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Original Article

Application of particle filtering for prognostics with measurement uncertainty in nuclear power plants

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ABSTRACT

For nuclear power plants (NPPs) to have long lifetimes, ageing is a major issue. Currently, ageing management for NPP systems is based on correlations built from generic experimental data. However, each system has its own characteristics, operational history, and environment. To account for this, it is possible to resort to prognostics that predicts the future state and time to failure (TTF) of the target system by updating the generic correlation with specific information of the target system. In this paper, we present an application of particle filtering for the prediction of degradation in steam generator tubes. With a case study, we also show how the prediction results vary depending on the uncertainty of the measurement data.

1. Introduction

Nuclear power plants (NPPs) have a design life of 40–60 years, and possibly more for new designs. Therefore, ageing management is the most important issue [1]. Current ageing management relies on methods for predicting future degradation states based on generic information, such as historical failure data, experimental data, and correlations derived from such data [2]. However, each system has different characteristics, as well as operational histories and environments, which influence the degradation process. If specific information on a target system is available, this would be useful for making predictions [3]. Prognostics methods to predict the future state of the target system and its time to failure (TTF) can integrate generic correlation with specific information related to the target system [18–22].

Prognostics is one of the tasks of prognostics and health management (PHM), which also includes detection of anomalies and diagnosis of faults [4]. PHM enables condition-based maintenance (CBM), which can establish optimum maintenance, replacement, and parts supply plans, thereby preventing unexpected accidents.

Prognostics can be categorized into three types depending on the information used. Fig. 1 represents the categorization of prognostics [5]. Type 1 prognostics methods make use of historical failure data to develop failure time distributions from historical TTF data and predicts the TTF of generic components. Type 1 prognostics includes Weibull analysis. Type 2 prognostics methods consider stress factors, such as temperature, load, vibration, etc., and develop correlations among these factors and the state of the components to predict the TTF for generic components under given operational environments. Type 2 prognostics includes linear regression models. Conventional ageing and integrity management methods belong to Types 1 and 2 prognostics. Type 3 prognostics reflects specific information of the specific components and include the general path model (GPM) [6,7] and particle filtering [8,9]. In this paper, we consider Type 3 prognostics and show how specific information can be integrated with generic information by particle filtering.

Prognostics has already been developed in various areas requiring high safety and reliability, such as aviation, the military, and railways [4,5]. However, there are not many cases of applications to NPPs, due to their strict maintenance policies.

This study modifies and updates the generic correlation (i.e.,

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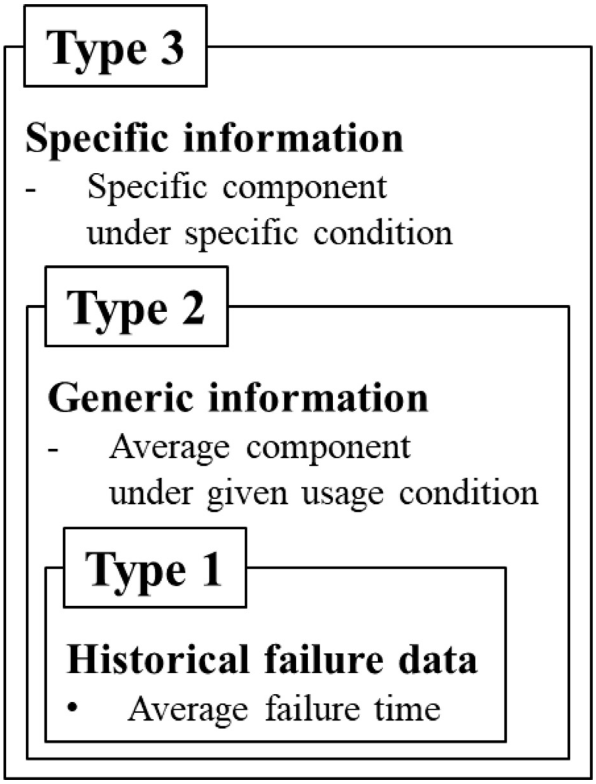

Fig. 1. Categorization of prognostics.

generic information) by using measurement data (i.e., specific information) from a target system or component so that different characteristics of individual systems or components can be considered. To accomplish this, we consider particle filtering as a prognostics method. Particle filtering can update parameters of a state estimation model by using newly observed data of the target system or component, and can then predict the future system state and its TTF with the updated model. In this paper, the prognostics method of particle filtering is applied to the case study of steam generator tubes. Through this case study, how to update the generic correlation by using measurements data will be shown. Thus, the effect of uncertainty in measurement is identified by a sensitivity study. From the study, how the prediction results vary depending on the uncertainty of the measurement data and how the uncertainty works to balance the generic information and specific information are presented.

The paper is organized as follows. Section 2 illustrates the basis of particle filtering and introduces the data from steam generator tubes used for the case study. Section 3 presents the results of the prognostics analysis. Lastly, Section 4 provides conclusions and future perspectives.

2. Prognostics method and case study

2.1. Prognostics using particle filtering

Particle filtering is a model-based method that predicts the state of a target component by updating a degradation model with the measurement data of the target [8,9]. It can be applied to complex, non-linear systems since the prediction is performed by simulating particles sampled by Monte Carlo simulation (MCS). In simple words, it is a recursive filter that predicts the current and future states by using information of the previous step based on the assumption of the Markov process. Particle filtering predicts the current state based on the previous step's information as a prior, updates the predicted state with measurement data as a likelihood, and finally, obtains a posterior of the current state. The posterior of the current step is used as the prior in the next step as sequential Bayesian updating.

