Prognostics using Particle filter for Steam Generator Tube Rupture in Nuclear Power Plants

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Abstract: For Nuclear Power Plants (NPPs) having long lifetime as 40~60 years, ageing management has been one of the important issues. Currently, the ageing management for NPPs is based on generic experimental data and correlation developed from such data. Nonetheless, environmental characteristics, operational history, and the current state of a specific NPP are not easy to be reflected for the correlation itself. To compensate for the limitations of the conventional approaches, prognostics that predicts time to failure by reflecting the specific state of individual NPP to the correlation itself can be useful. Among various prognostics methods, this paper uses the particle filter and demonstrates a case study for steam generator tube rupture. In the case study, we demonstrate a decrease in uncertainty of estimated time to failure obtained by the particle filter model as operational history is updated over time.

Keywords: Prognostics, Particle filter, Model-based method, Steam Generator Tube Rupture

1. INTRODUCTION

Nuclear Power Plants (NPPs) have a long lifetime as 40~60 years, and, as the operation period is getting longer, ageing management has been one of the important issues. Currently, the ageing management for NPPs is based on generic experimental data and correlation developed from such data. Nonetheless, environmental characteristics, operational history, and the current state of a specific NPP are not easy to be reflected for the correlation itself. To compensate for the limitations of the conventional approaches, prognostics that predicts time to failure by reflecting the specific state of individual NPP to the correlation itself can be useful. Prognostics is basically a method of extrapolating future degradation path and predicting time to failure by reflecting newly observed data of a target on information of historical data. It can update the generic data or correlation by target-specific data and can be useful for evaluating ageing degradation. Prognostics has been already widely used in various areas requiring high safety and high reliability, such as military, aviation, and chemicals. The accuracy of the prognostics depends on the amount of data. Recently, as usable data of NPPs is increasing with improved instrumentation technology, the applicability of prognostics for NPPs is increasing as well. In this paper, among various prognostics methods, we introduce particle filter that is a representative model-based method and demonstrate a case study for Steam Generator Tube Rupture (SGTR).

2. METHODOLOGY

2.1. Prognostics

Prognostics is a key technology for Prognostics and Health Management (PHM). It predicts degradation state and remaining useful lifetime of target system effectively, thereby it can prevent unexpected accidents. Thus, it enables Condition Based Maintenance (CBM) that makes possible to make optimum maintenance, replacement, and parts supply plan. PHM has been originally developed in aviation and applied to various area requiring high safety and high reliability such as military, chemicals, railway and so on. Recently, as usable data of NPPs is increasing with improved instrumentation technology, the applicability of prognostics for NPPs is increasing as well.

Various prognostics methods are being developed and the methods have to be chosen depending on the characteristics of target system and data. Prognostics can be categorized as model-based and data-driven methods. Model-based methods updates degradation model by using monitoring data of a target system, thereby it predicts degradation state more accurately by the updated target-specific model. Data-driven methods can be performed without degradation model if there are sufficient amount of data. It predicts future degradation path by analyzing pattern or trend of degradation propagation with historical failure data and updating monitoring data on it. In this paper, among the various methods, we introduce particle filter that is representative model-based methods.

2.2. Particle filter

Particle filter is a model-based method that predicts the state of a target component using the degradation model and monitoring data of the target. Thus, it is a recursive filter such as Kalman filter. The recursive filter predicts current state by using information of the previous step based on the assumption of Markov process. Unlike Kalman filter, particle filter can be applied to a non-linear system as it uses particles sampled from Monte Carlo Simulation (MCS) for prediction. Particle filter uses the previous step's information as a prior to predict the current state and updates the current step's monitoring data as a likelihood to obtain posterior of the current step. The posterior of the current step is used as the prior in the next step. It is like performing Bayesian update sequentially and also known as sequential Monte Carlo (SMC).

