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Comparison of model-based and data-driven prognostics : Case study for Steam Generator Tube Rupture

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1. Introduction

As the operation period of Nuclear Power Plants (NPPs) is getting longer, it is important to consider ageing effect. There are ageing management program such as probabilistic fracture mechanics. However, because it is based on the model derived from experimental data, it is hard to consider specific conditions of target components or systems.

To complement the limitation, prognostics can be applied. Prognostics predicts time to failure by analyzing monitoring data of target components as well as historical data. In other words, it updates historical data or existing model by reflecting specific condition of individual components so that future ageing degradation can be assessed more accurately.

Prognostics can be divided into model-based and data-driven methods depending on the usage of degradation model. In this paper, we performed prognostics for virtual steam generator tube with Monte Carlo Simulation (MCS) as a data-driven method and Particle filter as a model-based method, and performed comparative analysis on those two methods.

2. Methods

2.1 Prognostics with Monte Carlo Simulation (MCS)

MCS for prognostics predicts time to failure by performing state transition simulation using state transition probabilities of a target component. The state is assumed as growth rate of ageing degradation, and the state transition probabilities can be obtained from historical failure data based on Markov Chain model.

Markov Chain model is based on assumption of Markov process. The assumption is that present state includes the information of previous states and therefore next state is only dependent on present state. For Markov Chain model, the state transition probabilities can be represented as a matrix as shown in equation 1. In the matrix, a row means current state, and a column means state at next step. Therefore the element of the matrix means state transition probability that current state changes to other states at next step. For example, in equation 1, p_{2N} means probability that state '2' at current step changes to state 'N' at next step. With the matrix, state transition simulation is performed by MCS.

$$\bar{\bar{A}} = \begin{array}{c} i/j \\ 1 \\ 2 \\ \vdots \\ N \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & \cdots & N \end{array} \\ \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{bmatrix} \end{array} \tag{1}$$

The state at next step can be decided by inverse transform sampling method as shown in figure 1. It samples random number from uniform distribution using MCS, and then next state is decided by mapping the sample to cumulative density function (CDF) of the current state's transition probability. This process is repeated until an extent of degradation reaches to threshold. Because the state is assumed as growth rate of ageing degradation, the extent of degradation can be estimated by cumulating growth rate of a state at every step. The state transition simulation is repeated by MCS with massive samples and then time to failure distribution is obtained.

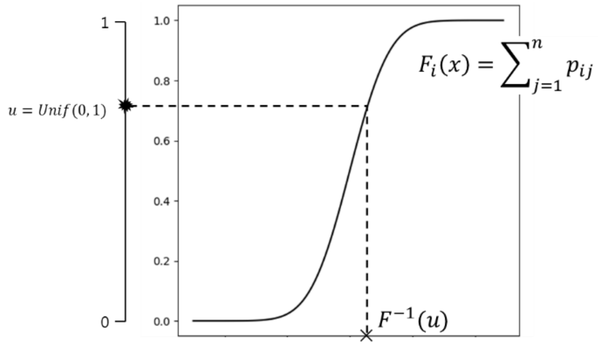

Fig. 1. Inverse transform sampling

2.2 Particle filter

Particle filter as one of recursive filter is similar to Kalman filter. But, it has higher versatility, because it uses samples (particles) for estimating distribution, it can be applied to nonlinear model.

As a recursive filter, particle filter predicts state of current step with information of previous step as a prior and updates the predicted state by reflecting measurement data of current step as a likelihood. Updated state that is posterior of current step is used as prior at next step. It is same as performing Bayesian update sequentially. Meanwhile, Particle filter as a representative model-based prognostics method needs degradation model and the model parameters are updated same as the state. It makes possible to predict more accurately reflecting current condition of target component on the model derived from historical data.

Particle filter for prognostics can be divided into four major steps; prediction, updating, resampling, and prognosis.

In the prediction step, the state is predicted with the information of previous step. First, for the model parameter θ , n of particles are generated from $f(\theta_k|\theta_{k-1})$. This means that the model parameter at k step is estimated from $f(\theta_{k-1})$ which is a distribution of the model parameter at $k-1$ step. Likewise, for the state s, n of particles are generated from $f(s_k|s_{k-1})$. Then, propagated state s at k step is obtained by degradation model composed of model parameter θ_k

In the update step, measurement data y_k is reflected. First, likelihood of y_k for the s_k is obtained. Then, the likelihood is normalized to make its sum is equal to one and used as a weight at resampling step.