The particle filtering algorithm can be explained by importance sampling [8–10]. Importance sampling is a method that enables the approximation of the required distribution by introducing an arbitrarily chosen distribution, which is called the importance distribution. It samples from the importance distribution and assigns a weight, which is a proportion of the importance distribution, to each sample. When approximating the posterior distribution, importance sampling can be used as follows. The weight of each sample θ^i is calculated using Equation (1).

$$w\left(\theta^i\right) = \frac{f\left(\theta^i \middle| y\right)}{g\left(\theta^i\right)} = \frac{f\left(y \middle| \theta^i\right) f\left(\theta^i\right)}{g\left(\theta^i\right)} \quad (1)$$

Here, $f(\theta^i|y)$ is the posterior distribution, y is an observation, and $g(\theta^i)$ is the importance distribution. By Bayes' theorem, $f(\theta^i|y) = f(y|\theta^i)f(\theta^i)$. Since the prior distribution is already known and close to the posterior, it can be used in the importance distribution. Then, the weight in Equation (1) becomes the likelihood. Particle filtering is performed by implementing importance sampling sequentially whenever the observation is obtained.

The degradation model for particle filtering should be expressed in a recurrence relation, as shown in Equation (2), in which the current state x_k of the kth time step is affected by the previous state x_{k-1}. Here, Θ is the vector of model parameters and ε is an error term.

$$x_k = f(x_{k-1},\ \Theta_k,\ \varepsilon_k) \quad (2)$$

Prognostics using particle filtering consists of four stages: prediction, update, resampling, and prognosis. In the prediction phase, the current state x_k is predicted using the information of the previous step. The model parameters Θ are estimated as well. First, for the model parameters Θ at the kth step, n particles are generated from $f(\Theta_k|\Theta_{k-1})$. This means that $f(\Theta_k)$ is estimated by $f(\Theta_{k-1})$, which is a distribution of the model parameter at the (k-1)th step. Because the model parameters are given as a distribution, the system error ε can be handled. For the state x at the kth step, similar to the model parameter, n particles are generated from $f(x_k|x_{k-1})$. Then, x_k is propagated through the model with Θ_k.

In the update phase, the measurement data y_k is reflected. For the measurement data y_k, the likelihood of each particle of state x is calculated. For example, if the state follows a normal distribution, the likelihood function is determined using Equation (3), where $\sigma_{measure}$ is the standard deviation of the measurement data representing its uncertainty. Then, the likelihood is normalized so that the sum is equal to 1, as shown in Equation (4), and it is used as a weight in the resampling phase.

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

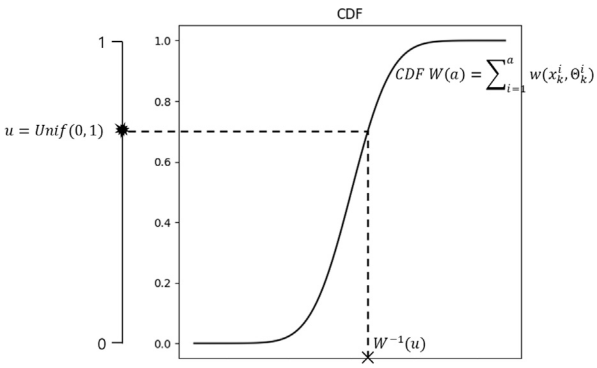

Fig. 2. Inverse transform sampling.

$$w\left(x_k^i,\ \Theta_k^i\right) = \frac{L\left(y_k|x_k^i,\ \Theta_k^i\right)}{\sum_{i=1}^{n} L\left(y_k|x_k^i,\ \Theta_k^i\right)} \quad (4)$$

In the resampling phase, x_k and Θ_k are resampled according to the weight obtained from the update phase. In this process, a particle that has a lower weight is eliminated and a particle that has a higher weight is sampled several times. For the sampling, we use the inverse transform sampling method, as shown in Fig. 2 [10]. First, a random number is generated from the uniform distribution with the range (0,1). Then, the particle is sampled by mapping the random number to the cumulative density function (CDF) of the weight. A total of n particles are resampled, and finally, the particles give the posterior of x_k and Θ_k. Then, recursively, the posterior probability distribution of the kth step is used as the prior of the $(k+1)^{th}$ step.

The above procedures are represented in Fig. 3. As shown in the figure, at the kth step, x_k is predicted from the previous step's posterior and it is updated by measurement data y_k.

Fig. 4 shows different results of the update phase for different levels of $\sigma_{measure}$. The prior distribution is updated by resampling according to the likelihood. By resampling, the distribution is shifted to the particle having a large likelihood. If $\sigma_{measure}$ is infinitely large (i.e., information of the measurement data is not reliable), the likelihood of the particles is given as follows by Equation (3).

$$\lim_{\sigma_{measure}\to\infty} L = \begin{cases} 0, & y_k = x_k^i \\ 0, & y_k \neq x_k^i \end{cases}$$

For high $\sigma_{measure}$, particles have lower and almost identical values of likelihood regardless of the measurement data y_k. As a result, all of the particles are resampled with almost the same frequency and, therefore, the updated distribution is almost the same as the original distribution. That is, the measurement data does not convey relevant specific information.

