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Preliminary Prediction of CET for Severe Accident using Machine Learning

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I. Introduction

- The core exit temperature (CET) is typically used to a criterion for determining the entry of a Severe Accident.
- If CET can be predicted, operators will be more effectively coping to the accident because it is possible to secure response time until the entry of SA.
- Recently, the importance of the 4^{th} industrial revolution technology such as an artificial intelligence (AI) is emerging and plant conditions including CET can be predicted using machine learning, a representative AI technique.
- In this study, the training data for machine learning was obtained from MAAP5 analysis of the OPR-1000.

Ⅱ. Selection of Training Variables

■ Mass and Energy balance

▶ Using variables for global primary system of MAAP5 code

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

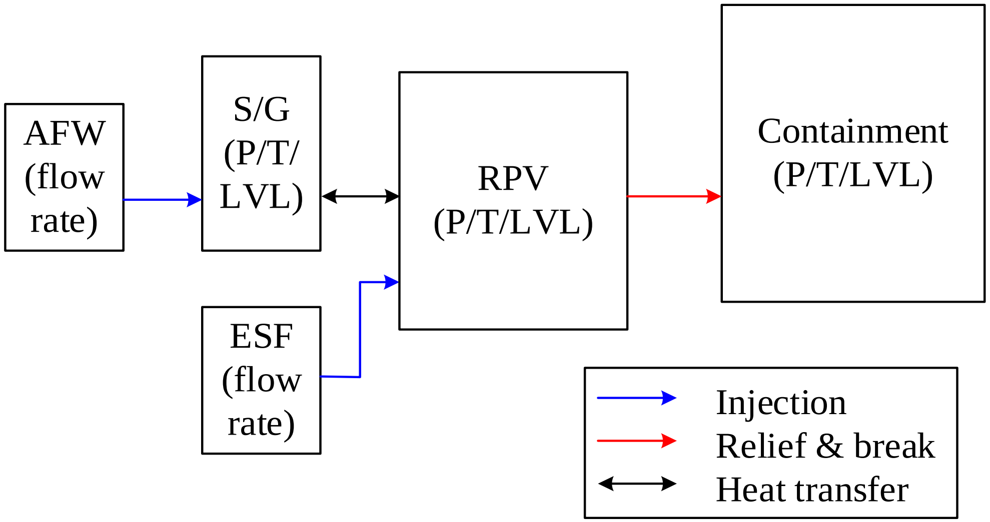
1	Total Initial Energy, evaluated at time zero
1.1	Initial water energy : UFLPSO
1.2	Initial core energy : UCRNO
1.3	Initial structure energy : UCSO
1.4	Initial corium energy : UCMPSO
2	Integrated Energy Addition
2.1	Decay energy inputs : UDECPS
2.2	Fission produce decay energy : UFPDEC
2.3	Zirconium 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 variables can't be measured during plant operations especially energy related variables.**

→ **This method aims to be applied to the NPPs as an assistance tool for decision making of operators.**

II. Selection of Training Variables

■ Diagram of mass and energy transfer for the system



■ Main 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

■ TCREXIT (CET) as a training variable

▶ The CET variables are only used in a training step not a prediction.

▶ Including the target variable (CET) in training dataset is typical method of supervised learning

