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Original Article

Prognostics for integrity of steam generator tubes using the general path model

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A B S T R A C T

Concerns over reliability assessments of the main components in nuclear power plants (NPPs) related to aging and continuous operation have increased. The conventional reliability assessment for main components uses experimental correlations under general conditions. Most NPPs have been operating in Korea for a long time, and it is predictable that NPPs operating for the same number of years would show varying extent of aging and degradation. The conventional reliability assessment does not adequately reflect the characteristics of an individual plant. Therefore, the reliability of individual components and an individual plant was estimated according to operating data and conditions. It is essential to reflect aging as a characteristic of individual NPPs, and this is performed through prognostics. To handle this difficulty, in this paper, the general path model/Bayes, a data-based prognostic method, was used to update the reliability estimated from the generic database. As a case study, the authors consider the aging for steam generator tubes in NPPs and demonstrate the suggested methodology with data obtained from the probabilistic algorithm for the steam generator tube assessment program.

1. Introduction

Concerns over reliability assessment of the main components in nuclear power plants (NPPs) related to aging and continuous operation have increased. Reliability assessments of the main components in NPPs are performed using experimental correlations and data from nondestructive tests and visual tests during maintenance. The parameters in the experimental correlations, obtained by performing experiments under general conditions, however, do not adequately reflect the characteristics of individual plants [1]. Therefore, the reliability of each component and each plant was estimated according to operating data and conditions. The prognostics method estimates the reliability of the components by using data obtained from monitoring and failure data related to the same components [2].

For a detailed interpretation of the prognostics approach, condition-based maintenance (CBM) and prognostics and health management (PHM) are explained in advance. Fig. 1 shows the CBM and PHM cycles [2]. As can be seen in Fig. 1, although the CBM and PHM are comprehensive technology, they differ depending on whether they consider current operating conditions. Here, current operating conditions refer to historical data and operating conditions (run-time data) of target components or systems. More specifically, the CBM considers current conditions (current state) and fault/failure conditions to determine the current fault/failure mode and effect. It can be used to schedule required repair and maintenance. The PHM includes the CBM and a prognostics method. The PHM refers specifically to the phase involved with predicting future behavior, including remaining useful lifetime (RUL), in terms of specific data for current operating conditions (run-time data) and components (or plant), and then required maintenance actions to maintain system health are scheduled.

Prognostics methods can be distinguished as physics-based or data-based. The physics-based methods are based on first principles when the underlying physical mechanisms of the components and systems are known. The physics-based methods are attractive for engineering systems because they explicitly account for the mechanical, material, and operational characteristics. In contrast, data-based methods are developed based on historical data with no explicitly defined understanding of the underlying physical mechanisms of the components or systems. The steam generator makes the steam by transferring heat from the reactor coolant to the feedwater. In addition, the steam generator performs as a multibarrier by preventing leakage of radioactive materials in events or accidents [3]. The steam generator tubes also have a key safety structure in accidents in NPPs. Hence, it is worthwhile to investigate a method to improve the reliability information of

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steam generator tubes by considering all available generic as well as component-specific data.

Through this research, it is applicable to integrating probabilistic safety assessment (PSA) and prognostics. By applying the characteristics of prognostics to the PSA, uncertainty in the PSA is reduced. Recently, the concept of updating the PSA model using monitoring and prognostics was proposed [4–9]. Fig. 2 shows the concept of integrating prognostics and the PSA model. The PSA model usually uses the event tree and fault tree (ET/FT) method. The main result of the ET/FT method is a core damage frequency (CDF) in Level 1 PSA. To calculate the CDF in the ET/FT method, reliability data such as the time-of-failure (TOF) distribution are used. As shown in Fig. 2, the upper side indicates the ET/FT method, and the position where the reliability data are applied by the red circle and rectangle. The reliability data can be updated using prognostics, which will reduce the uncertainty of the PSA model because the uncertainty of the input value of the ET/FT method is reduced. Hence, this method can reflect the aging and dynamic effects by using the updated reliability data with prognostics. In addition, it affects the areas that require a periodic update, such as the periodic safety review (PSR), the continuous operation of NPPs, and risk-informed applications (RIAs).