In contrast, as $\sigma_{measure}$ tends toward zero (i.e., information of the measurement data is reliable), the likelihood of the particles is as follows.

$$\lim_{\sigma_{measure}\to 0} L = \begin{cases} \infty, & y_k = x_k^i \\ 0, & y_k \neq x_k^i \end{cases}.$$

For low $\sigma_{measure}$, the particles that are close to the measurement data y_k have a large likelihood, whereas the others have a small likelihood. In other words, the likelihood is concentrated on the particles that are closer to the measurement data. As a result, the particles that are close to the measurement data are resampled frequently and, therefore, the distribution is shifted to the measurement data. That is, more specific information is conveyed.

In the prognosis phase, the 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 until the state reaches the failure threshold. Then, the TTF distribution can be obtained from the failure times of each particle whose state reaches the threshold.

2.2. Case study: steam generator tube ageing management

In a pressurized water reactor (PWR), a steam generator is located at the boundary between the primary side and the secondary side [11]. The steam generator turns the secondary side's feedwater into steam using the primary side's coolant heated in the reactor core. Since it removes decay heat from the reactor core and prevents leakage of radioactive materials, it is one of the most important safety components. The steam generator is operated under the extremely harsh conditions of high temperature and high-pressure fluids, including some radioactive materials. Accidents caused by stress corrosion cracking (SCC) and wear have been reported [12]. Then, steam generator tube rupture (SGTR) is considered, which is one of the initiating events in both

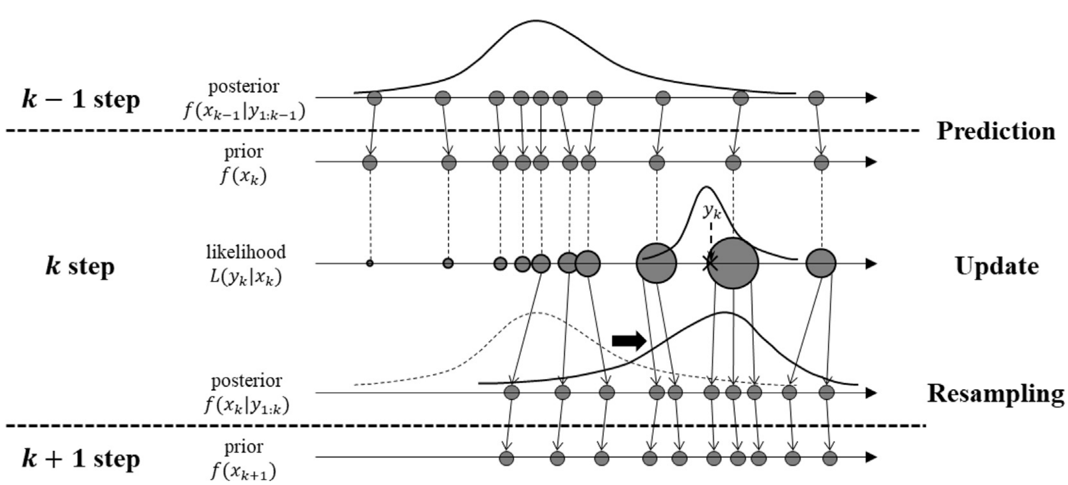

Fig. 3. Procedure of particle filtering.

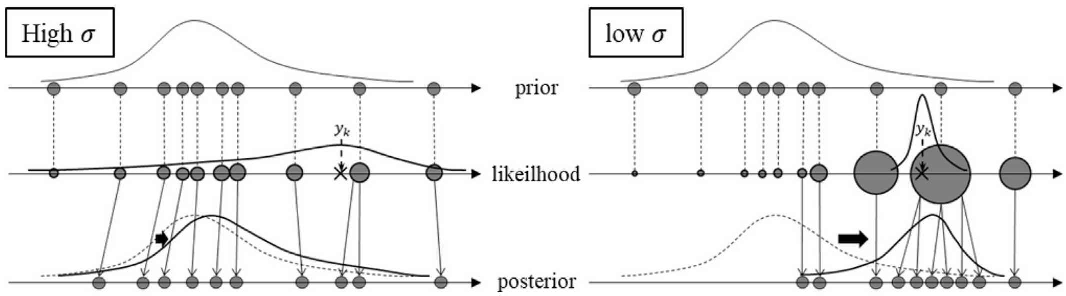

Fig. 4. Influence of measurement data with different uncertainties.

deterministic and probabilistic safety assessments. The integrity of the steam generator must be well managed for safety. Currently, according to the Steam Generator Management Program (SGMP), the integrity assessment for steam generators is divided into three steps with respect to the preventive maintenance time [2]. The first step is degradation assessment (DA), which is a preliminary assessment before preventive maintenance. The second step is condition monitoring assessment (CM), which assesses the current state at preventive maintenance. The last step is operation assessment (OA), which predicts the future state until the next preventive maintenance. For OA as a prediction step, probabilistic integrity assessment can be applied. This is performed with generic correlations and input data for the specific steam generator.

