Prediction of SMART Plant Conditions in DBA using Machine Learning

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1. Introduction

After the TMI accident, concern in the human factor for safety and efficiency of nuclear power plants has increased. Especially emergency situations, operator should conduct accurately diagnose plant conditions and carry out appropriate responses in limited time. It has been pointed out that human error can be effectively reduced if a number of measurement and alarm signals generated in an emergency situation are automatically analyzed and the operation support system, which can provide decision making to operator. Operation support technology can be implemented using AI techniques. These are developing rapidly in algorithms, application methods, and at the same time, there is a high possibility of innovation and growth through convergence with other ICT technologies. AI methodologies have been presented and verified by several researchers and institutions.

This study aims to predict condition of SMART (System-integrated Modular Advanced ReacTor) using machine learning AI technologies that can be based on operator support techniques. Because SMART adopts the passive system depends on the natural forces (e.g., gravitational force or natural circulation), of which uncertainties are significant, operation support technology may be more necessary in the accident situation.

For conducting machine learning, the wide range of reliable data base (DB) is required. Because there is little data from NPPs in the event of accident, so data production using computer code simulation should be conducted. Prior to data base production, variable selection is needed. By selecting representative variables that represent plant phenomena for machine learning, the accuracy of prediction and the efficiency of computation can be increased.

The machine learning is conducted using long short-term memory (LSTM) methodology. 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, a task that traditional RNNs struggle with. LSTMs use gated cells to store information outside the regular flow of the RNN. With these cells, the network can manipulate the information in many ways, including storing information in the cells and reading from them. The cells are individually capable of making decisions regarding the information and can execute these decisions by opening or closing the gates.

2. Passive Safety System in SMART

2.1 PSIS (Passive Safety Injection System)

The PSIS prevents core uncovery in case of a small break loss-of-coolant accident (SBLOCA) by injecting water into the RCS and removes heat from the core. The PSIS consists of four mechanically independent trains, and each train is composed of one core makeup tank (CMT) and one safety injection tank (SIT). The core makeup tank (CMT) injects the emergency boric acid solution into the reactor coolant system by the gravity under the high temperature and pressure condition during the system operation. The safety injection tank prevents uncovering of the core by supplying emergency cooling water and secures core cooling capacity for at least 72 hours in the event of a loss of coolant accident. The schematic of PSIS presents in Figure 1.

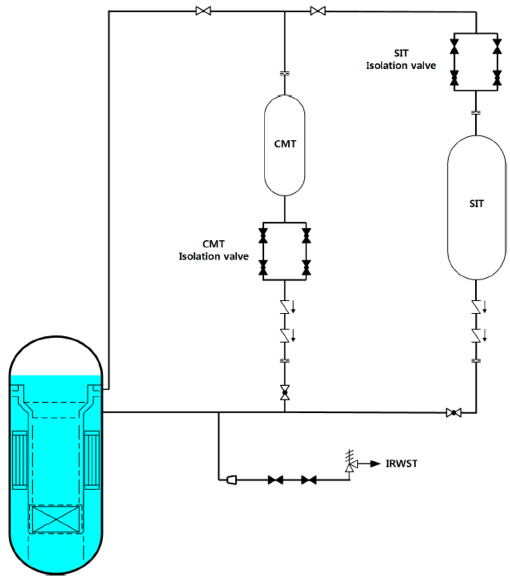

Figure 1.The Schematic of PSIS

2.2 PRHRS (Passive Residual Heat Removal System)

The PRHRS removes the RCS heat by natural circulation in emergency situations where normal steam extraction or feedwater supply is unavailable. The PRHRS cools the RCS to the safe shutdown condition after the accident initiation. The safety function is performed for at least 72 hours without any corrective action by operator or the aid of external AC power. The PRHRS consists of four independent trains and each train is composed of one emergency cooldown tank (ECT), one PRHRS heat exchanger (PHX) add one PRHRS makeup tank (PMT). Each train is connected to a set of two steam generators (SGs). Figure 2 presents the schematic of PRHRS.