In Chapter 2, the prognostics are explained in terms of the general path model (GPM)/Bayes method, and the data-related steam generator tubes are described in Chapter 3. The results of steam generator tubes prognostics are explained in Chapter 4. In Chapter 5, conclusions are described.

2. General path model/Bayes method

Although there are many prognostic methods, in this paper, GPM/Bayes method is used to predict the integrity of the steam generator tube. The GPM/Bayes method integrates the concepts of GPM and the Bayesian linear regression (where prior information is included), and is suggested in Ref. [10]. Thus, GPM and Bayesian linear regression are respectively explained. The GPM was originally proposed as a statistical method to use degradation measures to estimate the failure distribution for censored data [11]. The original GPM assumes that the degradation physics for target components is known. In addition, a two-stage method was proposed, which made the general path including degradation information. The general path was extrapolated to determine the estimated failure times and to evaluate their distribution.

However, in the case of prognostics, there is a limitation in that more accurate physics of the failure modes is required. Although such models help with understanding of degradation mechanisms, they may not be strictly necessary for RUL estimation. Some studies

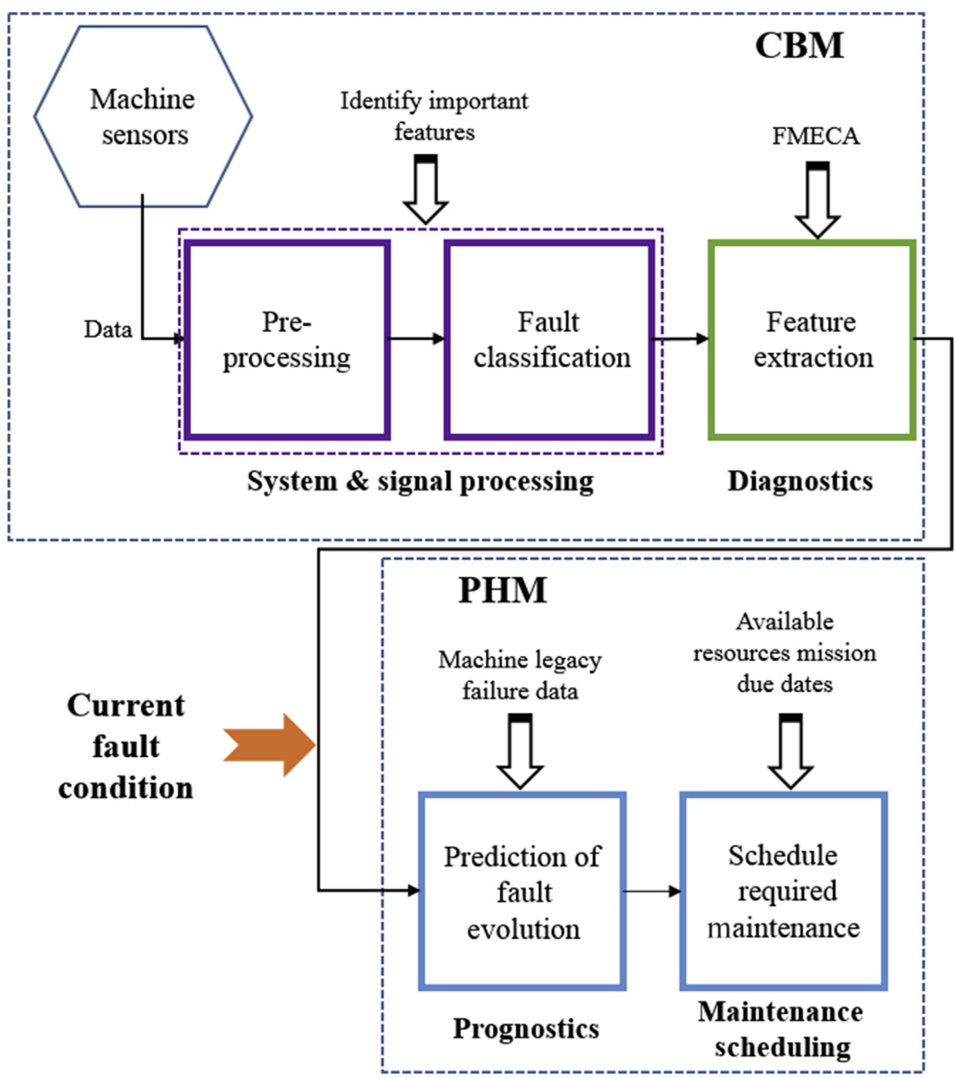

Fig. 1. The CBM and PHM cycles.
CBM, condition-based maintenance; FMECA, Failure modes, effects, and criticality analysis; PHM, prognostics and health management.