Prognostics using the Particle Filter consists of four stages: prediction, update, resampling, and prognosis. Particle filter requires a degradation model to predict the state and should be expressed in a recurrence relation, as shown in expression 1, in which the current state is affected by the previous state. Where, x is state, Θ is model parameters, ε is a system error. With the model particle filter performs as follows.

$$x_k = f(x_{k-1}, \Theta_k, \varepsilon_k) \quad (1)$$

In the prediction phase, the current state is predicted using the information of the previous step. Model parameter Θ is predicted as well as state x. First, for the model parameter Θ at k^{th} step, n particles are generated from $\mathrm{f}(\Theta_k|\Theta_{k-1})$. It means that Θ_k is predicted by $\mathrm{f}(\Theta_{k-1})$ that is the distribution of model parameter at k-1^{th} step. Because the model parameters are given as a distribution, the system error ε can be handled. Meanwhile, as the particles of Θ_k are just sampled from the distribution of the previous step, it is equal to the particles of Θ_{k-1}. Unlike the model parameter that is independent of time, the state changes every step by the model. For the state x at k^{th} step, as with the model parameter, n particles are generated from $\mathrm{f}(x_k|x_{k-1})$. Then, x_k is propagated by the model consist of Θ_k.

In the update phase, the monitoring data y_k is reflected. For the monitoring data y_k likelihood of each particle is calculated using the likelihood function of state x. If the state follows a normal distribution, the likelihood function is as equation 2. Where, σ is measurement noise. Then, the likelihood is normalized so that the sum of it equal to 1 as shown in equation 3, and used as a weight.

$$\mathrm{L}\left(y_k \middle| x_k^i, \Theta_k^i\right) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y_k - x_k^i)^2}{2\sigma^2}\right), \mathrm{i} = 1, 2, 3, \cdots, \mathrm{n} \quad (2)$$

$$\mathrm{w}(x_k^i, \Theta_k^i) = \frac{\mathrm{L}\left(y_k \middle| x_k^i, \Theta_k^i\right)}{\sum_{i=1}^{n} \mathrm{L}\left(y_k \middle| x_k^i, \Theta_k^i\right)} \quad (3)$$

In the resampling phase, x_k and Θ_k are resampled according to the weight obtained from the update phase. In this process, the particle that has small weight is eliminated and the particle that has high weight is sampled several times. For the sampling, we use inverse transform sampling method as shown in figure 1. First, a random number is generated from a uniform distribution $\mathrm{U}(0, 1)$. Then, the particle is sampled by mapping the random number to the cumulative density function (CDF) of the weight. n particles are resampled, and finally, the particles become the posterior of x_k and Θ_k. Posterior of k^{th} step is used as prior at $k+1^{th}$ step.

Above three phases are repeated until the current time when the monitoring is finished. By this, it is possible to update the model based on the characteristics (operational history, current state) of the target system and to provide more accurate predictions.

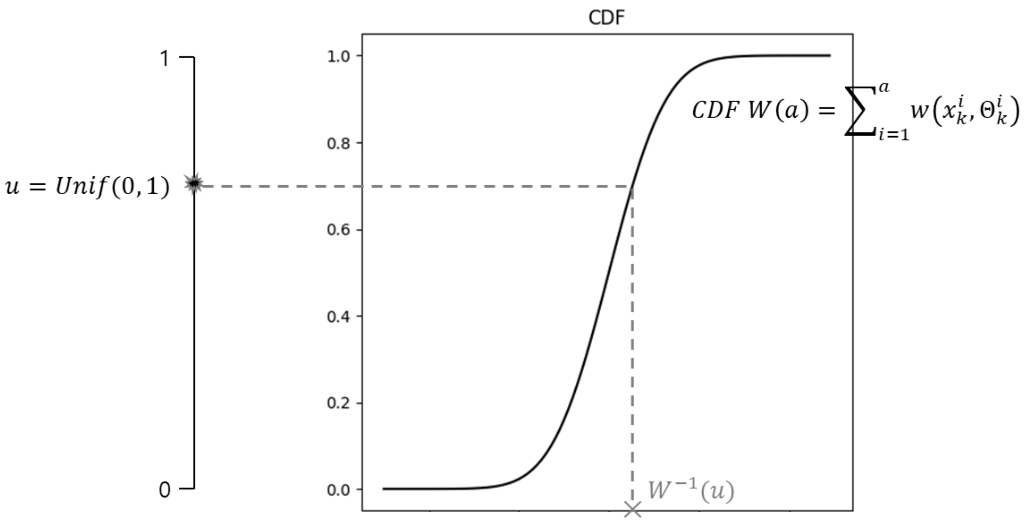

Figure 1 Inverse transform sampling

In the prognosis phase, future state and time to failure are predicted by using the updated model and current state. In this phase, the model is no longer updated. The state $x_{current}$ at the current time is propagated by the model composed of $\Theta_{current}$ until the state reaches the threshold. Then, time to failure distribution can be obtained with failure time of each particle that the state reaches the threshold.