In the resampling step, the particles of s_k and θ_k is resampled by the weight. The weight is transformed to CDF and resampling is performed by inverse transform sampling. Resampled s_k and θ_k are posterior of k step and used as prior at $k+1$ step.

The above process is carried out until current time when the measurement is finished and the future degradation state is extrapolated. There is no more update and the current state is propagated by finally updated degradation model until it reaches to threshold. With the proportion of particles that is reaches to threshold, time to failure distribution can be obtained.

2.3 Steam Generator Tube Rupture data

With those two prognostics methods, we performed prognostics for Steam Generator Tube Rupture (SGTR) as a case study. Steam generator is located at boundary between primary side and secondary side of Pressurized Water Reactor (PWR). It changes secondary side's feed water to steam by transferring heat of primary side's coolant. It removes decay heat of reactor core by the heat transfer and prevent leakage of radioactive materials. Removing decay heat and preventing leakage of radioactive materials are essential part for nuclear safety.

Because it is not possible to get actual steam generator tube data, we obtained simulation data from a virtual steam generator by using PASTA (Probabilistic Algorithm for Steam generator Tube Assessment) program. PASTA performs assessment of integrity of steam generator tube. We obtained 130 data sets that is burst probability over time. Burst probability is obtained at every EFPY (Effective Full Power Year, 1 EFPY =18 months). We regarded the tube is ruptured when the burst probability exceeds 40% and used the value as a threshold. 100 sets are assumed as historical failure data and used for training, and remaining sets are assumed as monitoring data and used for testing. We divided testing sets into 4 cases according to the amount of monitoring data to show the characteristic of prognostics that the accuracy increases, as more monitoring data is updated.

3. Results

3.1 Prognostics with Monte Carlo Simulation

As mentioned above, the data is burst probability over time and has continuous value. For obtaining the state transition probability, the raw data need to be changed into discrete value representing the state. First, because the state is assumed as growth rate of degradation, we changed raw data into growth rate of degradation Δd, and classified it as the state according to equation 2.

$$s = \begin{cases} 1 & 0 \le \Delta d < 0.01 \\ 2 & 0.01 \le \Delta d < 0.02 \\ & \vdots \\ 9 & 0.08 \le \Delta d < 0.09 \end{cases} \tag{2}$$

Then, from the training data, we obtained state transition matrix and performed prognostics using MCS for each cases as shown in figure 2.

3.2 Particle filter

Particle filter is performed based on a degradation model. In this paper, Paris' law is assumed as a degradation model. Equation 3 shows Paris' law. Where, a is crack length, C and m are constants that depend on the material, environment and stress ratio, Δk is the range of the stress intensity factor, and $\Delta\sigma$ is stress range.

$$\frac{da}{dN} = C(\Delta k)^m, \Delta k = \Delta\sigma\sqrt{\pi a} \tag{3}$$

For particle filter, initial distribution of model parameter is needed, and it can be obtained from training data by fitting the data to the degradation model. For fitting, we obtained simple linear equation as the natural logarithm of the model. Model parameter $\frac{m}{2}$ as a slope and $\ln C\,(\Delta\sigma\sqrt{\pi})^m$ as an intercept of the equation 4 are obtained for each training sets.

$$\begin{aligned} \ln\frac{da}{dN} &= \ln C + m\ln\left(\Delta\sigma\sqrt{\pi a}\right) \\ &= \ln C\,(\Delta\sigma\sqrt{\pi})^m + \frac{m}{2}\ln a \\ &= \mathrm{m}'\ln a + \mathrm{C}' \\ \left(\mathrm{m}' = \frac{m}{2}\right.&\left., \mathrm{C}' = \ln C\,(\Delta\sigma\sqrt{\pi})^m\right) \end{aligned} \tag{4}$$

Then, we assumed the distribution of the parameter as normal distribution and obtained mean and standard deviation as shown in table 1.