Because of inaccessibility to the steam generator tube failure data from the operating power plants, we generated simulation data from a virtual steam generator by using the PASTA (Probabilistic Algorithm for Steam generator Tube Assessment) program [13]. PASTA performs assessment of the integrity of steam generator tubes. It is a probabilistic assessment program that accounts for the uncertainty of various variables. PASTA calculates burst pressure as one criterion of tube integrity. Burst pressure is the pressure that equipment can handle before rupturing or bursting. Assessment is possible for axial, radial, and wear cracks; for axial cracks, the burst pressure model is given in Equation (5) [13]:

$$P_B = 0.58(\sigma_y + \sigma_u)\frac{t}{R_i}\left[1.104 - \frac{L}{L+2t}h\right], \tag{5}$$

Where

P_B: burst probability
σ_y: yield strength of the material
σ_u: tensile strength of the material
R_i: inner radius of the tube
L: length of the crack
t: thickness of the tube
d: depth of the crack

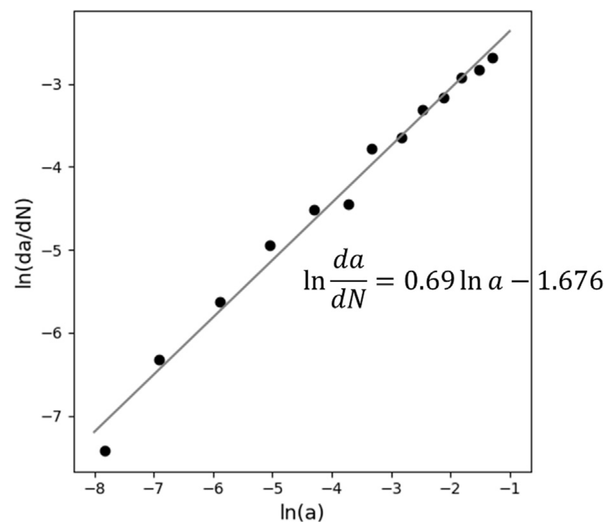

Fig. 5. Fitting data to the degradation model.

h: depth ratio of the crack $= \frac{d}{t}$

The model is derived from data of burst experiments with various crack sizes. For probabilistic modeling, PASTA considers the uncertainty of yield, tensile strength, and crack inspection. MCS is used to obtain the distribution of burst pressure. Then, the burst probability is obtained as a ratio of the number of simulations that are lower than the burst criterion to the total number of simulations launched. Due to the limitation of failure data availability, we assumed the data from PASTA is a field dataset and used it for prognostics. In other words, some of the data were used to calibrate the generic model, while the rest were regarded as measurement data acquired from the operating plant.

We generated 276 data sets of burst probability over time from PASTA. Burst probability is obtained at every EFPY (effective full

Table 1
Training data set and results.

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	

Table 2
Results of the K-S test for the model parameters.

	Maximum discrepancy	P-value
m′	0.089	0.086
C′	0.078	0.179

power year, 1 EFPY = 18 months). We regarded the tube as being ruptured when the burst probability exceeded 40%. In practice, when the burst probability exceeds 40%, plugging or sleeving is performed [11,14]. 209 sets were assumed to be historical or generic failure data and were used to determine the model parameters, while the remaining sets were assumed to be measurement data and were used for testing. We divided the testing sets into four cases according to the time window of observations. The cases correspond to the accumulated data during 3, 6, 9, and 12 EFPY, respectively.

3. Results

3.1. Estimation of TTF distribution

In this paper, Paris' law [15] is assumed as the degradation model:

$$\frac{da}{dN} = C(\Delta k)^m,\ \Delta k = \Delta\sigma\sqrt{\pi a}, \quad (6)$$

where a is the crack length, C and m are constants that depend on the material and environment, Δk is the range of the stress intensity factor, and Δσ is the stress range. In this study, *a* is regarded as the burst probability.

By taking the logarithms in Equation (6), we obtained Equation (7). Then, the model parameters m/2 and $\ln C(\Delta\sigma\sqrt{\pi})^m$ are obtained by fitting 209 training data sets.

$$\ln\frac{da}{dN} = \ln C + m\ln(\Delta\sigma\sqrt{\pi a}) \quad (7)$$

$$= \ln C(\Delta\sigma\sqrt{\pi})^m + \frac{m}{2}\ln a$$

$$= m'\ln a + C'$$

$$\left(m' = \frac{m}{2},\ C' = \ln C(\Delta\sigma\sqrt{\pi})^m\right)$$

Table 1 shows the results with one of the training data sets, where *a* is burst probability and dN = 1 (EFPY).

Fig. 5 shows the result of fitting the data of Table 1 to Equation (7). In the figure, the dots represent the training data and the line represents the fitted equation. For this set, m′ is equal to 0.69 and C′ is equal to −1.676.

By fitting the 209 training data sets as above, the initial distribution of the model parameters is obtained. Because we have no information about the distribution, we simply assumed that the parameters follow a Gaussian distribution, which is the most commonly used distribution. Assuming that the model parameters follow a Gaussian distribution, the means and standard deviations of the parameters are obtained as:

$$m' \sim N(0.671,\ 0.049)$$

$$C' \sim N(-1.745,\ 0.156).$$

To verify that the parameters follow the assumed distribution, we performed the Kolmogorov-Smirnov (K-S) test, which is commonly used for testing for normality [16]. Table 2 shows the results of the K-S test for the model parameters.

Both assumed distributions are verified as acceptable distributions at the 5% significance level.

In addition, Fig. 6 shows Q-Q (quantile-quantile) plots for the model parameters. A Q-Q plot is a graphical method for comparing two probability distributions and is commonly used to compare a data set to a theoretical model [17]. By using a Q-Q plot, it is possible to intuitively identify whether the data follow a Gaussian distribution. The linearity of the points in the figure suggests that the data are normally distributed.