2.3. Steam Generator Tube data

Using particle filter, we performed prognostics for Steam Generator Tube Rupture (SGTR) as a case study. A steam generator is located at the boundary between the 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 prevents leakage of radioactive materials. Removing decay heat and preventing leakage of radioactive materials are the 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 an assessment of the integrity of steam generator tube. We obtained 130 data sets that are 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. Each case have monitoring data for 3, 6, 9 and 12 EFPY respectively.

3. RESULT

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. In this study, a is regarded as burst probability.

$$\frac{da}{dN} = C(\Delta k)^m, \Delta k = \Delta\sigma\sqrt{\pi a} \qquad (4)$$

For particle filter, the 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 as equation 5. We regarded model parameters as $\frac{m}{2}$ and $\ln C\,(\Delta\sigma\sqrt{\pi})^m$ which are slope and intercept of the equation 5. Then those model parameters are obtained by fitting 100 training data sets.

$$\begin{aligned} \ln\frac{da}{dN} &= \ln C + m\ln\left(\Delta\sigma\sqrt{\pi a}\right) \\ &= \ln C\,(\Delta\sigma\sqrt{\pi})^m + \frac{m}{2}\ln a \\ &= \mathrm{m}'\ln a + \mathrm{C}' \qquad (5) \\ \left(\mathrm{m}' = \frac{m}{2}\right.&, \left.\mathrm{C}' = \ln C\,(\Delta\sigma\sqrt{\pi})^m\right) \end{aligned}$$

Table 1 shows one of the training data sets. We obtained natural logarithm of the a and $\mathrm{da/dN} = (a_k - a_{k-1})/\mathrm{dN}, (\mathrm{k} = 2, 3, \cdots, 14)$, where, a is burst probability, $dN = 1\ (EFPY)$.

Table 1 One of the training data sets

EFPY	1	2	3	4	5	6	7
a	0.0004	0.001	0.0028	0.0064	0.0135	0.0244	0.0361
$\ln a$	-7.82405	-6.90776	-5.87814	-5.05146	-4.30507	-3.71317	-3.32146
$\ln\frac{da}{dN}$	-7.41858	-6.31997	-5.62682	-4.94766	-4.51899	-4.44817	-3.78099
EFPY	8	9	10	11	12	13	14
a	0.0589	0.085	0.1217	0.1639	0.2176	0.2765	0.3448
$\ln a$	-2.83191	-2.4651	-2.1062	-1.8085	-1.5251	-1.28554	-1.06479
$\ln\frac{da}{dN}$	-3.64582	-3.30498	-3.16534	-2.92434	-2.83191	-2.68385	

Figure 2 shows the result of fitting the data of table 1 to the equation 5. In the figure, dots represent training data and line represents fitted equation. For this set, m' is equal to 0.69 and C' is equal to -1.676.