on overcoming several limitations of the original GPM have been conducted by other authors [12,13]. In the GPM/Bayes method, the degradation path is assumed as an increasing function, and the general path is established by using Bayesian linear regression. It is not necessarily a linear model. In this paper, GPM/Bayes assumes that the degradation path is fitted to linear, quadratic, and exponential equations. Fig. 3 shows the concept of the GPM/Bayes for prognostics [14]. In the GPM/Bayes method, a general path was made from the failure information (indicated as "failure path" in Fig. 3).

Bayesian linear regression is one of the Bayesian update methods, where the prior distribution is updated with newly acquired data to generate a posterior distribution of the model parameters [15–17]. The Bayesian linear regression model of GPM/Bayes is explained through the following steps. The concept of prognostics involves using failure data and monitoring data of the target component to extrapolate the RUL.

In the first step, prior data to make the general path are calculated by interpolation using the failure data. Eq. (1)–(3) express the general linear regression model. After the projection information is obtained using the failure data, the projection information becomes the prior information in the Bayesian linear regression [18,19].

$$Y = XB + \varepsilon \tag{1}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \quad X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix} \tag{2}$$

$$B = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} = \left(X^T X\right)^{-1} X^T Y \tag{3}$$

where X is an $m \times n$ matrix of m observation variables and n predictor variables; Y is an $m \times 1$ matrix of the response variable; ε is the random fluctuation or error; ε is independent and normally distributed with mean 0 and variance σ^2. In other words, Y is independently and normally distributed with mean XB and variance

