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Prognostics for Steam Generator Tube Rupture using Markov Chain model

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1. Introduction

As the operation period of Nuclear Power Plants (NPPs) is getting longer, it is effective that predicting of ageing effect to NPPs by reflecting plant-specific condition data for risk management and maintenance optimization.

This paper will describe the prognostics method for evaluating and forecasting the ageing effect and demonstrate the procedure of prognostics for the Steam Generator Tube Rupture (SGTR) accident. Authors will propose the data-driven method so called MCMC (Markov Chain Monte Carlo) which is preferred to the physical-model method in terms of flexibility and availability.

2. Methods

2.1 Prognostics

Prognostics is a key technology of PHM (Prognostics and Health Management) that monitors, diagnoses and prognoses integrity of system in a real time manner. [1, 2] Thus, prognostics enables to prevent accidents in advance and to establish a maintenance and repair plan.

Prognostics is classified into 3 type according to available information.

Type 1 prognostics is conventional failure analysis that is performed based on reliability. It uses failure distribution model made from existing failure data and with this, predicts condition and lifetime averagely. Weibull, exponential, normal distribution analysis belong to Type 1 prognostics.

Type 2 prognostics is operation condition based analysis that considers environmental effects (temperatures, loads, vibration, etc.) on a component. Regression analysis and Markov chain model belong to Type 2 prognostics.

Type 3 prognostics is degradation due to ageing based analysis. It can predict more precisely than Type 2 prognostics by considering ageing effects on components as well as environmental effects.

This paper suggests Markov chain model belonging to Type 3 prognostics that can consider degradation due to ageing for considering ageing effects on NPPs

2.2 Markov Chain Model

Markov chain model is based on assumption of Markov process; Present state includes the information of previous states and next state is only dependent on present state. [3, 4]

According to the assumption, if we have the information of present state and transition probability matrix, it is possible to predict next state. Transition probability matrix is composed of the probabilities that a certain state transfers to the other states at the next time.

Equation 2.2.1 represents the transition probability matrix.

$$\bar{\bar{A}} = \begin{array}{c c} i/j & \begin{array}{cccc} 0 & 1 & \cdots & N \end{array} \\ \begin{array}{c} 0 \\ 1 \\ \vdots \\ N \end{array} & \begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0N} \\ p_{10} & p_{11} & \cdots & p_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N0} & p_{N1} & \cdots & p_{NN} \end{bmatrix} \end{array} \qquad (2.2.1)$$

The rows of the transition probability matrix mean present state and the column means a state of the next time. In other words, an element of the matrix p_{ij} means the probability of transition to the state j from the present state i at next time. Thus, sum of each rows is 1.

It is called MCMC that integrates Markov chain model with Monte Carlo Simulation (MCS). MCS methods performs simulation based on the probabilistic information of the subject system by generating a huge number of random sampling numbers.

For the prognostics, MCMC can be used as follow.

First, transition probability matrix is made from existing failure data.

Next, simulation of transferring state is performed. MCS degrades the system until the extent of performance degradation reaches to a threshold by transferring state based on the transition probability matrix. The time that the extent of performance degradation reaches to the threshold is time-to-failure. Thus, residual useful lifetime (RUL) is difference between present time and the time-to-failure.

2.3 Case study – Prognostics for SG tube

We performed prognostics for Steam Generator Tube Rupture (SGTR) accident as a case study. SGTR is caused by rupture at steam generator tube that is boundary between reactor coolant system and main steam system. Because radioactive materials can be leaked to external environment through the ruptured tube and secondary system, SGTR can cause severe consequences. Thus, it has relatively high frequency of initiating event.

As a data for the case study, we used degradation data obtained by using PASTA (Probabilistic Algorithm for Steam generator Tube Assessment) program that performs assessment of integrity of steam generator tube. [5] Degradation data is represented as growth of burst probability over time. The burst probability is recorded at every EFPY (Effective Full-Power Year). And in this study, 1 EFPY is 18 months. If the burst probability exceeds 40%, it is regarded as 'failure', then simulation is stopped immediately. In such a manner, we obtained 130 data sets. We assumed 100 of those as an existing failure data, and assumed the rest 30 as a monitoring data for the study. For the 30 of monitoring data, we made those into 3 cases that have the burst probability data until 6, 9, 12 EFPY respectively to show the characteristic of prognostics that accuracy of prognosis increases, as more monitoring data is accumulated.

3. Results

- Pre-processing of data

Degradation data is represented as growth of burst probability over time. Markov chain model is performed based on transition probability of state. And the state must be discrete variable. Therefore, burst probability that is continuous variable have to be changed into discrete variable to apply Markov chain model to the degradation data. For this, we divided the data into several numbers of interval and assigned state numbers like $\mathbf{0}, \mathbf{1}, \mathbf{2}, \cdots$ to each data as figure 1.