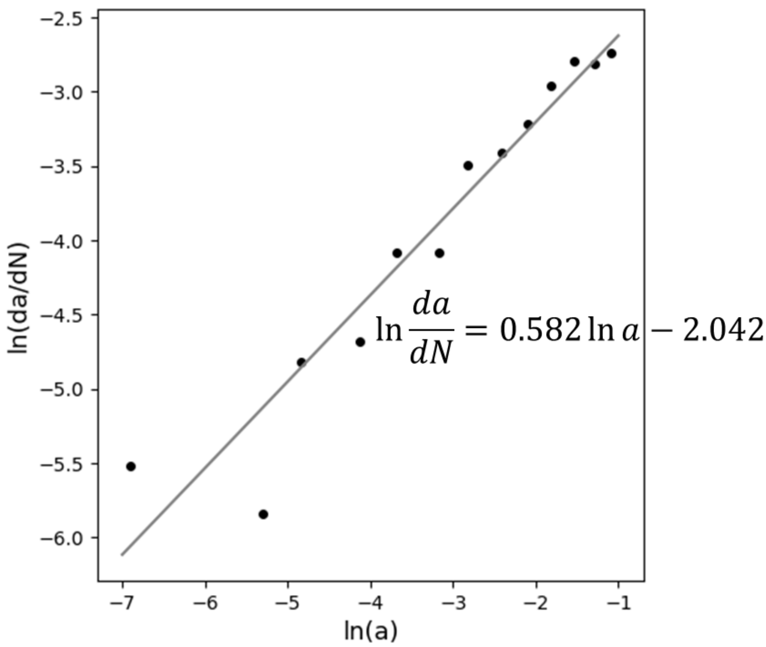

Figure 2 Fitting training data to model

By fitting the 100 training data sets as above, the initial distribution of the model parameters is obtained. We assumed that the model parameters follow a normal distribution and obtained each parameters' mean and standard deviation as equation 6, 7.

$$\mathrm{m}' \sim \mathrm{N}(0.665, 0.049) \quad (6)$$
$$\mathrm{C}' \sim \mathrm{N}(-1.765, 0.160) \quad (7)$$

For particle filter as a recursive filter, the degradation model needs to be transformed into recurrence relation that current state depends on the previous state. Paris' law can be transformed into recurrence relation as equation 8.

$$\begin{aligned} a_k &= C_k(\Delta\sigma\sqrt{\pi a_{k-1}})^{m_k} dN + a_{k-1} \\ &= \exp(\mathrm{C}'_k)\, {a_{k-1}}^{m'_k} dN + a_{k-1} \end{aligned} \quad (8)$$

The likelihood function for the update is assumed as a lognormal distribution. Equation 9 represents likelihood function of lognormal distribution.

$$\mathrm{L}\left(y_k \middle| a_k^i, \Theta_k^i\right) = \frac{1}{y_k\sqrt{2\pi}\zeta_k^i} \exp\left(-\frac{(\ln y_k - \eta_k^i)^2}{2{\zeta_k^i}^2}\right), \quad (9)$$
$$\Theta_k^i = \left(\mathrm{m}'^i_k, \mathrm{C}'^i_k\right), \qquad \mathrm{i} = 1, 2, 3, \cdots, \mathrm{n}$$

where,

$$\zeta_k^i = \sqrt{\ln\left(1 + \left(\frac{\sigma}{a_k^i}\right)^2\right)}, \qquad \eta_k^i = \ln(a_k^i) - \frac{1}{2}{\zeta_k^i}^2$$

Then, we performed prognostics using monitoring data. Table 2 shows the change of model parameters according to the number of updated monitoring data and root mean square error (RMSE) between the updated model and raw data. The updated model shows lower RMSE than initial model and trend that RMSE decreases as the number of monitoring data increases. It means that it is possible to update the model by reflecting the characteristics of the target.

Table 2 Updated model parameter and RMSE with raw data

	m'	C'	RMSE
Initial	0.665	-1.765	5.23E-3
3	0.737	-1.858	9.30E-3
6	0.713	-1.821	3.21E-3
9	0.702	-1.792	9.41E-4
12	0.705	-1.703	1.77E-4

Figure 3 and table 3 show the results of prognostics using particle filter. In the figure, dots, horizontal line, line and two black dotted line represents monitoring data, threshold, mean and 5% and 95% percentile of estimated burst probability respectively. The vertical line is present time point that measurement is finished. In the table, the error means the difference between the actual time to failure and predicted one. Actual time to failure is 16.559 EFPY. The results show that the uncertainty and error decrease as monitoring data increase.