III. Results of Analysis and Prediction

■ Accident scenarios for Training and Test Case

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

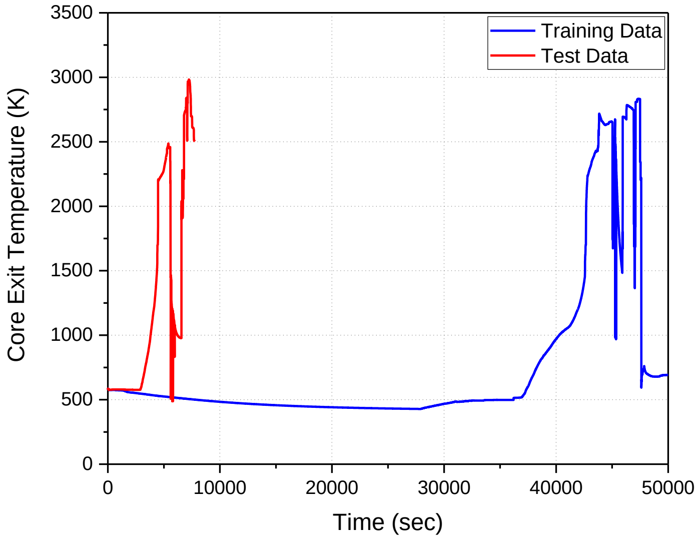
■ Results of Training and Test Case

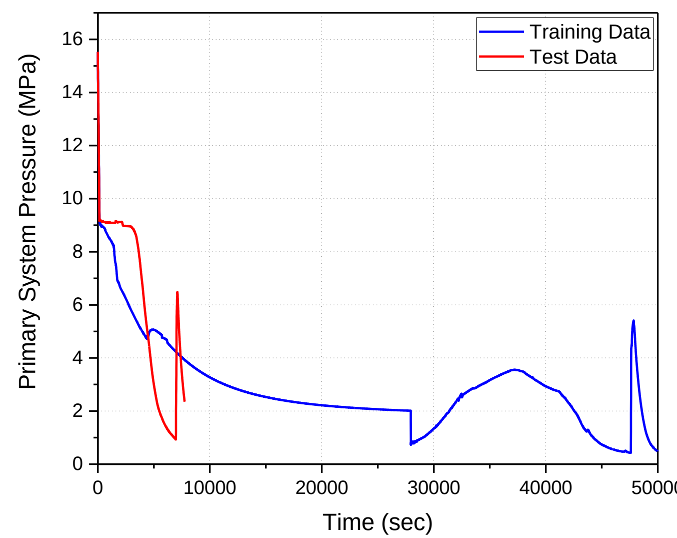
Seq.	Time (sec)	
	Training case	Test case
Core Uncover	36,773	2,862
CET exceeds 1200F	39,607	3,698
Relocation to Lower Head	47,597	6,970
RPV failure	50,835	7,751

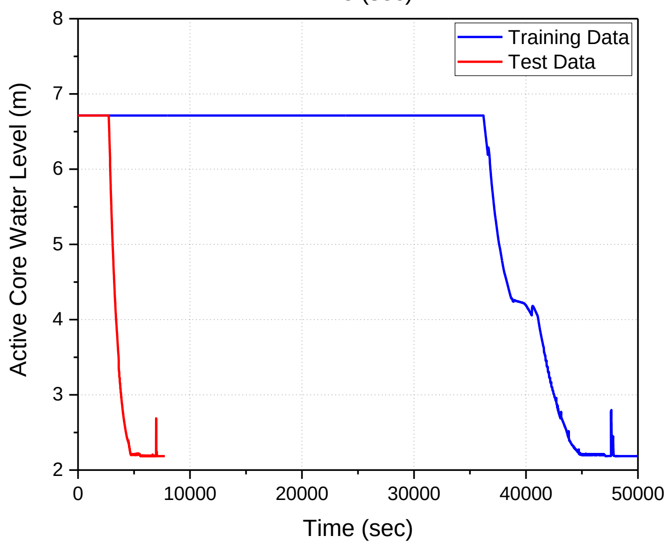
▶ Since the CET is not functionally required after the RPV failure, the analysis was terminated when the RPV was failed.

