Loss of Coolant Accident Classification in Real Time using Dynamic Bayesian Network

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1. Introduction

In a nuclear power plant, there are a lot of instrumentations to check the change of operating conditions. However, most of the accident judgement is decided by operator's insight. If an algorithm that informs the most possible reactor state to operator is formulated, a reactor trip from misdiagnosis can be decreased.

Dynamic Bayesian Network (DBN) is selected for this purpose to determine the reactor condition in this study. DBN is a Bayesian Network that has relation with other time steps. Bayesian Network is a graphical model of probability that expresses a conditional probability of random variable using directed acyclic graph. Classification, prediction and filtering can be done if it is used. There are many advantages for applying DBN. First, additional instrumentations are not needed. RPS monitoring parameters are only used in this model to demonstrate this point. Also, a real time probability calculation is possible.

This study's initial objective is to classify the Loss of Coolant Accident (LOCA) type. Three types of LOCA exist: Small Break LOCA(SBLOCA), Medium Break LOCA (MBLOCA), and Large Break LOCA(LBLCA). It is clear that the classification is based on the pipe rupture area. An approximate rupture location estimation is also performed to determine if the break took place in hot leg or cold leg.

2. Dynamic Bayesian Network

2.1. Dynamic Bayesian Network

Bayesian Network begins from Bayes' theorem.

$$\mathrm{P(A|D)} = \frac{\mathrm{P(A)P(D|A)}}{\mathrm{P(D)}} \qquad (1)$$

where D is Data, and A is Accident. In here, P(A) is a priori probability, P(D|A) is likelihood. P(D) is normalizing constant, and if we use the property, $\sum_i \mathrm{P}(\mathrm{A}_i|\mathrm{D}) = 1$, it can be calculated. As we want to determine the class of LOCA by only using monitoring data without the knowledge of a priori probability, uniform probability is first assumed. Equation (1) implies Equation (2).

$$\mathrm{P(A|D)} \propto \mathrm{P(A)P(D|A)} \propto \mathrm{P(D|A)} \qquad (2)$$

As data is provided in real time, we consider probability as a function of time (DBN). There could be two types of probability whether it considers the entire time or specific time. It can be expressed as equation (3).

$$\begin{aligned}&\mathrm{P}(\mathrm{A}_i^{tot}|\mathrm{D}^{1:T})\\&= \mathrm{P}(\mathrm{A}_i^1, \mathrm{A}_i^2, \cdots, \mathrm{A}_i^T|\mathrm{D}^{1:T}) \Big/ \sum_i \mathrm{P}(\mathrm{A}_i^1, \mathrm{A}_i^2, \cdots, \mathrm{A}_i^T|\mathrm{D}^{1:T})\end{aligned} \qquad (3)$$

In equation (3), $\mathrm{P}(\mathrm{A}_i^{tot})$ is the probability that considers the entire time, and $\mathrm{P}(\mathrm{A}_i^T)$ is the probability at specific time $t = \mathrm{T}$. If we assume that observed data is independent of other time steps to simplify the DBN structure, equation (4) can be obtained.

$$\mathrm{P}(\mathrm{A}_i^1, \mathrm{A}_i^2, \cdots, \mathrm{A}_i^T|\mathrm{D}^{1:T}) = \prod_t \mathrm{P}(\mathrm{A}_i^t|\mathrm{D}^t) \qquad (4)$$

As mentioned earlier, data is RPS monitoring parameters. That is, $\mathrm{D}^t = \{O^{t,1}, O^{t,2}, \cdots, O^{t,15}\}$. In Equation (4), $\mathrm{P}(\mathrm{A}_i^t|\mathrm{D}^t)$ can be expressed as equation (5) using the property of BN, equation (2).

$$\mathrm{P}(\mathrm{A}_i^t|\mathrm{D}^t) = \mathrm{P}(\mathrm{D}^t|\mathrm{A}_i^t) \Big/ \sum_i \mathrm{P}(\mathrm{D}^t|\mathrm{A}_i^t) \qquad (5)$$

2.2. DAG

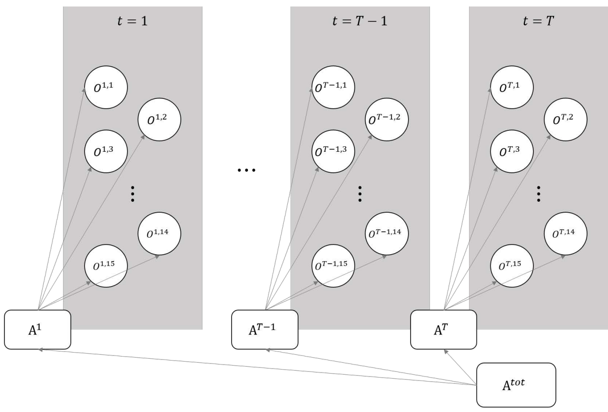

Fig. 1. Directed Acyclic Graph of this model

Directed Acyclic Graph (DAG) contains Bayesian Network. Dependency of each node can be easily checked.