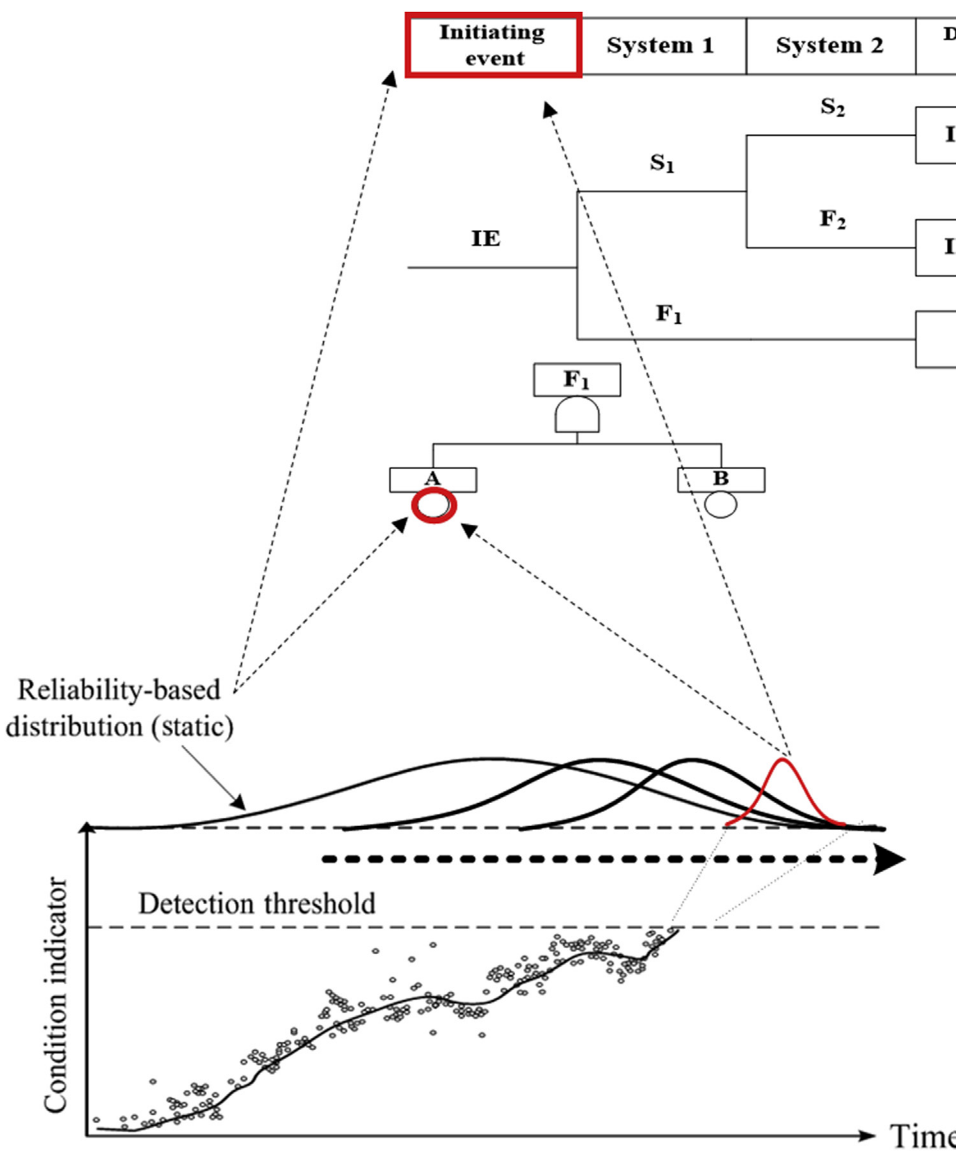

Fig. 2. Concept of the integration of the prognostics and PSA model.
PSA, probabilistic safety assessment.

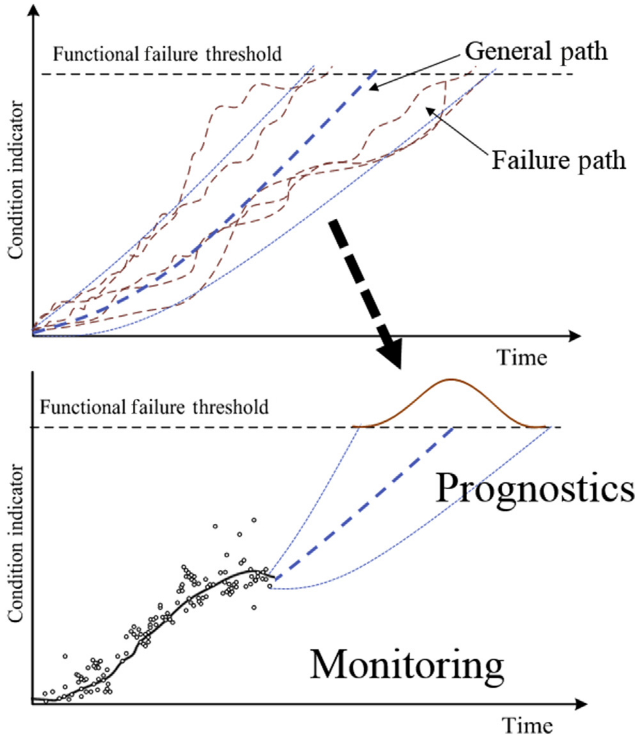

Fig. 3. The concept of the GPM/Bayes for prognostics.
GPM, general path model.