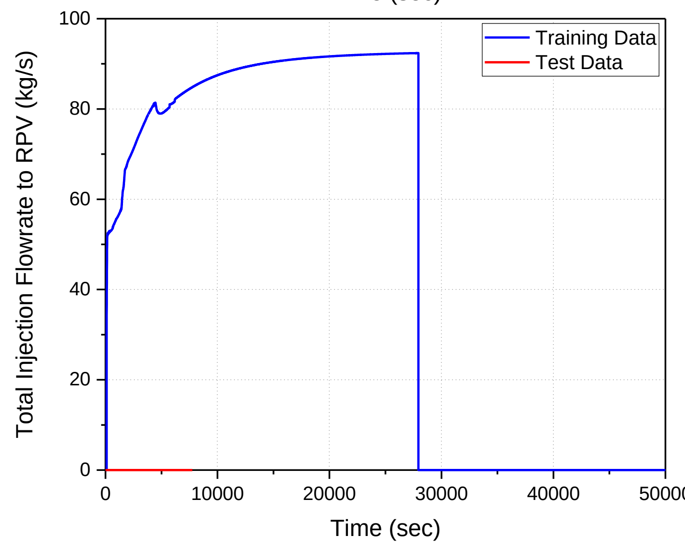
III. Results of Analysis and Prediction

■ Results of Main Variables

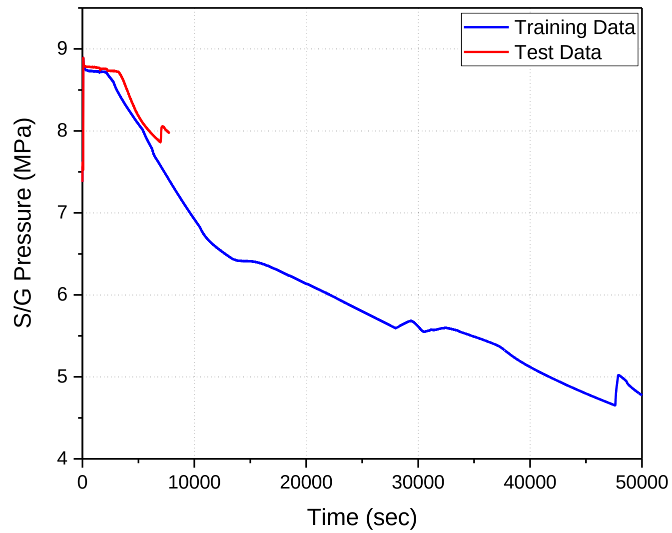


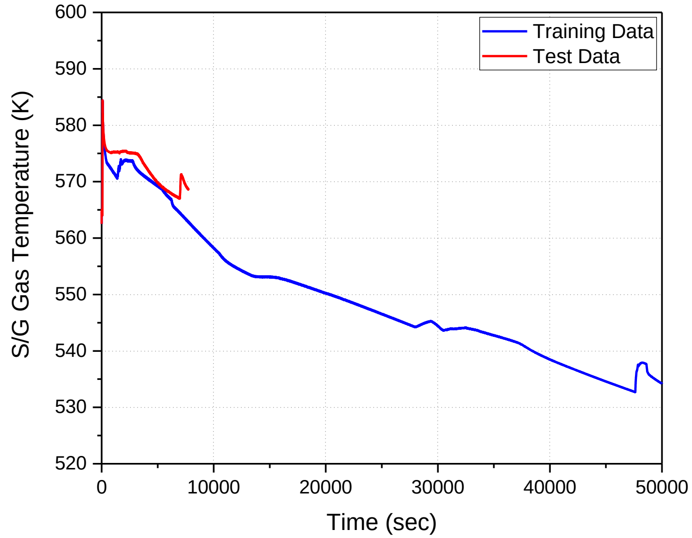


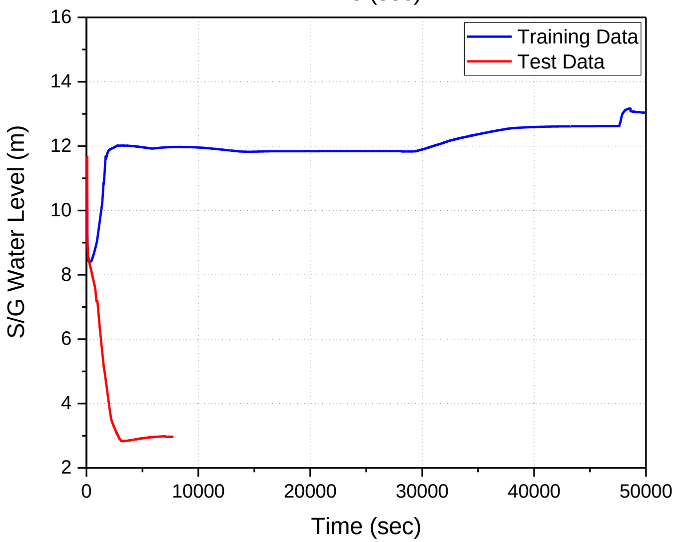


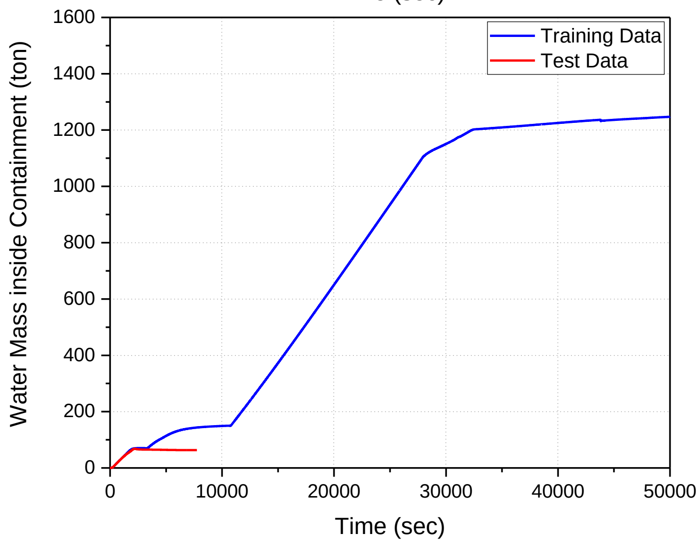


■ Results of Main Variables

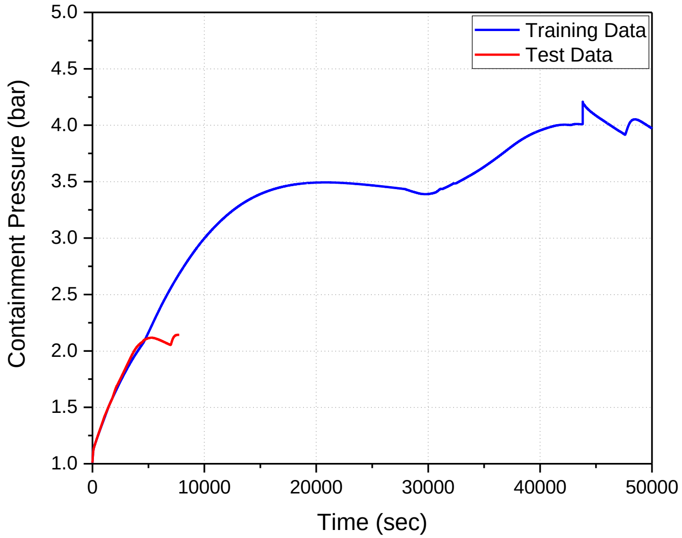