In figure 1, $O^{t.n}$ means the observed data number n at time t. There are 15 RPS monitoring parameters. 3 of them are pressures (pressurizer, 2 steam generator), and 6 of them are temperatures (2 cold leg, 4 hot leg). 4 of them are pump speeds, and others are steam generator water level. We assume that each observation parameter follows a Gaussian distribution for each accident. That is,

$$O^{t,n} \sim \sum_i N\left(\mu_i^{t,n}, \sigma_i^{t,n}\right) \tag{6}$$

where i is the number of accident type. Using the DAG of this model, we can get an equation (7)

$$\mathrm{P}(\mathrm{D}^t|\mathrm{A}_i^t) = \prod_n \mathrm{P}(O^{t,n}|\mathrm{A}_i^t) \tag{7}$$

3. Accident Data Generation

By using MARS(Multi-dimensional Analysis of Reactor Safety)-KS code, accident data for both training and testing is generated. MARS-KS is developed for analyzing multi-dimensional thermal hydraulic transition in a light water reactor system [1]. APR1400 model is used for the accident classification. APR1400 is 1400MW$_e$ light water reactor developed in South Korea 2002. LOCA is classified by the rupture size and rough location. Criteria of rupture area is introduced in Table 1 according to NRC Report. Rough location implies that the break occurred at either hot leg or cold leg. 1000 data is generated for each case, and 6000 data is used in total. For each training case, MATLAB random function generates rupture area for given range.

	Rupture diameter [m]
SBLOCA	0.0127 ~ 0.0508
MBLOCA	0.0508 ~ 0.1524
LBLOCA	0.1524 ~

Table 1. Range of rupture area from NRC report [2]

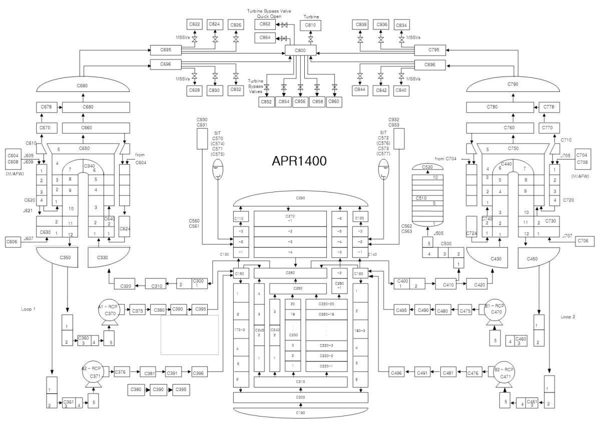

Fig. 2. APR 1400 MARS-KS nodalization [3]

Figure 3. shows the mean and standard deviation of each time step of some observation parameters. They are trained by the distribution of training data sets, and $\mu_i^{t,n}$,

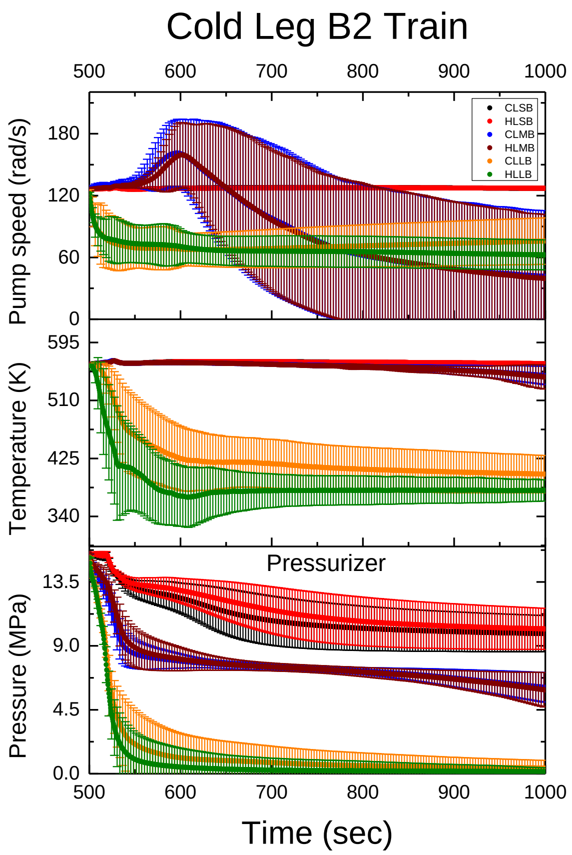

Fig. 3. Mean and Std. of several observation parameters.

