UWESF
2.5	Pump energy inputs : UMCPMP
2.6	Ablated reactor vessel wall : URPVB
2.7	Radiation from reactor cavity : UPTRD
3	Integrated Energy Loss
3.1	Letdown & relief flows : ULETPS
3.2	Break flows : UBRTOT
3.3	Corium debris outflow : UDEBRS
3.4	Primary system heat losses : QPHSCN
3.5	Losses to secondary : U2SEC

Most of the above mentioned variables (especially energy related variables) can't be measured through instrumentations during plant operations. For the CET prediction methodology to be applied to the NPPs in the near future as an assistance tool for decision making of operators, it is necessary to select the actual measurable variables as training data. Therefore, the main training variables are selected as shown in Table 3, considering the injection flowrate into the RPV, the relief and break flowrate from the RVP to the containment, and the heat-transfer behavior between RPV and steam generator as shown in Figure 1.

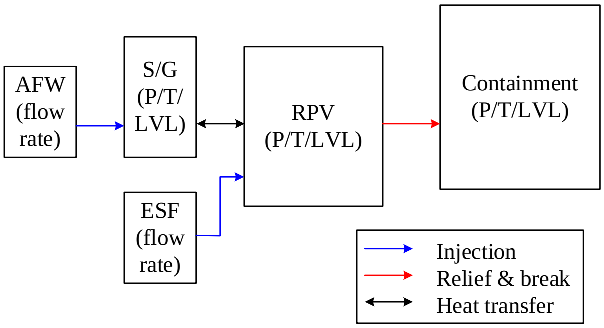

Figure 1. Schematic diagram of mass and energy transfer for the system

CETs are included in Table 3 as training data from the result of training case to learn the predict model, but are not used to predict CETs in test case. It is a typical method of supervised learning in machine learning.

Table 3. Selected Training Variables

Regions	Variables
RPV	PPS: Primary system pressure TCREXIT: Core exit temperature MWCOR: Water mass inside core (Replaceable with core water level)
ESF	WESF: Total injection flowrate to RPV
Containment	PEX0: Containment pressure TGRB: Containment temperature MWCT: Water mass inside containment (Replaceable with containment water level)
S/G	PSGGEN: S/G pressure TGSG: S/G temperature MWSG: S/G water mass (Replaceable with S/G water level)
AFWS	WAFSG : Injection flowrate to S/G

3. Results of Analysis and Prediction

In this study, a small break loss of coolant accident (SBLOCA) is selected as severe accident analysis scenario using MAAP5 code for OPR-1000 plant. Since CET is not functionally required after the RPV is failed, the analysis was performed until the time when the RPV was failed. Table 4 indicates major accident scenarios for training and test (prediction) cases

Table 4. Training and Test (prediction) cases

	Training case	Test case
Init. Event	SBLOCA	SBLOCA
Break size	2 in	2 in
ESF	HPSI available (assumes failure of recirculation mode) SIT available	HPSI unavailable SIT available
AFWS	MD-AFWP available	MD-AFWP unavailable

Figure 2 represents CETs of training and test cases. The training case was successful to carry out safety injection (SI) and auxiliary feed-water injection, so the CET remained relatively stable at the beginning compared to the test case. However, due to a failure of the recirculation mode of SI system after refueling water tank (RWT) was depleted, the CET exceeds 1,200 °F at 39,500 sec and met a severe accident entry condition. On the other hand, the test case failed to perform SI system and auxiliary feed-water pump from beginning, and the CET exceeds 1,200 °F at 3,690 sec after core inventory was depleted.

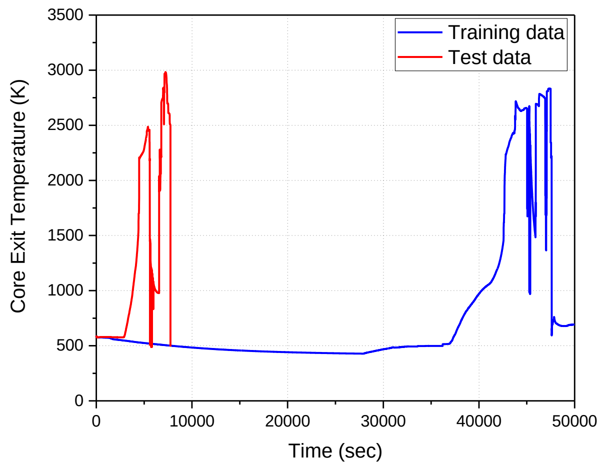

Fig. 2 CET of Training and Test cases in SBLOCA

Figure 3 represents a result of CET prediction in SBLOCA. The prediction result was analyzed through machine learning with LSTM technique by using variables from the test case except CET result. The CET prediction result was similar to the MAAP5 analysis result in general, but there were differences between the prediction and the MAAP5 analysis results in sections with large CET changes. This difference may be due to the use of data based on a single scenario for machine learning of the predict model.

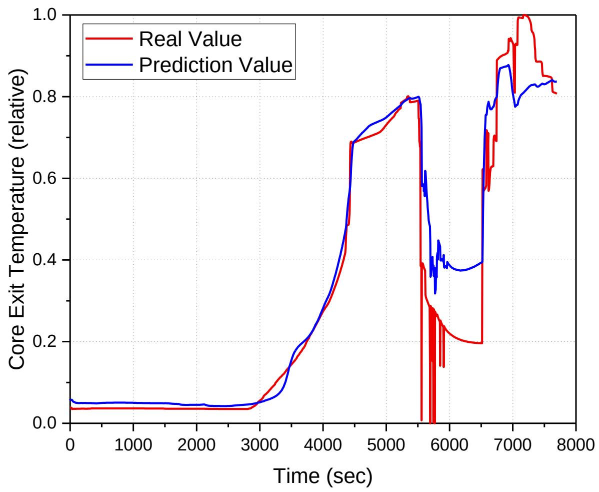

Fig. 3 CET Prediction in SBLOCA

4. Conclusions

In this study, the prediction of the CET used to entry condition of a severe accident was performed using key variables acquired with MAAP5 code and machine learning, a representative AI technique. The prediction performance is considered to be improved through iterative machine learning by collecting training variables from analysis results of various scenarios, which is planned to future works. This study is expected to provide an idea or methodology for developing assistant system of operators' decision making.

ACKNOWLEDGEMENT

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