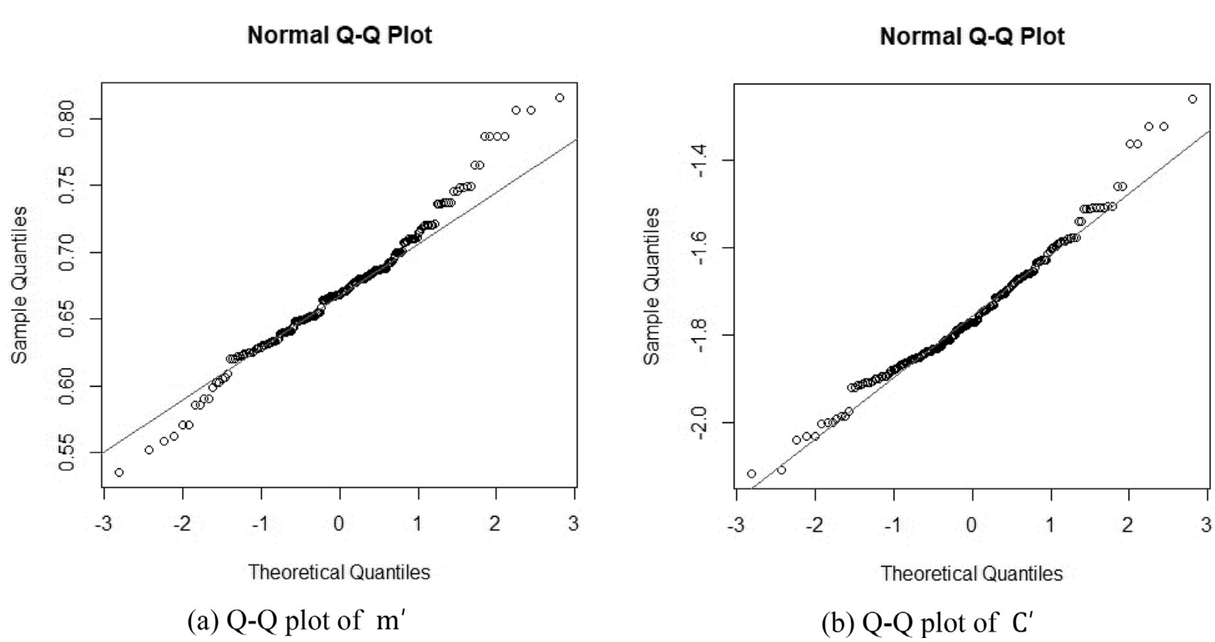

Fig. 6. Q-Q plots of the model parameters.

Input

- **measure_data[t]**: (real array) measurement data, **t**: current time when a measurement is finished
- **s**: (real value) standard deviation of the measurement data
- **thresh**: (real value) threshold value of the degradation state
- **initial_x[2]**: (real array) mean and standard deviation of the initial state
- **initial_Θ[p,2]**: (real array) mean and standard deviation of the initial model parameters, **p** : number of parameters
- **n**: (integer value) the number of particles

Output

- **TTF[n]**: (real array) time to failure

Variables or Arguments

- **x[k,n]**: n particles of the estimated state
- **Θ[k,p,n]**: n particles of the parameters
- **k**: (real value) time step

```
# initial distribution of the state x and the parameters Θ
x[1,:]=random.normal(initial_x[1], initial_x[2], n)
for i in (1:p)
  Θ[1,i,:]=random.normal(initial_Θ[i,1], initial_Θ[i,2], n)
end

k=1
While min(x[k,:]) < thresh
  k=k+1
  x[k,:]=f(x[k-1,:],Θ[k-1,p,:])                                # Equation (8)

  if k <= length(measure_data)                                 # updating with measurement data
    likel[:]=exp(-(measure_data[k]-x[k,:])^2/(2*s[k]^2))/(s[k]*(2*pi)^0.5))   # calculating likelihood
    cdf[:]=cumulative_sum(likel[:])/sum(likel[:])              # Equation (3, 4)
    r=random()
    for i in (1:n)                 # resampling by inverse transform sampling (Figure 2)
      index=count(cdf[:] < r)
      temp_x[i]=x[k,index]
      temp_Θ[:,i]= Θ[k,:,index]
    end
    x[k,:]=temp_x[:]
    Θ[k,:,:]= temp_Θ[:,:]
  else
    x[k,:]=random.normal(x[k,:],s)                             # prognosis
  end
end

for i in (1:n)
  TTF[i]=count(x[:,i]<thresh)
end

return TTF[:]
```

Fig. 7. Pseudocode of particle filtering.