$\sigma_i^{t,n}$ are calculated. Error bar present 1σ for a Gaussian distribution. When test data is given at discrete time, as similar to real situation, probability to be included at each accident is calculated. It means that $\mathrm{P}(O^{t,n}|\mathrm{A}_i^t)$ is calculated at each time step using $\mu_i^{t,n}$, and $\sigma_i^{t,n}$.

4. Model Performance

60 test data is used to evaluate the performance. Each case has 10 random accidents. It could be 20 accidents from the perspective of only considering break area without approximate location (Hot leg or Cold leg). Real time calculation is monitored as shown in figure 4.

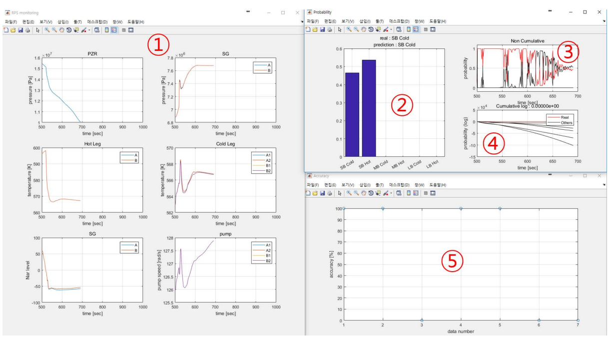

Fig. 4. Real time accident probability

In figure 4, RPS monitoring data is updated at graph ①. After updated, probability calculation is performed, and graphs ②, ③, and ④ are displayed. As calculation time is less than 0.5 ms, real time calculation is feasible. Graph ② shows the probability at specific time, $P(A_i^t)$, and graph ③ is time history of graph ②. Graph ④ is probability considering the entire time, $P(A_i^{tot})$. Graph ⑤ shows the total accuracy per each test data. X-axis is the test data number.

Figure 5. shows the accuracy of the model. In the perspective of break area size, the classification is perfectly done 100%. However, for tracking the LOCA location, the accuracy is decreased slightly to 90% above.

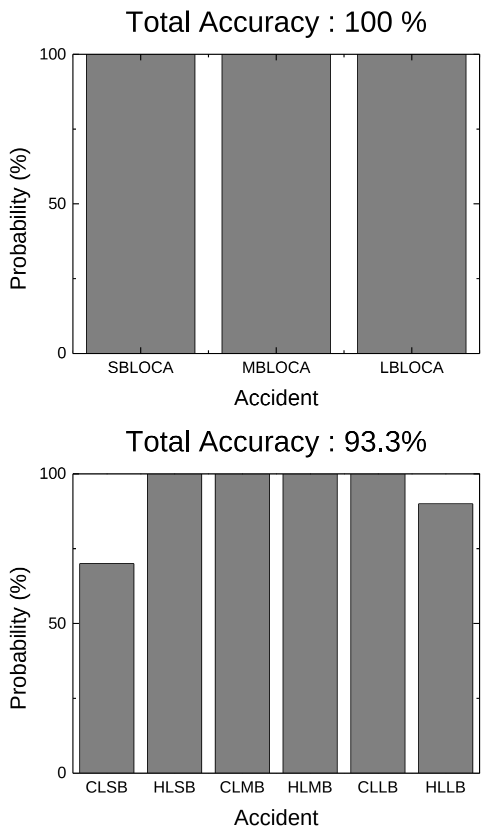

Fig. 5. Classification accuracy

5. Conclusions and Future works

By using Dynamic Bayesian Network, LOCA was classified successfully in near real time. Classification accuracy is 100% when only the rupture size is considered. However, when considering both rupture size and location, accuracy become slightly lower for the random test data.

Many future improvements can be quickly identified from this study. First, more accident types should be added for classification. For instance adding SGTR, control rod withdrawal accident, and others are needed. Second, removing the assumption that reactor state does not change is needed. The last but not least improvement is changing the assumed distribution from Gaussian to other distribution or testing other DAG structure to improve the accuracy. Changing DAG means that some variables are now dependent to other variables and this will be the case in the real nuclear power plant.

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