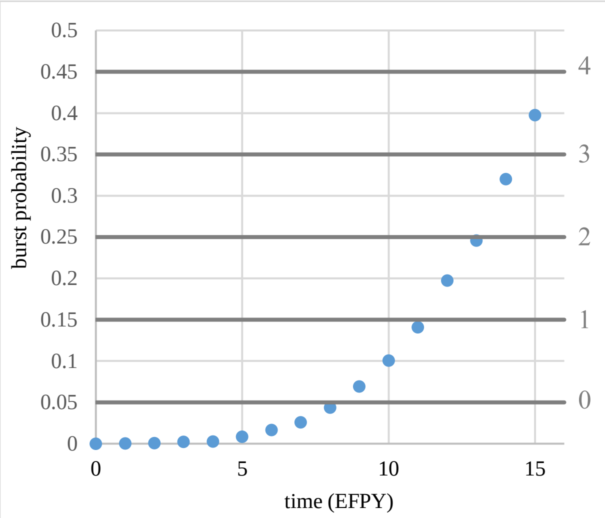

Figure 1. Preprocessing of data

- Training part

Prognostics process using Markov chain model is separated by two parts; Training and Test part.

At training part, transition probability matrix is obtained from existing failure data. The matrix is obtained by counting p_{ij} in equation 2.2.1 at every time. For example, if the system having state of 1 transfers to 2, then p_{12} become $p_{12} + 1$. Afterward, each components of the counted matrix are divided by sum of corresponding row's components to be represented as ratio (or probability). Table 1 represents the transition probability matrix obtained from 100 of training data (existing failure data).

Table 1. Transition probability matrix of failure data

State i/j	0	1	2	3	4
0	0.72195	0.27805	0	0	0
1	0	0.66415	0.33585	0	0
2	0	0	0.52607	0.47393	0
3	0	0	0	0.49412	0.50588
4	0	0	0	0	1

- Test part

At test part, time-to-failure and RUL is predicted by using MCS with monitoring data and the transition probability matrix obtained from training part. Present state (last state of monitoring data) is transferred to the other state by MCS based on transition probability matrix. Transition simulation is performed until burst probability reaches to threshold. That is, the simulation is stopped when the state becomes '4' that means threshold point, 0.4 of burst probability. Time-to-failure is decided as the time that the state reaches to '4' and RUL is difference between present time and the time-to-failure. For 30 of monitoring data sets, we performed transition simulation for 10,000 times using MCS.

Figure 2 represents time-to-failure probability distribution. It is result of 10,000 times of simulation with one of the monitoring data sets.

The figure shows that case 3 that has 12 EFPY monitoring data has narrowest distribution, on the contrary, case 1 that has 6 EFPY monitoring data has widest distribution. This shows one of characteristics of prognostics that more monitoring data enables more accurate prediction with less uncertainty.

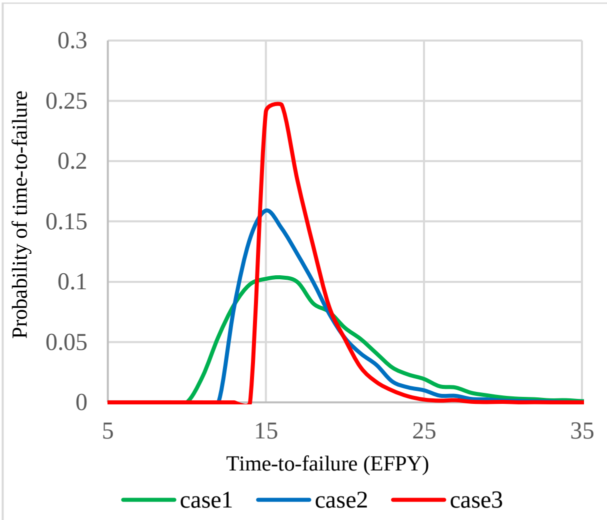

Figure 2. Time-to-failure probability distribution

4. Conclusions

The Markov chain model which is one of prognostics methods was described and the pilot demonstration for a SGTR accident was performed as a case study.

The Markov chain model is strong since it is possible to be performed without physical models as long as enough data are available. However, in the case of the discrete Markov chain used in this study, there must be loss of information while the given data is discretized and assigned to the finite number of states. In this process, original information might not be reflected on prediction sufficiently. This should be noted as the limitation of discrete models.

Now we will be studying on other prognostics methods such as GPM (General Path Model) which is also data-driven method as well as the particle filer which belongs to physical-model method and conducting comparison analysis. Because, on the contrary to Markov chain, other methods can predict the extent of degradation as continuous value, it is expected that the one can replace or complement the pros and cons of the others.

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