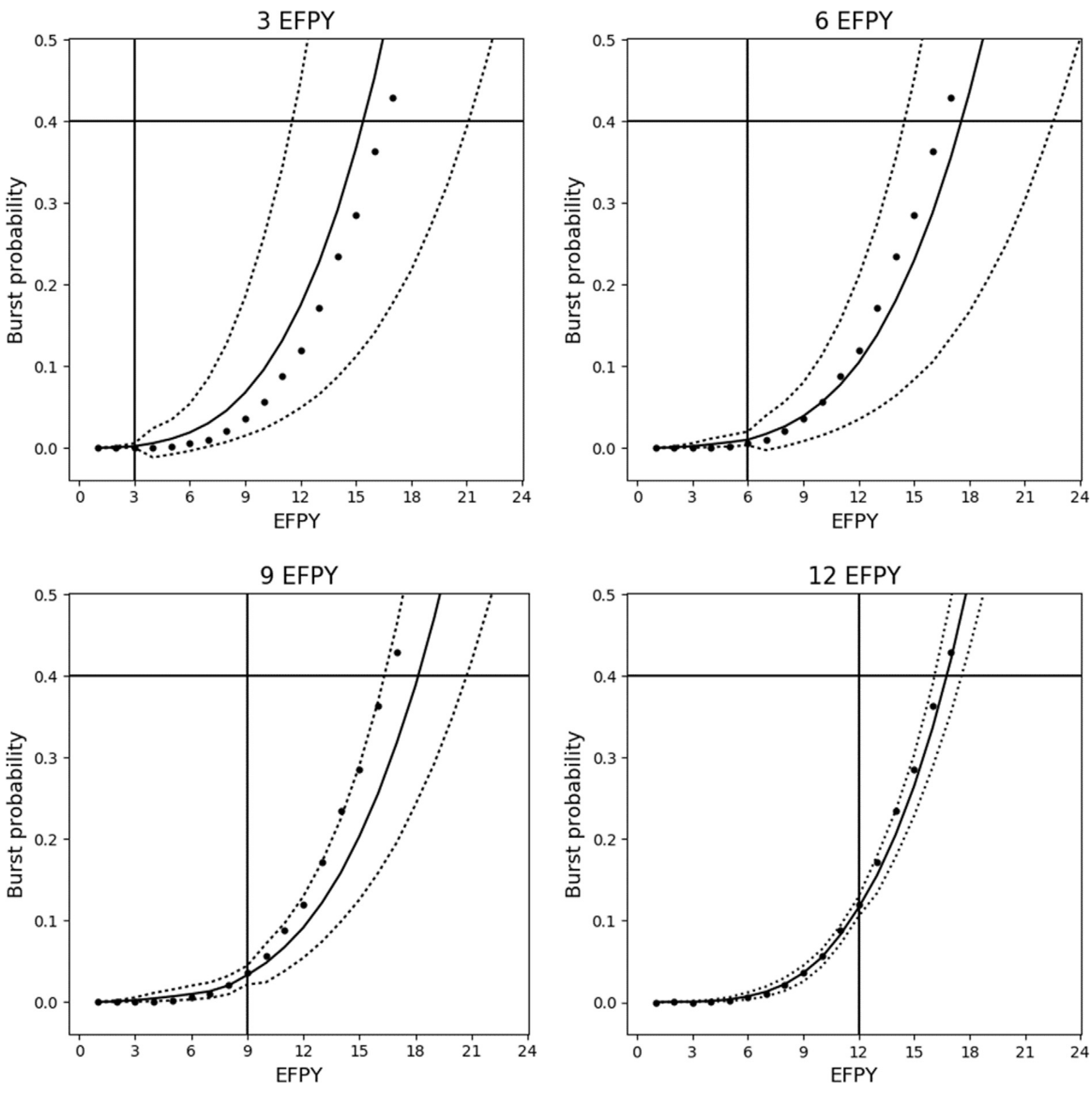

Fig. 8. Prognostic results using particle filtering with different amounts of measurement data.

Table 3
Prognostic results using particle filtering with different amounts of measurement data.

Number of measurement data	Mean	Median	5^{th} percentile	95^{th} percentile
3	15.669	15.350	11.464	20.830
6	17.950	17.596	14.524	22.512
9	18.459	18.322	16.424	21.068
12	16.923	16.891	16.137	17.802

To apply particle filtering, we transformed the degradation model into a recurrence relation in which the current state depends on the previous one:

$$a_k = C_k(\Delta\sigma\sqrt{\pi a_{k-1}})^{m_k} dN + a_{k-1} \tag{8}$$

$$= \exp\left(C_k^{'}\right) a_{k-1}{}^{m_k^{'}} dN + a_{k-1}.$$

We assumed that the likelihood function is a normal distribution (Equation (3)) with $\sigma_{measure} = 0.01$.

Fig. 7 provides the developed pseudocode of the particle filtering.

Fig. 8 shows the results obtained using particle filtering with differing amounts of measurement data from 3 EFPY to 12 EFPY. The total number of particles is 10,000. In the figure, the dots, solid line, and two dotted lines represent the measurement data, threshold, mean, and the 5th and 95th percentiles of the estimated burst probability, respectively. The horizontal line gives the threshold value and the vertical line indicates the current time when the measurement is finished. In addition, we present the mean, median, and 5th and 95th percentile values of the obtained TTF distribution in Table 3. As expected, the results show that uncertainty decreases as the updated amount of measurement data increases.

Additionally, to identify the effect of the number of training data sets on the prediction accuracy, we performed a sensitivity study for the number of training data sets. We constructed the model with 10, 50, 100, 150, and 200 training sets, and Fig. 9 shows the results of prognostics from the constructed models. In the figure, the results show a similar tendency among all cases, except for the case with a very small number of training data sets. If the number of training data sets is above a certain number, then it does not significantly affect the prediction result.

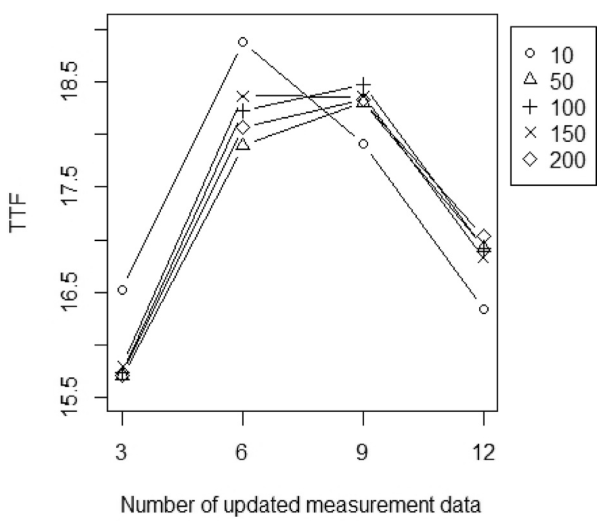

Fig. 9. Prognostics results with different numbers of training data.