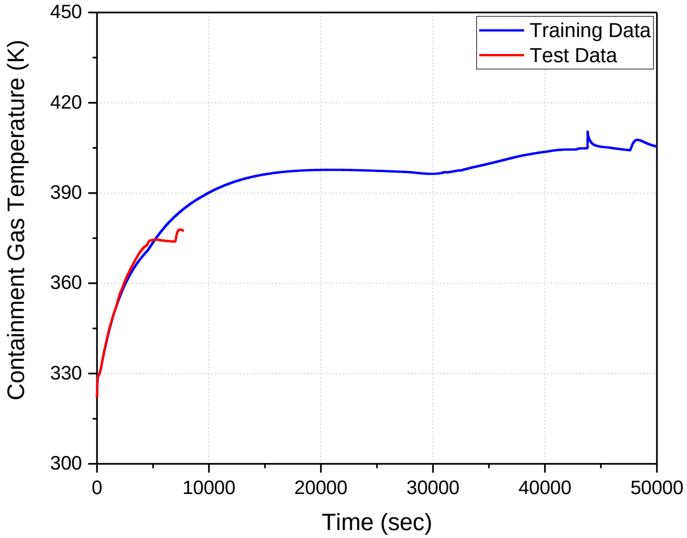






■ Results of Main Variables





■ Extraction of Dataset

▶ Training Dataset of 10,000 from Training Case

▶ Prediction Dataset of 1,500 from Test Case

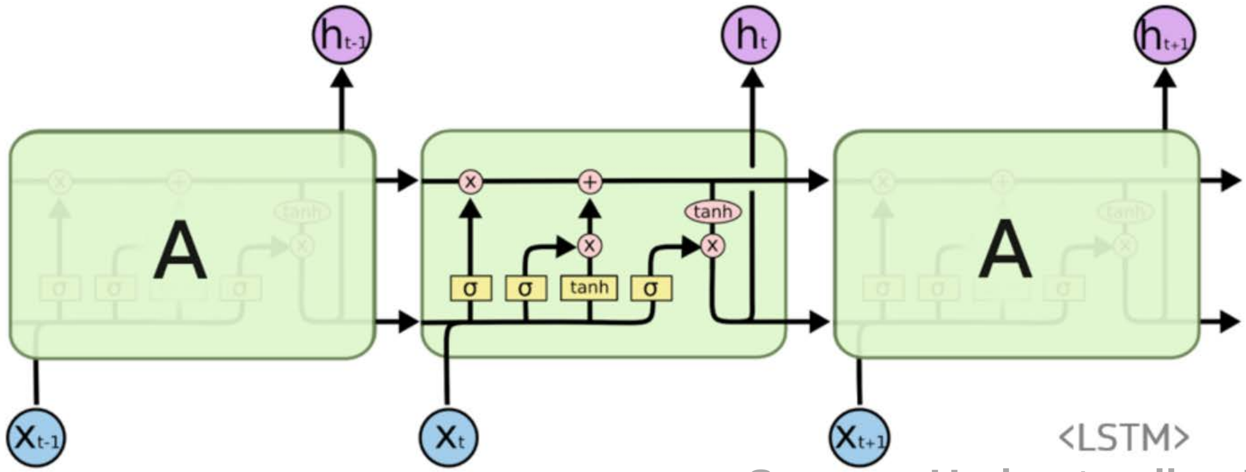
■ **LSTM (Long Short Term Memory, Hochreiter, S., & Schmidhuber, J. (1997))**