Table I: Mean and standard deviation of model parameters

	m′	C′
μ	0.671	-1.745
σ	0.049	0.156

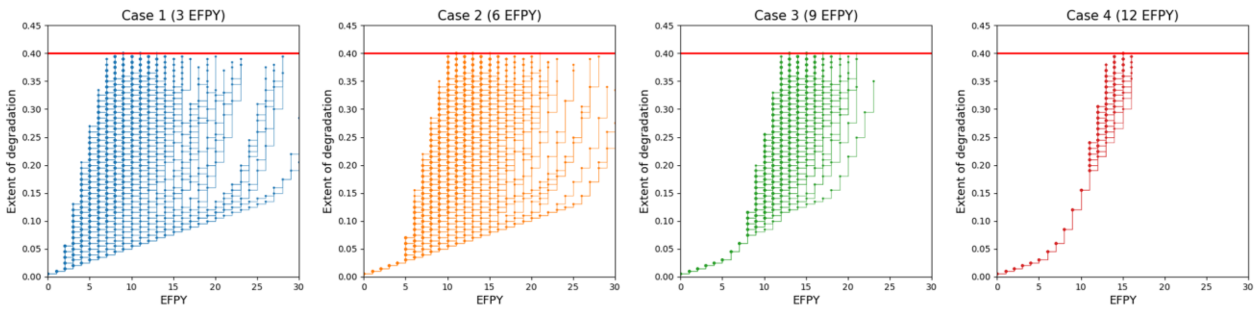

Fig. 2. Results of prognostics using MCS

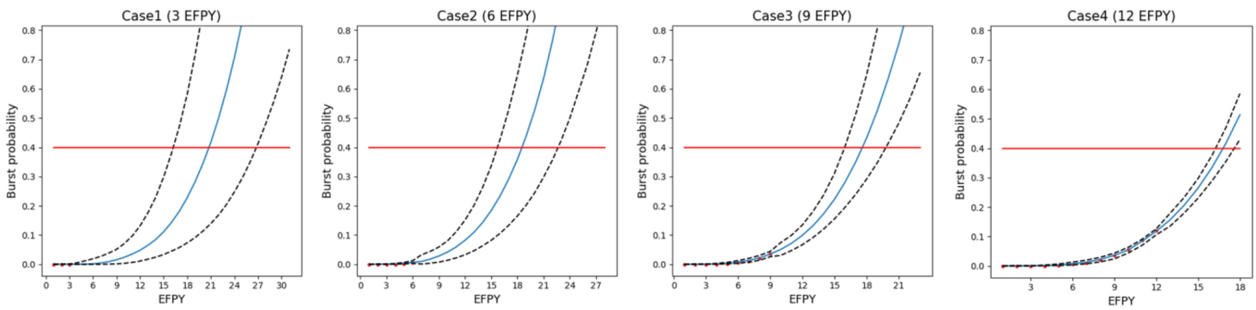

Fig. 3. Results of prognostics using Particle filter

For particle filter as a recursive filter, the degradation model needs to be transformed into recurrence relation that current state is depend on previous state. Paris' law can be transformed into recurrence relation as equation 5. Then, we performed prognostics using particle filter for each case as shown in figure 3.

$$\begin{aligned} a_k &= C_k(\Delta\sigma\sqrt{\pi a_{k-1}})^{m_k} dN + a_{k-1} \\ &= \exp(\mathrm{C'}_k)\, a_{k-1}{}^{m'_k} dN + a_{k-1} \end{aligned} \tag{5}$$

3.3 Comparison between MCS and Particle filter

Table 2 shows the results of the two prognostics methods. Error means difference between the results and actual time to failure of raw data (=16.559 EFPY). As shown in figure 2~3 and table 2, either methods show that the error and variance decrease as the amount of monitoring data increase.

Table II: Comparison of results

Case	MCS			Particle filter		
	μ	σ	Error	μ	σ	Error
1	11.075	1.537	0.331	20.598	3.194	0.244
2	13.833	1.517	0.165	18.161	2.184	0.097
3	15.234	1.06	0.08	17.210	1.173	0.039
4	15.648	0.563	0.055	16.279	0.493	0.017

Though the two methods show similar trend in error and variance, particle filter has lower error. For variance, particle filter has larger value with a few monitoring data though, it decreases sharply with an increase of monitoring data and for the case 4 particle filter has lower variance.

MCS as a data-driven method can be performed without degradation model, if there are sufficient data and therefore, has higher versatility than model-based method. However, it probably needs preprocessing and from it, information of raw data can be lost.

If there are degradation model, model-based prognostics is applicable and it has higher accuracy. However, for the Particle filter, degradation model needs to be transformed into recurrence relation. Thus, when there is no initial distribution of model parameter and the model is complex, it is hard to assume the initial distribution.

3. Conclusions

In this paper, we performed prognostics for SGTR with MCS as a data-driven method and Particle filter as a model-based method. In terms of accuracy, Particle filter shows better results. However, for the versatility, MCS is better, because degradation model and initial distribution of the model parameter is essential for the Particle filter. In terms of accuracy and versatility, two methods have strengths and limitations, therefore it is necessary to choose the appropriate method depending on the circumstances.

For the further study, we will evaluate the performance of two method with other various aspects and study on the way to improve the performance.

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