3.2. Sensitivity analysis with respect to measurement uncertainty

Particle filtering is a method for using specific information as well as generic information. It reflects specific information to the generic correlation and updates its parameters. From the viewpoint of a Bayesian update, the prognostic result using the generic

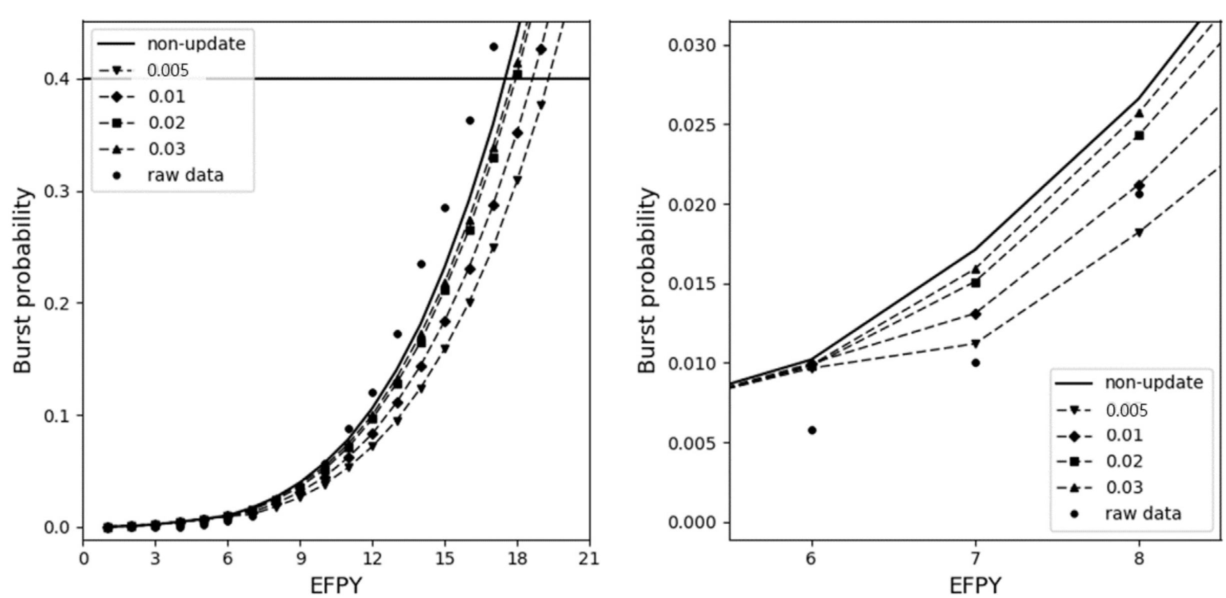

Fig. 10. The results of prognostics with different uncertainty in the measurement data.

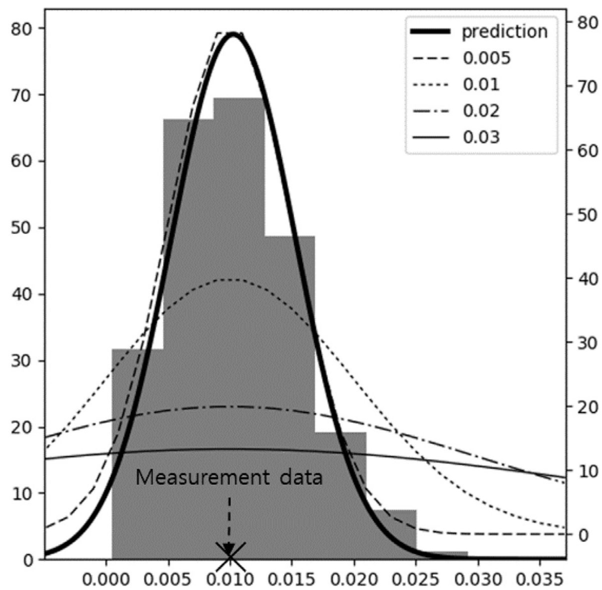

Fig. 11. Likelihood with various uncertainties of measurement.

information corresponds to prior information, while that of updating the specific information belongs to posterior information. In this case, the specific information takes the role of the likelihood. Obviously, the confidence of prior information and likelihood affect the result of prognostics. Therefore, for optimized results, balancing the uncertainty of prior information and the likelihood is important. In the above section, Fig. 4 explained how the prior information and the likelihood contribute on the TTF and its standard deviation. The control of the uncertainty of prior information and the likelihood is done by adjusting the uncertainty of measurement $\sigma_{measure}$, which affects the update phase. Fig. 10 shows the results for various levels of uncertainty in the measurement data represented by $\sigma_{measure}$. As the uncertainty gets smaller, the significance of the likelihood becomes larger, which means the measurement is dominant in determining the prognostics results. In contrast, when uncertainty in the measurement data is larger, the prior generic information is more important and weighs more in the posterior. Each model is updated until 6 EFPY with the same uncertainty in the measurement data, $\sigma_{measure} = 0.01$. Then, at 7 EFPY, the updating is done with the different levels of uncertainty, as indicated in the legend. Correspondingly, in the figure, we see that with large uncertainty, the updated model is closer to the original model (non-update), whereas, with smaller uncertainty, the updated model is closer to the measurement data at 7 EFPY.

Fig. 11 shows the predicted distribution and likelihood for the measurement data. The figure is a histogram of predicted particles and the bold line is the fitted normal distribution. With small uncertainty in the measurement data, the likelihood is concentrated on the particles that are close to the measurement value by Equation (2). Therefore, the posterior distribution is also close to the measurement. With large uncertainty, the likelihood is scattered out to all particles regardless of measurement data. Therefore, the posterior distribution is closer to the prior distribution.