σ^2. B is an $n \times 1$ vector of regression coefficients and unknown parameters. B is the prior information and is calculated using Eq. (3).

$$\beta \sim N\left(\mu_\beta, \sigma_\beta\right); \quad prior \tag{4}$$

$$\Sigma_\beta = \left[1 \big/ \sigma_\beta^2\right] \tag{5}$$

$$Y^* = \begin{bmatrix} Y \\ \beta_0 \end{bmatrix}, \quad X^* = \begin{bmatrix} X \\ I_k \end{bmatrix}, \quad \Sigma^* = \begin{bmatrix} \varepsilon & 0 \\ 0 & \Sigma_\beta \end{bmatrix} \tag{6}$$

$$\hat{\beta} = \left(X^{*T}\Sigma^{*-1}X^*\right)^{-1}X^{*T}\Sigma^{*-1}Y^*; posterior \tag{7}$$

In the next step, predictions are made using Eqs. (4)–(7), which append the prior information (Eq. (3)) to the monitoring data. X^* should be appended with an additional row with a value of 1 at the last position and zeros elsewhere. Y^* should be appended with the prior value. Σ^* is the variance–covariance noise matrix, which indicates the accuracy of each entry in the Y-vector. The variance–covariance matrix is augmented with a final row and a final column of zeros, and the variance of the prior information is the diagonal element. The linear regression model is not necessarily a linear model, but is linear in parameters. Finally, $\hat{\beta}$ is the posterior information (i.e., reparameterized data) obtained using Eq. (7). To calculate the RUL and its uncertainties, extrapolation with posterior information is carried out and Monte Carlo simulation (MCS) is used to estimate the uncertainty.

The framework of GPM/Bayes for prognostics is illustrated in Fig. 4. As can be seen in Fig. 4, the framework of GPM/Bayes for prognostics consists of a training section and a test section. In the training section, as mentioned earlier, training data are fitted to the assumed equation and the threshold values are calculated. The threshold values are calculated by obtaining the lower 5% value of the last points. The last process in the training section is to obtain prior information through GPM/Bayes. After the training section, in the test section, GPM/Bayes is performed again using the fitted equation, threshold value, and prior equation. The GPM/Bayes results are posterior information that contains the measured data and are used in an MCS to estimate the uncertainty [20–22].

3. Steam generator tube aging data

The steam generator tubes are likely to be damaged to a higher degree than other components because of their low thickness, which is necessary for increasing the heat transfer rate. In the case

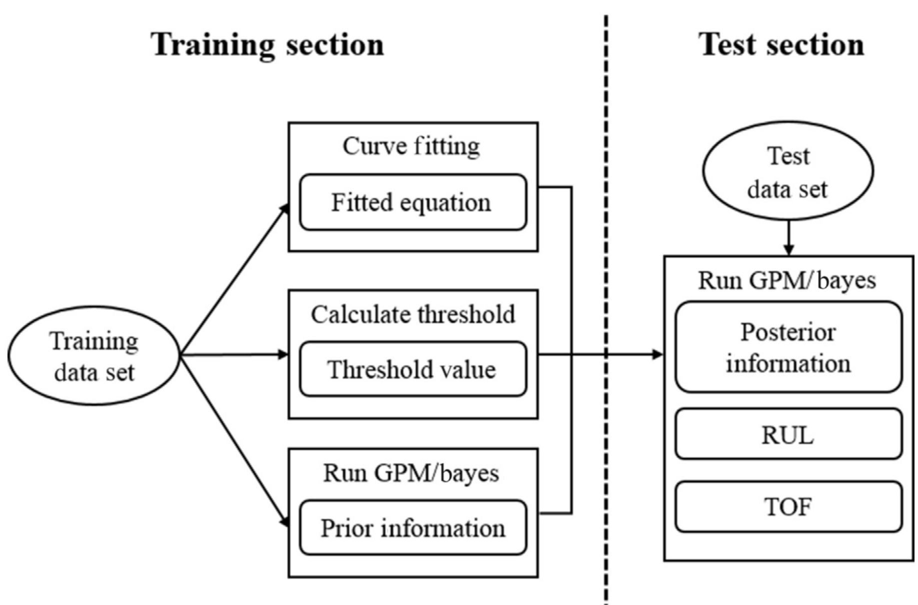

Fig. 4. Framework of GPM/Bayes for prognostics.
GPM, general path model; RUL, remaining useful lifetime; TOF, time-of-failure.