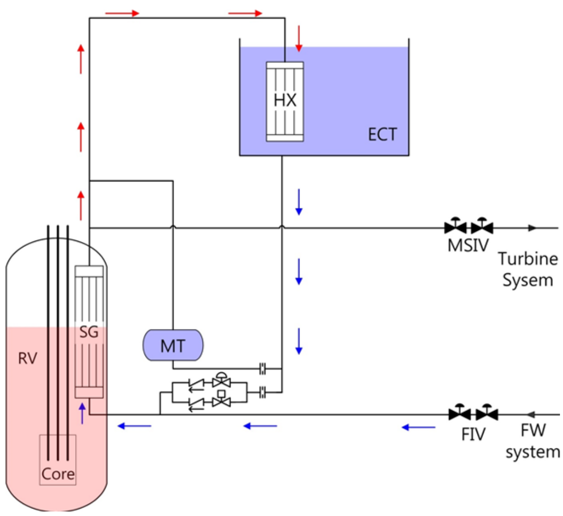

Figure 2.The Schematic of PRHRS

3. Variable Selection

The thermal hydraulic behavior of SMART can be identified from the equation of mass & energy balance equations. The variables for machine learning are selected considering these equations. When selecting variables, passive safety system of SMART such as PSIS (passive safety injection system) and PRHRS (passive residual heat removal system) is considered.

3.1 Mass Balance

The mass balance of SMART can be simply determined as considering inflow by PSIS, Mass release of break and PSV. Mass balance equation of reactor pressure vessel (RPV) can be made as follows.

$$\dot{m}_{net} = \dot{m}_{CMT} + \dot{m}_{SIT} - \dot{m}_b - \dot{m}_P.$$

$\dot{m}_{net}$: Total Mass Change in RPV
$\dot{m}_b$: Mass Release from Break [kg/s]
$\dot{m}_P$: Flow Rate of Released Coolant by PSV [kg/s]
$\dot{m}_{CMT}$: Injected coolant flow rate from CMT [kg/s]
$\dot{m}_{SIT}$: Injected coolant flow rate from SIT [kg/s]

3.2 Energy Balance

The core decay heat in the RCS is delivered to the PRHRS through the steam generator (SG) and the delivered residual heat is removed by the condensation heat transfer from the PRHRS heat exchanger to the coolant in the emergency cooling tank (ECT) through the natural circulation. This process presents in Figure 3.

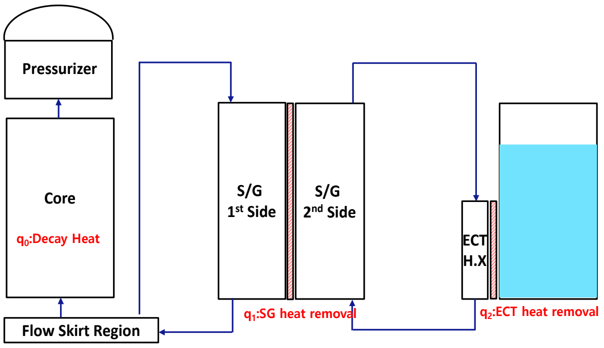

Figure 3.Schematic of the Energy Balance of SMART

Energy Balance can be established as the following equation.

Primary Side Heat Balance

$$q_0 - q_1 - \dot{m}_{PSV} h_0 - \dot{m}_{break} h_0 = C_1$$

Secondary Side Heat Balance

$$q_1 - q_2 = C_2$$

q_0 : Core Decay Heat [W]
q_1 : S/G Heat Removal [W]
q_2 : PRHRS Heat Removal [W]
h_0 : Enthalpy of RCS [J/kg]
h_{PSV} : Enthalpy of Released Coolant by PSV [kg/s]

3.3 Variable Selection

Variables utilized in machine learning are selected considering the mass energy balance in SMART. The change in mass of RPV, CMT, SIT ($\dot{m}_{net}$, $\dot{m}_{CMT}$, $\dot{m}_{SIT}$) can be determined by checking these levels. Mass release rate from break and PSV ($\dot{m}_b$, $\dot{m}_P$) is determined by thermos dynamic state of RCS. The heat removal of the steam generator (q_1) is made by boiling heat transfer, which is determined by the thermodynamic conditions and flow rate of the RCS and the secondary system. And the PRHRS heat removal (q_2) is made by condensation heat transfer, which is determined by the thermos-dynamic conditions of the secondary system. The 25 thermal hydraulic variables are selected for machine learning. And variable lists present in Table 1.