4. Conclusions

Basically, ageing and integrity management of components and systems in NPPs are based on the controlled generic information and plant-specific data from periodic inspection. Due to the high standards for ensuring safety, it is hard to find the applications of particle filtering method in nuclear fields, which is commonly used for updating model parameters in various engineering applications. Therefore, this paper introduced the particle filtering method and demonstrated its procedure through case studies. Particle filtering is a model-based method that allows updating of a generic correlation (i.e., based on generic information) with measurement data (i.e., specific information) to predict the TTF. Advanced condition monitoring technologies can allow for the effective use of specific information for the individual components and systems, so the knowledge update process on the basis of observation such as the particle filtering is expected to be an emerging trend even in safety-critical fields.

The development of the method was exemplified by a case study regarding steam generator tube degradation considering Paris' raw. Thus, the effect of measurement uncertainty was evaluated by a sensitivity study. The sensitivity study demonstrated how to update the model while balancing between generic and specific information according to their uncertainty. Nevertheless, there are some limitations. In practice, it is not easy to define the uncertainty for existing and new information because of various error factors such as malfunctioning of measuring instrument, human error and so on. Furthermore, it is not clear whether a plant-specific data can modify a degradation evaluation model at a decision-making situation due to managerial or regulatory characteristics, which needs inter-disciplinary study along with field tests.

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References

[1] Nuclear Safety and Security Commission, Design Life Time of Nuclear Power Plants, http://nsic.nssc.go.kr/intrst/view.do?ppleIntrstInfoSn=22&ppleIntrstCtgrySn=44. (Accessed 4 July 2018).
[2] H. Cothron, Steam Generator Management Program: Steam Generator Integrity Assessment Guideline, 1019038, EPRI, 2009.
[3] E. Zio, Reliability engineering: old problems and new challenges, Reliab. Eng. Syst. Saf. 94 (2) (2009) 125–141.
[4] N.H. Kim, D. An, J.H. Choi, Prognostics and Health Management of Engineering Systems, Springer International Publishing, Switzerland, 2017.
[5] J.B. Coble, J.W. Hines, Prognostic algorithm categorization with PHM challenge application, in: Prognostics and Health Management, 2008. PHM 2008. International Conference on, IEEE, 2008, October, pp. 1–11.
[6] J. Coble, J.W. Hines, Applying the general path model to estimation of remaining useful life, Int. J. Prognostics Health Manag. 2 (1) (2011) 71–82.
[7] H. Kim, J.T. Kim, G. Heo, Prognostics for integrity of steam generator tubes using the general path model, Nucl. Eng. Technol. 50 (1) (2017) 88–96.
[8] D. An, J.H. Choi, N.H. Kim, Prognostics 101: a tutorial for particle filtering-based prognostics algorithm using Matlab, Reliab. Eng. Syst. Saf. 115 (2013) 161–169.
[9] E. Zio, G. Peloni, Particle filtering prognostic estimation of the remaining useful life of nonlinear components, Reliab. Eng. Syst. Saf. 96 (3) (2011) 403–409.
[10] E. Zio, The Monte Carlo Simulation Method for System Reliability and Risk Analysis, vol. 39, Springer, London, 2013.
[11] J. Kim, Nuclear Power Plants System – System and Design, Korea Atomic Industrial Forum, 2011.
[12] J. Hong, Nuclear Materials, Hanshouse, 2012.
[13] H. Kim, H. Shim, C. Oh, S. Jung, Y. Chang, H. Kim, Development of probabilistic program for structural integrity assessment of steam generator tubes, in: The Korean Society of Mechanical Engineers Fall Annual Conference, 2012, pp. 477–481.
[14] Nuclear Regulatory Commission, Bases for Plugging Degraded PWR Steam Generator Tubes (No. REG/G–1.121 (8-76)), Nuclear Regulatory Commission, 1976.
[15] P. Paris, F. Erdogan, A critical analysis of crack propagation laws, J. Basic Eng.

85 (4) (1963) 528–533.
[16] H. ALFREDO, W.H. TANG, Probability concepts in engineering, Planning 1 (4) (2007) 1–3.
[17] R. Gnanadesikan, Methods for Statistical Data Analysis of Multivariate Observations, vol. 321, John Wiley & Sons, 2011.
[18] H. Kim, S.H. Lee, J.S. Park, H. Kim, Y.S. Chang, G. Heo, Reliability data update using condition monitoring and prognostics in probabilistic safety assessment, Nucl. Eng. Technol. 47 (2) (2015) 204–211.
[19] G. Kim, G. Heo, H. Kim, Prognostics for steam generator tube rupture using Markov chain model, in: Korean Nuclear Society Spring Meeting 2016, 2016.
[20] G. Kim, H. Kim, Y. Chang, S. Jung, G. Heo, Data-Driven prognostics for major piping in nuclear power plants, in: Asia Pacific Conference of the Prognostics and Health Management Society 2017, 2017.
[21] G. Kim, G. Heo, Comparison of model-based and data-driven prognostics: case study for steam generator tube rupture, in: Korean Nuclear Society Spring Meeting 2018, 2018.
[22] G. Kim, H. Kim, G. Heo, Prognostics Using Particle Filter for Steam Generator Tube Rupture in Nuclear Power Plants. Probabilistic Safety Assessment and Management, 2018, p. 14.