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Study of Real Time Accident Initiator Tracking Algorithm for Small Modular Reactor

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1. Introduction

PWR contains a large number of instruments for detecting changes in the state of the reactor. However, as the judgement of the root cause to the changes is still made by the operator, it is depended on the technical capability of the operator. Especially, in a small module reactor (SMR) which is receiving a lot attention for the development, it would be helpful to have a system that can inform the operator the reactor conditions by interpreting the readings from the existing instrumentations. A small modular reactor named ATOM (Autonomous Transportable On-demanded reactor Module) is now under development in KAIST. This reactor aims to self-govern its operation and this paper is one of the many research works to achieve the goal. In this paper, a leak detection system by interpreting the signals from the instrumentations reading is first done. For this, Dynamic Bayesian Network is used. The Bayesian Network expresses a set of random variables and their conditional dependency using directed acyclic graph.

When generating a cognitive model with Bayesian Network, a lot of accident data set such as pressure, temperature, mass flow, etc is needed for training. In the early development stage, simulation results replace the real accident data. Among accident data, reactor protection system (RPS) parameters are used as they do not require any additional instrument.

Meanwhile, although the model is well trained, its accuracy can be changed if training condition and testing condition is different. For this test, training data that has leakage on the Pilot Operated Relief Valve (PORV) are generated in beginning of cycle (BOC) condition. Test data which has leak in random time is generated in both BOC and EOC (end of cycle) condition, and accuracy is compared. For the accuracy, delay time that measures the difference between accident time and model-guessed time is used.

2. Model Information

2.1. Dynamic Bayesian Network

In this model, Dynamic Bayesian Network (DBN) is used. DBN comes from Bayesian probability:

$$\mathrm{P}(X|y) = \frac{\mathrm{P}(X)\mathrm{P}(y|X)}{\mathrm{P}(y)} \tag{1}$$

where X is reactor state, and y is observed data in our case. As real time data is provided discretely, Dynamic Bayesian Network is considered as a function of time:

$$\begin{aligned} \mathrm{P}(X_t|y_{1:t}) &= \mathrm{P}(X_t|y_{1:t-1}, y_t) \\ &\propto \mathrm{P}(y_t|y_{1:t-1}, X_t) \cdot \mathrm{P}(X_t|y_{1:t-1}) \end{aligned} \tag{2}$$

The subscript means the time, and it can be expanded as follow:

$$\begin{aligned} &\mathrm{P}(y_t|y_{1:t-1}, X_t) \cdot \mathrm{P}(X_t|y_{1:t-1}) = \\ &\mathrm{P}(y_t|y_{t-1}, X_t) \cdot \sum \mathrm{P}(X_t|X_{t-1})\mathrm{P}(X_{t-1}|y_{1:t-1}) \end{aligned} \tag{3}$$

In equation (3), first-order Markov assumption is used. Markov assumption is that a variable is only dependent of its parent, not its grandparents and ancestors. $\mathrm{P}(X_t|X_{t-1})$ is the state-transition function, and we use uniform probability for this as we consider only observing data not priori probability. Now, we can obtain the following equation:

$$\begin{aligned} \mathrm{P}(X_t|y_{1:t}) = \mathrm{P}(y_t|y_{t-1}, X_t) \\ \cdot \sum \mathrm{P}(X_t|X_{t-1})\mathrm{P}(X_{t-1}|y_{1:t-1}) \end{aligned} \tag{4}$$

This recursion relation is used for model training and testing, and specific methods are described below. Directed acyclic graph is in Figure 1. In this paper, general RPS monitoring parameter is only used: Hot leg and cold leg temperature, pressurizer and steam generator pressure and pump velocity. Also, its derivative is used for training.