of the Optimized Power Reactor 1000, which is the standard NPP in Korea, two steam generators are installed; a single one has about 10,000 tubes. As the steam generator is a key component in NPPs, it is designed having a 10% margin of tubes because there can be no replacement during the design life time.

There are many types of degradation mechanisms for steam generator tubes. By the end of the 1970s, thinning was known as the most important degradation mechanism; however, stress corrosion cracking has since been recognized as a major factor. Stress corrosion cracking has often been reported in actual incidents in domestic and foreign plants [23]. Structural integrity and burst integrity of steam generator tubes are required to prevent leakage of radioactive materials from the primary side. Damage to steam generator tubes is the initiating event of steam generator tube rupture, which is known as a significant accident in NPPs. In this paper, burst probability, which is used for probabilistic fracture mechanics, was considered to estimate the integrity of the steam generator tube. In fact, the burst pressure (PB) or the burst probability, which is the ratio of the estimated PB to the threshold pressure, is one of the metrics used to evaluate the integrity of steam generator tubes. To estimate such metric, many conditions, various properties, and complex models are necessary and integrated.

In this study, a probabilistic assessment for an outside axial crack was conducted according to the probabilistic algorithm for steam generator tube assessment (PASTA) program [24]. PASTA is a Windows program based on an optimized probabilistic integrity assessment method to evaluate the integrity of steam generator tubes. The algorithm for calculating PB for consideration of a probabilistic axial external crack is illustrated in Fig. 5 and in the PB equation [25]. Structural integrity assessment for steam generator tubes was performed through three steps.

In the first step, a degradation assessment is performed as a preliminary analysis before performing the in-service inspection of the steam generators. In the second step, condition monitoring assessment is performed to check whether the performance criteria of steam generators are satisfied during the previous period. In the final step, an operational assessment is performed to determine whether the performance criteria of steam generators will remain satisfied until the next inspection period. In this step, the equation considering the probabilistic theory determines the PB of the outer cracks in the axial direction. The mathematical model for calculating the PB is based on the results of the burst test for large-scale

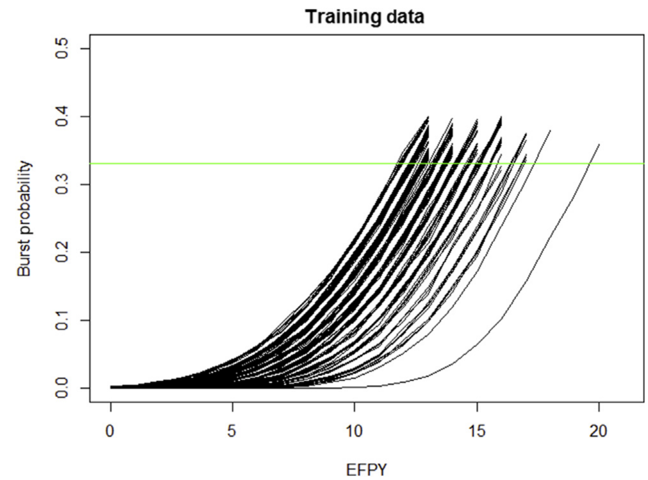

Fig. 6. The burst probability of training set.
EFPY, effective full power years.

Table 1
Summary of training results.