▶ One of Major Models of RNN (Recurrent Nenural Network)

▶ A solution of the Long-term Dependency

▶ To predict future data by considering historical data more macroscopically, as well as just previous data

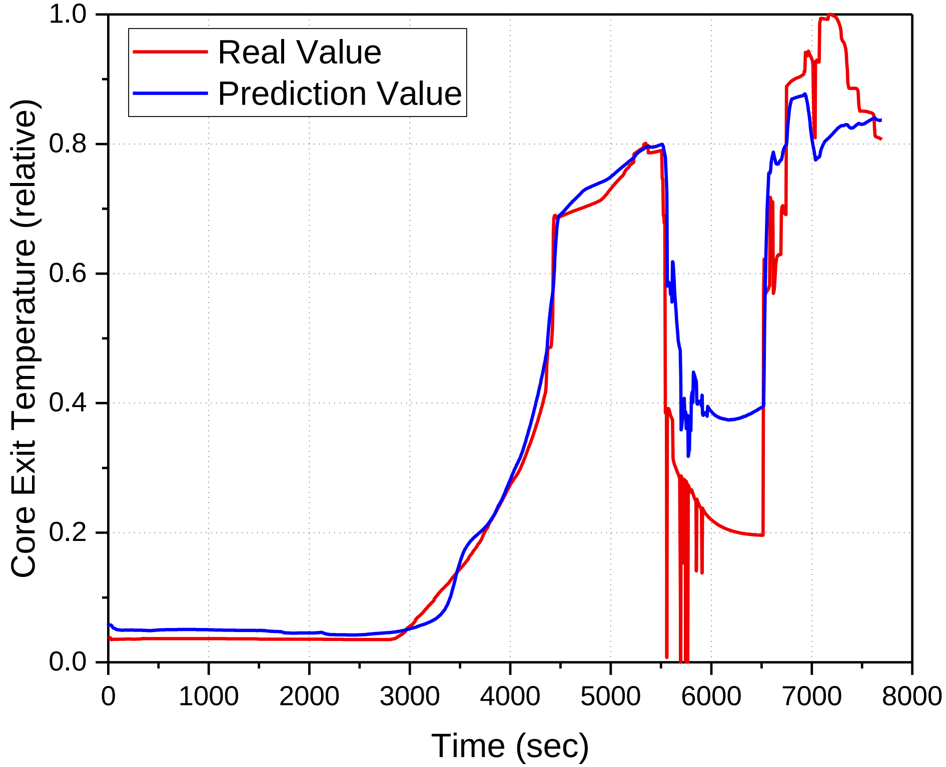
■ **Architecture of LSTM**



<LSTM>

Source : Understanding LSTM Networks

■ Result of CET Prediction using LSTM



- ▶The prediction result is generally similar to behavior of MAAP5
- ▶Some differences are existence in the sections with large CET changes.

IV. Conclusions

- The prediction of the CET was performed by MAAP5 code and Machine Learning, especially LSTM techniques.
- The most important thing is a variable selection
  - ▶Variables which are closely related to the target variable for the accuracy of the prediction results
  - ▶Measureable variables for the applicability of this approach
- To improve the prediction performance, it is needed that iterative machine learning using collected training dataset from analysis results of various scenarios, which is planned as a future works.
- This approach is expected to provide an idea or methodology for developing the assistant system of operator’s decision making.

THANK YOU