Table 1.Selected Variable for Machine Learning

Number	Selected Variable
1	Reactor Pressure Vessel Level
2	Core Make up Tank (CMT) #1 Level
3	Core Make up Tank (CMT) #2 Level
4	Core Make up Tank (CMT) #3 Level
5	Core Make up Tank (CMT) #4 Level
6	Safety Injection Tank (SIT) #1 Level
7	Safety Injection Tank (SIT) #2 Level
8	Safety Injection Tank (SIT) #3 Level
9	Safety Injection Tank (SIT) #4 Level
10	Pressurizer Pressure
11	Pressurizer Temperature
12	RCS Flow Rate
13	Core Power
14	Main Steam Line #1 Pressure
15	Main Steam Line #2 Pressure
16	Main Steam Line #3 Pressure
17	Main Steam Line #4 Pressure
18	Main Steam Line #1 Temperature
19	Main Steam Line #2 Temperature
20	Main Steam Line #3 Temperature
21	Main Steam Line #4 Temperature
22	Main Steam Line #1 Flow Rate
23	Main Steam Line #1 Flow Rate
24	Main Steam Line #1 Flow Rate
25	Main Steam Line #1 Flow Rate

4. The Numerical Demonstration

4.1 Selection of Accident Scenario

The first case is the prediction of plant condition in small break loss of coolant accident (SBLOCA) due to 25 mm crack. This scenario is proper to evaluate the passive safety system, because both PSIS and PRHRS are actuated. In this case, machine learning data for prediction, is SBLOCA due to 50 mm guillotine break with 2 PSIS and loss of main feedwater (LOMF) with 2 PRHRS.

The second case is the prediction of plant condition in steam generator tube rupture (SGTR). This scenario is proper for predicting plant state in unstable hydrothermal behavior. It is assumed that any safety feature is not available in this scenario, RCS pressure and temperature is fluctuating due to PSV operation. Machine learning data for prediction is used as half of the initial data in this case.

The data base for prediction and machine learning are produced using MARS-KS thermal hydraulic computation analysis program and cases are presented in Table 2.

Table 2.Machine Learning and Prediction Cases

No	Machine Learning	Prediction
1	SBLOCA - 50mm break - 2 PSIS Actuation	SBLOCA - 25mm break - 2 PSIS Actuation - 2 PRHRS Actuation
	LOMF - 50mm break - 2 PRHRS Actuation	
2	SGTR (0~129,500 s)	SGTR (129,500 ~259,000 s)

4.2 Machine Learning using LSTM

Simulation time of each accident case is 3 day (259,000) and time step is 100 sec. The data of 2,590 rows are used for each accident analysis case.

Number of epochs and batch size are set as 80 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 41,440 (2590 / 5 x 80) iterations per accident case as shown in Figure 4.

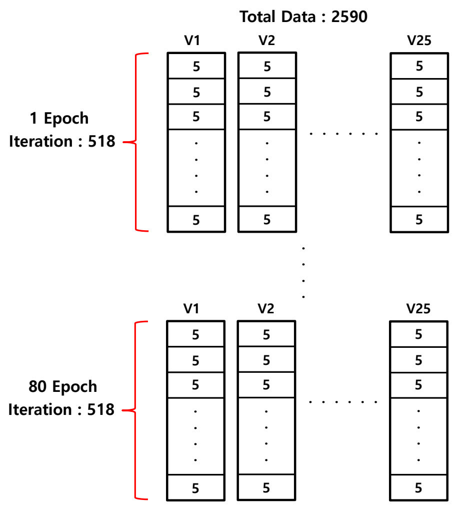

Figure 4.Schematic of Machine Learning

4.3 The Analysis Result

In the first case, coolant is discharged and the RCS pressure decreases rapidly through the break. The low pressurizer pressure signal activates PSIS (Passive Safety Injection) and the highly borated water is injected into the annulus in the reactor pressure vessel by the gravity. Simultaneously with the reactor trip, the RCPs begin to coast down and the feedwater pumps stop. In this case, it is assumed that 2 PSIS and