Description	Results
Equation	$\beta_2 x^2 + \beta_1 x + \beta_0$
Prior (β)	$\begin{bmatrix} 0.002873 & -0.01552 & 0.01616 \\ 0.000194 & 0.003745 & 0.0062 \end{bmatrix}$
Variance (Σ)	0.000321
Threshold value	0.330839

ruptures of various sizes, derived from engineering analyses such as regression analysis. The PB is expressed as Eq. (8) [25].

$$P_B = 0.58(S_y + S_u)\frac{t}{R_i}\left[1 - \frac{L}{L + 2t}h\right] \tag{8}$$

where S_y is the yield strength, S_u is the tensile strength, R_i is the inner radius, L is the crack length, t is the thickness, h is the crack thickness ratio ($= d/t$), and d is the crack thickness.

For actual application, to reduce the measurement error, each variable was preprocessed before being applied to Eq. (8). In this

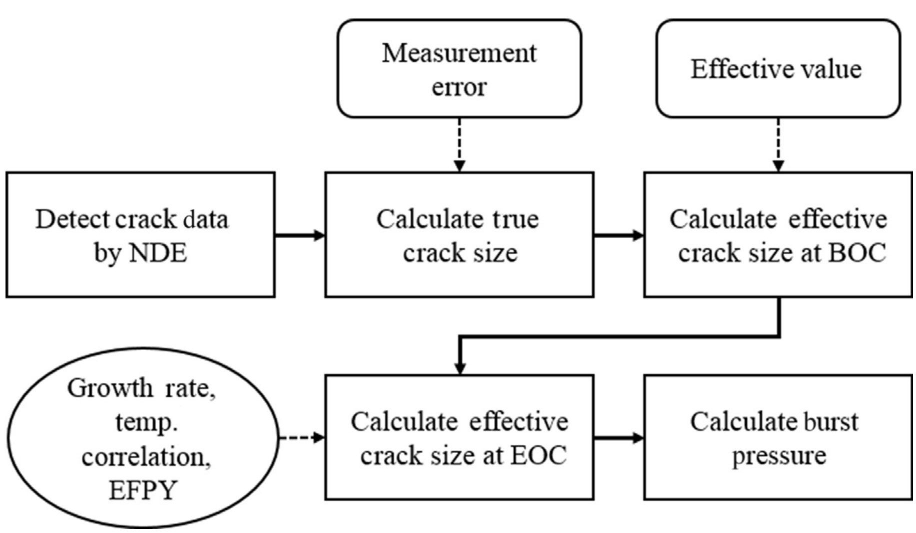

Fig. 5. Algorithm for calculating burst pressure.
BOC, beginning of cycle; EFPY, effective full power years; EOC, end of cycle; NDE, non destructive examination.

paper, preprocessed variables were used. MCS was performed to calculate each crack growth size when the PB reached the threshold pressure. The burst probability was obtained from the ratio of the number of PBs below the threshold pressure and the MCS number.

The total number of tubes is 250; all burst probability values are propagated using the abovementioned procedure. For the prognostics data set, it is assumed that a new crack does not occur during the simulation. In practice, when the burst probability is near 0.4 at the overhaul, tube plugging is performed. Thus, the threshold value was set to the value of effective full power years (EFPY) before the PB exceeded 0.4. The data set is arbitrarily separated into categories of training and testing; the latter is the data set used for validation. The training set is 80% of the data set and the remainder is used for the test set. Thus, data of 200 cracks were used for the training set (failure data) and data of the remaining 50 cracks (unfailed data, which means failure not occurred) were used for testing. Fig. 6 shows the training set.

4. Results

As previously mentioned, the data set is arbitrarily separated into training and test data sets, where the latter data set is used for validation. The training set is 80% of the data set and the remainder is used for the test set. Thus, data of 200 cracks were used for the training set (failure data) and data of the remaining 50 cracks (unfailed data) were used for testing. Training data are regarded as failure data, such as generic data in conventional reliability assessment. Test data are regarded as measured data or real-time operating data, and are used to show the effect of updating measured data, and test data will be separated by 3 EFPY intervals.