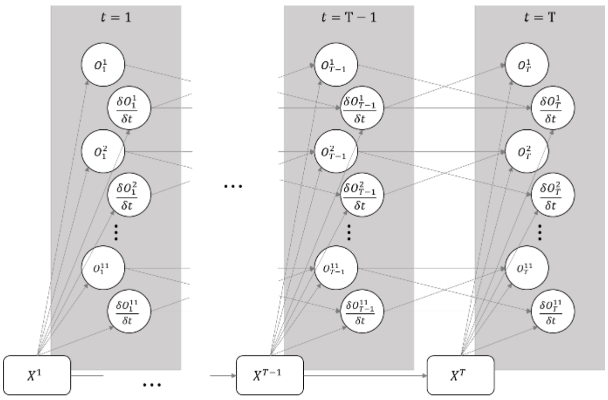

Fig. 1. Directed Acyclic Graph

2.2. ATOM reactor

ATOM is small modular reactor with water-cooled, soluble-boron-free. It is currently in development, and its main parameters are in Table 1. Also, its nodalization for simulation data generation is in Figure 2. PORV was accidentally opened at the top of the blue box in Figure 2.

Table 1. Main parameters of the ATOM

Parameter	ATOM [100MW_e]
Core thermal power	330 MW_{th}
Core Coolant Flow rate	1565 kg/s
Pressurizer pressure	15.0 Mpa
Core inlet temperature	268 ℃
Core outlet temperature	311 ℃
MDNBR	3.4
Max. Cladding Temperature	355 ℃
Max. Fuel Temperature	1499 ℃
Feedwater flow rate	157 kg/s
Feedwater temperature	183 ℃
Feed water pressure	4.64 Mpa
Degree of Superheat	26 ℃

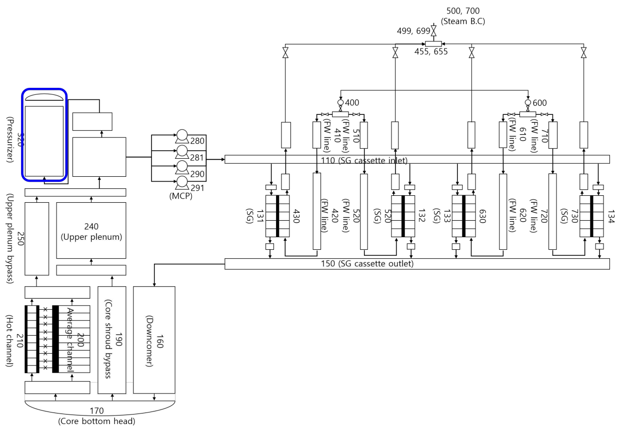

Fig. 2. Nodalization of ATOM

2.3. Accident data

ATOM is an integrated reactor with most of the primary components in the reactor pressure vessel. It is not physically possible to have a large break LOCA because the pipe size is small. In this paper, PORV open scenario is only used to mimic a small break LOCA condition and the model determines the reactor state in real time. MARS-KS v1.4 code is used for accident simulation. Training data is generated in BOC condition, and the number of data is 1,000 which has different open area from uniformly distributed random number in the given range: from 0.5 inch to 2 inch diameter. 500 seconds of data set after the accident was used as training data. Figure 3 shows some variables of the training data set. It represents the average of the training data variable and the error bar shows the standard deviation. Testing data is generated in both BOC and EOC conditions, and accident occurs randomly from 0 to 400 seconds. As both training data and test data are randomly generated, the probability to have same open area is very low.

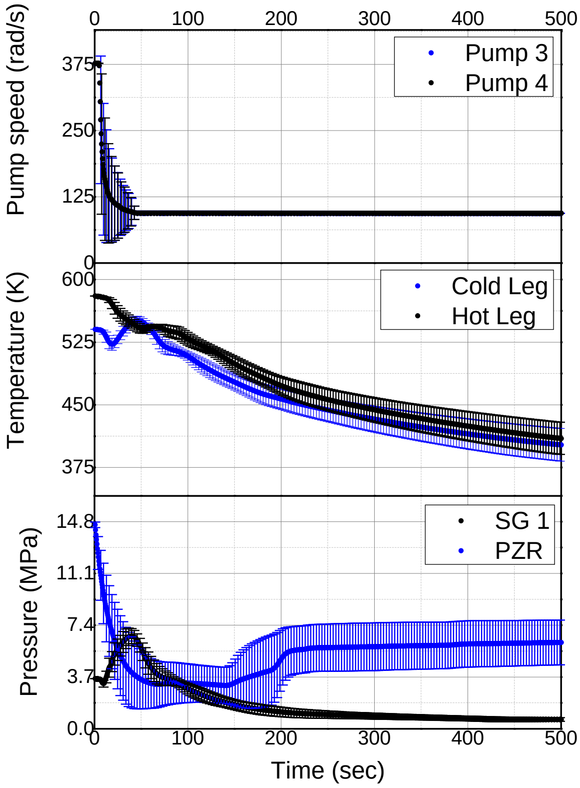

Fig. 3. Mean and standard deviation of several observation parameters.