2 PRHRS is available. Figure 5 and 6 present the above result and the result is similar between the actual values and the prediction values.

The second case is RCS pressure prediction in SGTR. An SGTR is the result of a rupture of a once-through helical tube. If an SGTR takes place, reactor and RCP is tripped by a low PZR pressure or a high steam line pressure. And the passive residual heat removal is activated by the low feedwater flow rate signal. However PRHRS is assumed to be unavailable in this case. So the RCS pressure is increasing due to loss of heat removal and PSV repeats open-close cycling. The data of SGTR accident analysis for machine learning of 259,000 seconds are used. For learning up to 124,500 seconds, and RCS pressure is predicted up to 259,000 seconds. Figure 7 presents the above result. The trends are predicted similarly, but there is a slight difference between the actual data and the prediction values.

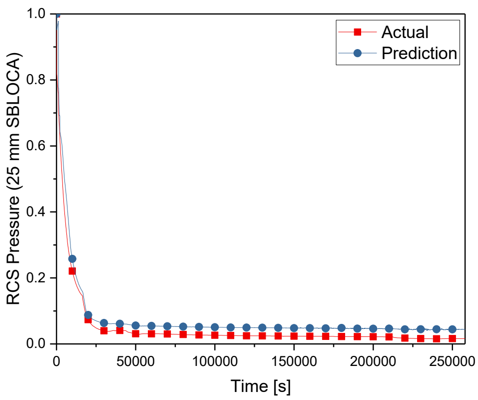

Figure 5.Pressure Prediction in SBLOCA

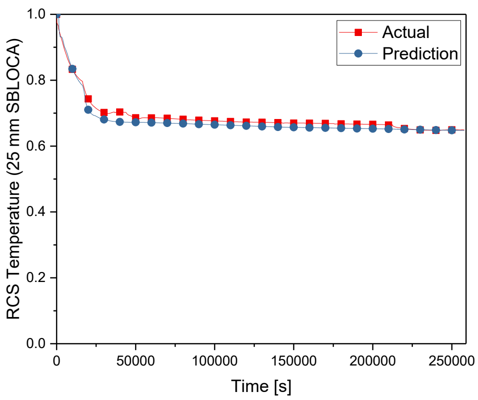

Figure 6.Temperature Prediction in SBLOCA

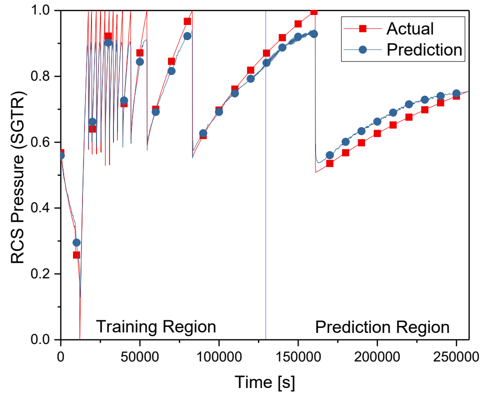

Figure 7.Pressure Prediction in SGTR

5. Conclusions

Plant condition prediction using machine learning is conducted using accident analysis data and LSTM methodology.

The essential variables including passive safety system for machine learning based on the physics, and plant condition prediction using machine learning is conducted. As a result, the actual and predicted values are similar.

And physical-based analysis using thermal hydraulic codes requires a lot of time, but AI enables high-speed prediction. Therefore, this technology can be used for real-time and optimization analysis and it can be based on operator support systems or autonomous nuclear technology.

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