Data-Driven Prognostics for Major Piping in Nuclear Power Plants

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ABSTRACT

As operation period of Nuclear Power Plants (NPPs) is getting longer, necessity of reflecting ageing effect is increasing. Especially, when it comes to the piping in NPPs such as reactor coolant system piping or steam generator tubes, it is vulnerable to stress corrosion crack (SCC) or wear due to the fluid with high temperature, high pressure and radiation. Accidents related to such cases have been reported. Since ruptures of the piping can result in severe accidents, it is important to predict and prevent them in advance. Current NPPs ageing management is performed with the physical model based on generic experimental data, which cannot properly consider each NPPs' different operation environment or history. Prognostics using plant specific data can compensate this limit of ageing management using the physical model. Recently, as usable data of NPPs is increasing with the development of instrumentation technology, applicability of prognostics for NPPs has been increased. Therefore, this paper suggests some prognostics methods such as GPM (General Path Model), MCMC (Markov Chain Monte Carlo) and Particle filter that can consider ageing degradation for the major piping in NPPs. It is expected that prognostics results can be used in Probabilistic Safety Assessment (PSA) considering current or future ageing degradation.

1. INTRODUCTION

NPPs are usually designed with 40~60 years lifetime, and if there are extension of lifetime, the NPP can be operated for 80 years. Because of this long lifetime, as the operation period is extended, ageing degradation effect becomes significant. In case of long period operated NPPs, its failure rate or unavailability of components are likely to be higher than newly constructed NPPs. The PSA for NPPs uses generic failure rate of components. The generic data did not reflect ageing degradation effect and has static value. However, practically, the failure rate is likely to be increased due to ageing effect. The generic data cannot also reflect different operation conditions or history of each NPPs.

Especially, the components such as large piping of reactor coolant system or steam generator tubes, which is performing important role for safety by preventing leakage of radioactive materials and removing decay heat of reactor core continuously, are vulnerable to SCC and wear, because of the fluid with high temperature, high pressure and radiation. Accidents related to such cases have been reported.

This paper suggests introducing prognostics that can consider ageing degradation effect to the steam generator tubes that is major piping of NPPs. Basically, prognostics predicts the future behavior of ageing degradation by analyzing newly observed data of components based on accumulated previous failure data, and eventually it predicts the time to failure. As instrumentation technology has developed lately, the available data are increased in NPPs. Therefore, the applicability of prognostics also becomes better.

This paper introduces concept of applying prognostics to major piping in NPPs, current state and further study.

2. BACKGROUND

Steam generator is located at boundary between primary side and secondary side of Pressurized Water Reactor (PWR). It removes decay heat of reactor core by heat transfer between primary side coolant and secondary side feed water and prevent leakage of primary side coolant containing radioactive materials. Removing decay heat and preventing leakage of radioactive materials are essential part for nuclear safety.

Steam generator is operated under harsh condition that is high temperature, pressure and radiation. In practice, the accidents due to SCC and wear has reported from domestic and foreign. Thus, steam generator tube rupture (SGTR) accident is one of the initial accidents justified in PSA for NPPs, and is important part for NPP safety assessment.

Currently, integrity assessment for steam generator tube is performed based on fracture mechanic formulas such as 'Paris law' that is derived from generic experimental data. Plant specific operation condition, history and current condition of components are not reflected on the formulas. Therefore, actual degradation of components is larger or lesser than one predicted by physics.

It can be possible that performing integrity assessment reflecting plant specific operation condition and ageing degradation by using monitoring data in real time. In this study, among the various prognostics methods, we used MCMC, GPM and Particle filter that can consider ageing degradation. Ageing degradation is characterized by parameters such as effect of crack size, vibration and temperature.

3. METHODOLOGY

3.1. MCMC

MCMC is the method that combining Markov Chain model and Monte Carlo simulation (MCS). 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. According to the assumption, if we have the information of present state and system state transition probabilities, it is possible to predict next state. The transition probabilities can be represented as matrix. MCMC method introduces MCS to Markov chain model. Using huge number of random sampling number from MCS, MCMC performs system state transition simulation based on the transition probabilities matrix with time steps. Meanwhile, it is assumed that each states affect to system degradation, so extent of system degradation can be calculated with frequency of each states that is counted during the transition simulation. The extent of degradation is calculated at every time step of the simulation. The simulation is stopped when the extent of degradation exceeds the system threshold, and eventually, the end of the simulation time step is time to failure.

Procedure of MCMC can be divided by two parts; Training part and Test part. At training part, it obtains system state transition probabilities and regression model calculating extent of degradation by analyzing previous failure data. At test part, it predicts time to failure by analyzing currently observed monitoring data based on training part's information.