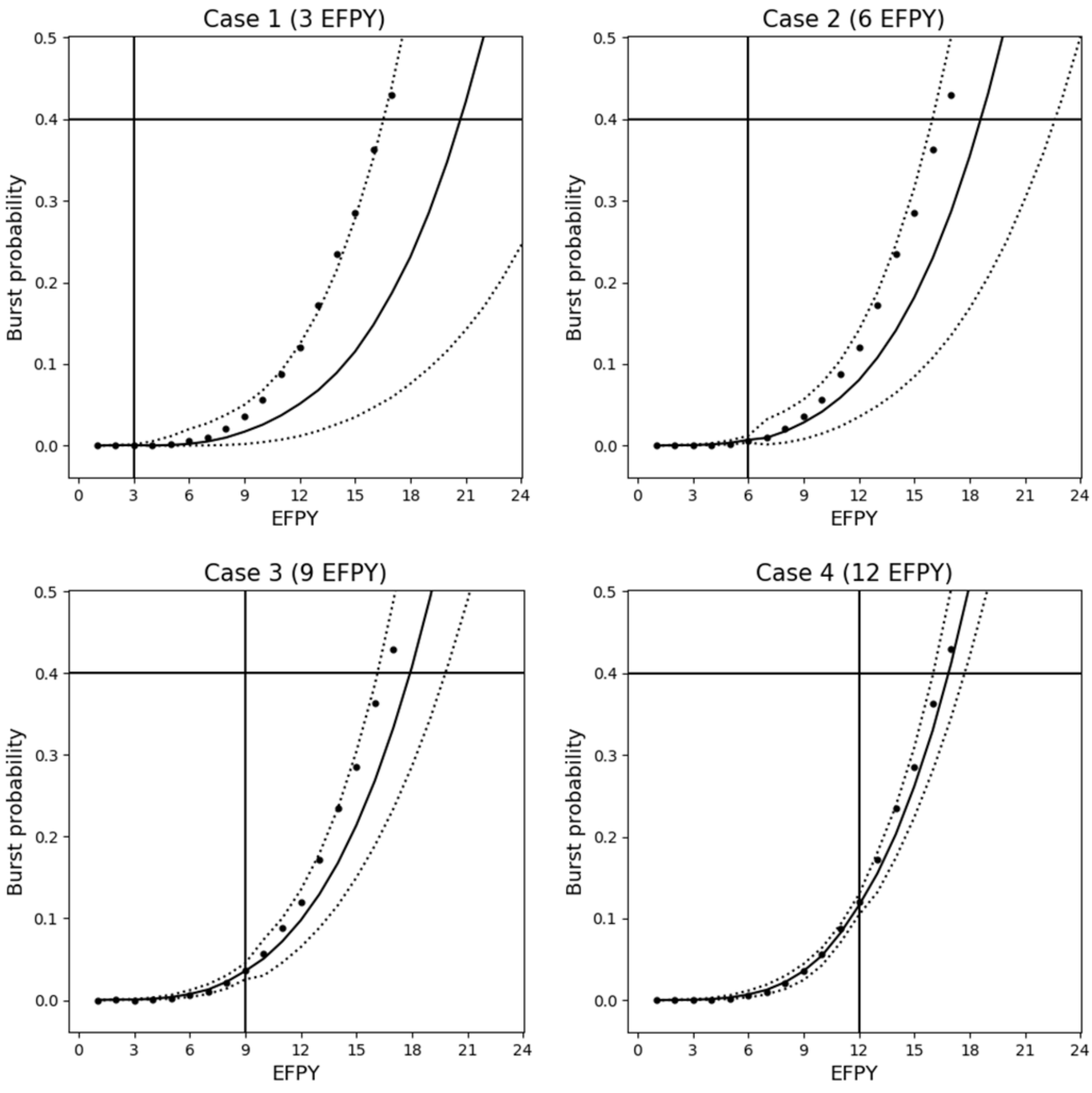

Figure 3. Results of prognostics using Particle filter

Table 3 Results of prognostics using Particle filter

Case	Particle filter		
	μ	σ	Error
1	20.592	3.320	0.244
2	18.229	2.145	0.101
3	17.267	1.103	0.043
4	16.297	0.562	0.016

4. CONCLUSION

Prognostics is a method to update existing information (generic data or model) by reflecting the characteristics of a target and to confidently predict when the failure will occur in the future. Particle filter, which is a representative model-based method, predicts time to failure by using a target components' degradation model and monitoring data. By updating the model, it can reflect a target's characteristics such as operation condition and extent of ageing degradation. Therefore, it enables accurate prediction. In this paper, we perform prognostics for SGTR using particle filter. Though the results with a few monitoring data at the beginning of measurement shows high uncertainty and error, as the number of monitoring data increase and time to failure is getting closer over time, the accuracy increases and the error decreases.

Prognostics is useful itself in the sense that it confidently predicts time to failure and makes possible to make an optimum maintenance and replacement plan. Furthermore, if the results of prognostics are reflected to Probabilistic Safety Assessment (PSA) for NPPs, it becomes possible to perform a plant-specific or ageing dependent PSA. By this, future risk change over time can be estimated. For the further study, we will study on updating initiating event of PSA by reflecting results of prognostics.

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