2.4. Training and test method

From model training, $P(y_t|y_{t-1}, X_t)$ is updated. For calculating the probability, its distribution should be determined such as continuous normal distribution, beta distribution, and discrete distribution. In this model, equal width discretization is used: dividing the interval with the same length. For each variable, calculate the maximum and minimum values for all times of training data, and divide this range into a uniform size. When the probability is calculated, the interval between the measurement data of the previous and the current time is included for training the model. For this process, the number of intervals is an element determined by the user, and we use 4, 6 and 8 for this value.

When the actual (test) data comes in, the process of calculating the real-time reactor state probability by the model is as follows. Whenever data comes in, it calculates the probability that the reactor will be in a specific state using the previous data and the current data.

It provides the probability in real time, and reactor state is judged as an accident when the probability of accident is larger than the probability of being in a normal state.

3. Performance of Model

The number of test case is 25 for both BOC and EOC conditions. The number of interval 4, 6 and 8 is used and delayed time is plotted in Figure 4. Table 2 shows the delayed time in more detail.

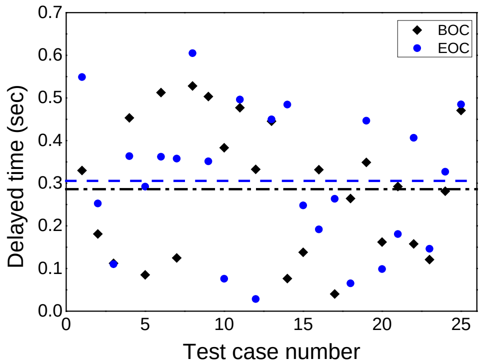

Fig. 4. Delayed time of BOC and EOC

Table 2. Detailed Delayed time of BOC and EOC

# of interval	BOC Mean (sec)	BOC Stdev. (sec)	EOC Mean (sec)	EOC Stdev. (sec)
4	0.286	0.157	0.306	0.164
6	0.286	0.157	0.306	0.164
8	0.286	0.157	0.306	0.164

Surprisingly, the number of interval does not affect the results. Difference of mean time is 0.02 sec at least 20 times smaller than one time step, 0.5 sec. The delay time of all data is less than 1 second, and it can be seen that it is judged by an accident within two time steps. From these results, a model trained in the BOC condition can be considered to be a good discriminator even in the EOC condition under PORV stuck open scenario.

4. Conclusion

To provide operators with real-time probability of reactor status, we constructed an artificial intelligence model using Dynamic Bayesian networks. Meanwhile, it was not assured whether artificial intelligence trained in BOC condition can show similar performance in the EOC condition. Therefore, it is applied to ATOM reactor to test the performance. PORV open accident is used and the number of data for training was 1000 data set. Test data was generated in random time, and the number of data generated in BOC and EOC condition was 25. Delayed time, the difference between the actual accident time and the time taken for the model to determine as an accident, was measured to be 0.286 and 0.306 seconds in BOC and EOC respectively. The delay time of all data is less than 1 second, and it can be concluded that a model trained in the BOC condition can be considered to be a good discriminator even in the EOC condition, and it can be used in every cycle in case of normal state and PORV open state.

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REFERENCES

[1] KAERI, MARS CODE MANAL Vol. 1 Code Structure, System Models, and Solution Methods, 2009.
[2] USNRC, "Reactor Safety Study_An Assessment of Accident Risks in U.S. Commercial Nuclear Power Plants", WASH-1400, 1975.
[3] V. Mihajlovic, M. Petkovic, Dynamic Bayesian Networks: A State of the Art", CTIT Technical Report Series, pp.1-37, 2001.
[4] Yin Yang, Geoffrey I. Webb, "A Comparative Study of Discretization Methods for Naïve-Bayes Classifiers", Proceedings of the 2002 Pacific Rim Knowledge Acquisition Work-shop, Japan, pp. 159-173, 2002.