3.2. GPM/Bayes

GPM/Bayes is the method that introducing Bayesian linear regression to GPM method. GPM needs physical model to perform prognostics. Whereas, GPM/Bayes can perform prognostics without physical model, if there are sufficient data. GPM/Bayes obtains posterior distribution of time to failure with prior information obtained from previous failure data's degradation path and likelihood obtained from monitoring data by using Bayesian linear regression. Likewise MCMC, GPM/Bayes also can be divided by two parts; Training part and Test part. At training part, it obtains regression model parameters from each previous failure data sets, and combine those parameters. Equation 3.1~3.5 show the above process. The combined parameter is used as a prior. (Equation 3.6)

$$Y = bX \tag{3.1}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{3.2}$$

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \tag{3.3}$$

$$\Sigma_y = \begin{bmatrix} \sigma_{y1}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{y2}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{yn}^2 \end{bmatrix} \tag{3.4}$$

$$b = (X^T X)^{-1} X^T Y \tag{3.5}$$

$$b \sim N(b_0, \Sigma_b); prior \tag{3.6}$$

At test part, posterior information is obtained. Newly observed monitoring data is used as likelihood, and it is combined with the prior information. (Equation 3.7~3.9) Finally, posterior information is obtained with Equation 3.10. With the posterior information, future degradation path is extrapolated, and time to failure is obtained.

$$Y^* = \begin{bmatrix} Y' \\ b_0 \end{bmatrix} \tag{3.7}$$

$$X^* = \begin{bmatrix} X' \\ I_p \end{bmatrix} \tag{3.8}$$

$$\Sigma^* = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_b \end{bmatrix} \tag{3.9}$$

$$\hat{b} = (X^{*T}\Sigma^{*-1}X^*)^{-1}X^{*T}\Sigma^{*-1}Y^*; posterior \tag{3.10}$$

3.3. Particle filter

Particle filter represents posterior distribution of model parameter with finite particles and its weight with using MCS. Particle filter is performed with three steps as follow. First step is predicting step. Posterior distribution of previous step becomes prior distribution of current step, and preliminary posterior is obtained by applying the prior to an ageing degradation model. Second step is updating step. By using newly observed data as likelihood, it applies weight to the preliminary posterior. Final step is resampling step. In this step, samples are redistributed by overlapping or removing. Then finally, posterior distribution is obtained.

4. RESULT

This section briefly shows process of prognostics in practice by introducing case study that is currently performed. We have performed prognostics for steam generator tube as case study for verifying an applicability. We obtained degradation data from PASTA (Probabilistic Algorithm for Steam generator Tube Assessment) program that performs assessment of integrity of steam generator tube. The data is represented as growth of burst probability over time.

4.1. MCMC

MCMC is performed by analyzing transition of system states. Therefore, justifying the system states is needed. And the states should be represented as discrete number. In this case, the data has continuous value. Therefore preprocessing of raw data is needed. We justified the system state as a growth rate of burst probability, grouped the growth rate with certain range, and assigned discrete number to those groups. After that, prognostics is performed through the training and test parts as mentioned in previous section. Figure 1 briefly shows the procedure of MCMC for steam generator tube.

4.2. GPM/Bayes

Unlike MCMC, GPM/Bayes does not need preprocessing of data. It performs prognostics by analyzing degradation path of raw data. At training part, it selects proper regression model, and obtains parameters for each degradation paths, that is previous failure data sets, by fitting each paths to the model. Then, prior information is obtained by combining those parameters. Next, at test part, newly observed monitoring data is used as likelihood. With the prior and likelihood, posterior information that is updated with information of current target component is obtained. Finally, with updated model, future time to failure can be predicted.

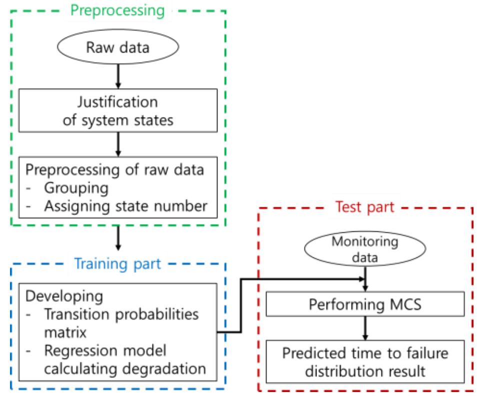

Figure 1. Procedure of MCMC for steam generator tube.

4.3. Particle filter

Particle filter is performed with physical model, unlike MCMC and GPM/Bayes. Because, it considers not only data but also information of physical model, it is possible to prognoses more accurately. In this study, we selected Paris law (Equation 4.1) that is widely used in material science to describe growth of fatigue crack as an ageing degradation model.

$$\frac{da}{dN} = C(\Delta K(a))^m \tag{4.1}$$

Where, da/dN is the crack growth rate
(a: crack length, N: number of loading cycle)

$\Delta K(a)$ is the stress-intensity factor

C, m are empirically derived constants

In equation 4.1, we arbitrarily changed distribution of C and m that is derived empirically, and performed updating procedure for the model parameter by reflecting newly observed data as likelihood.

5. CONCLUSION

The purpose of this study is to introduce prognostics to the major piping in NPPs. Currently, integrity assessment of piping in NPPs is performed based on fracture mechanic formulas, but it seems that prognostics can support the current tasks by updating reliability of the components. In this study, we use MCMC, GPM, Particle filter methods, and we introduced the concept of applying prognostics to steam generator tubes. In an aspect of establishing maintenance plan, the result of prognostics presenting time to failure is effective. Furthermore, if we reflect the result to PSA, it will be possible to evaluate risk changing with time in long-term period perspective.

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BIOGRAPHIES

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