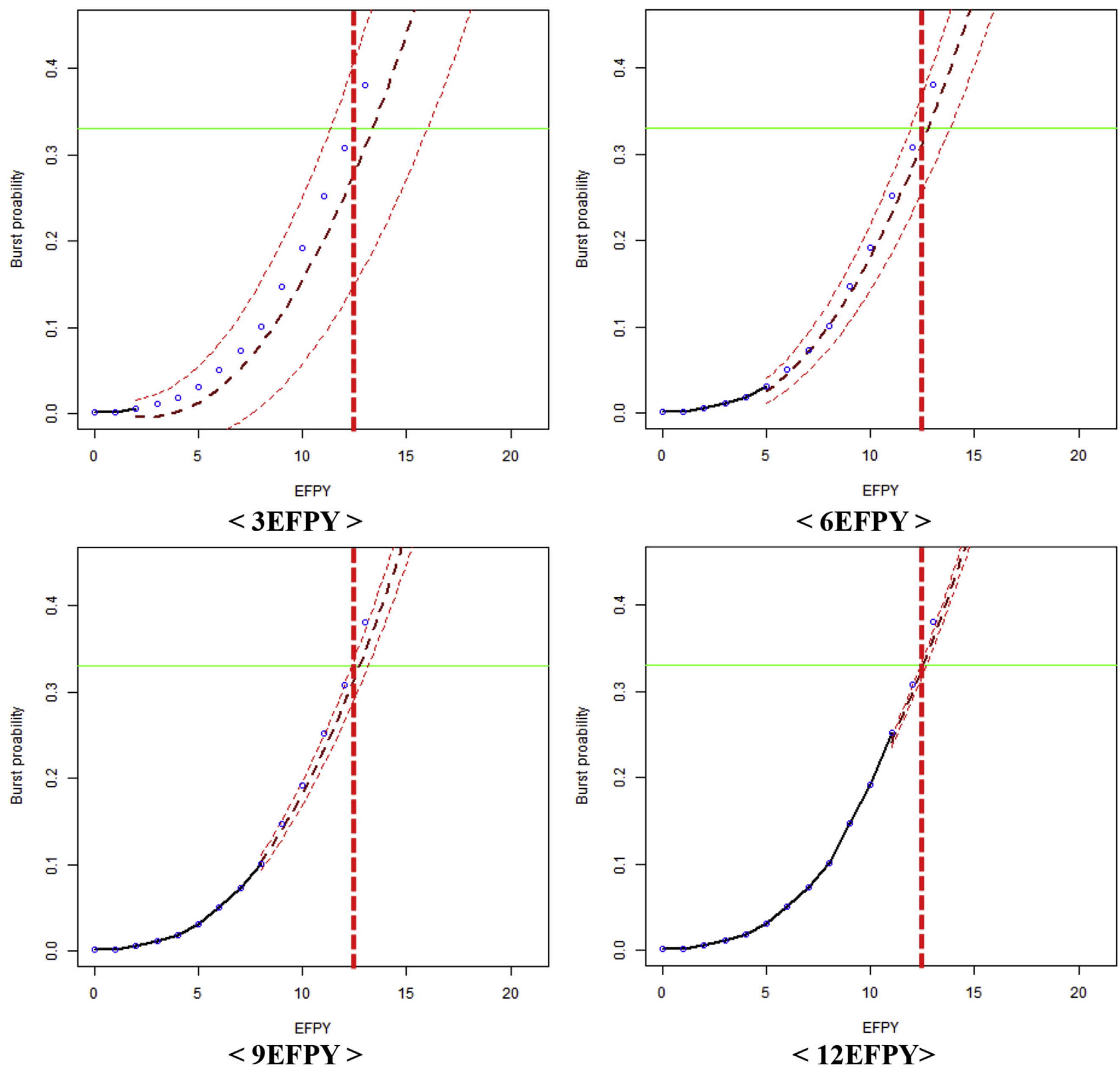

Fig. 7. The results of GPM/Bayes for each part.
EFPY, effective full power years; GPM, general path model.

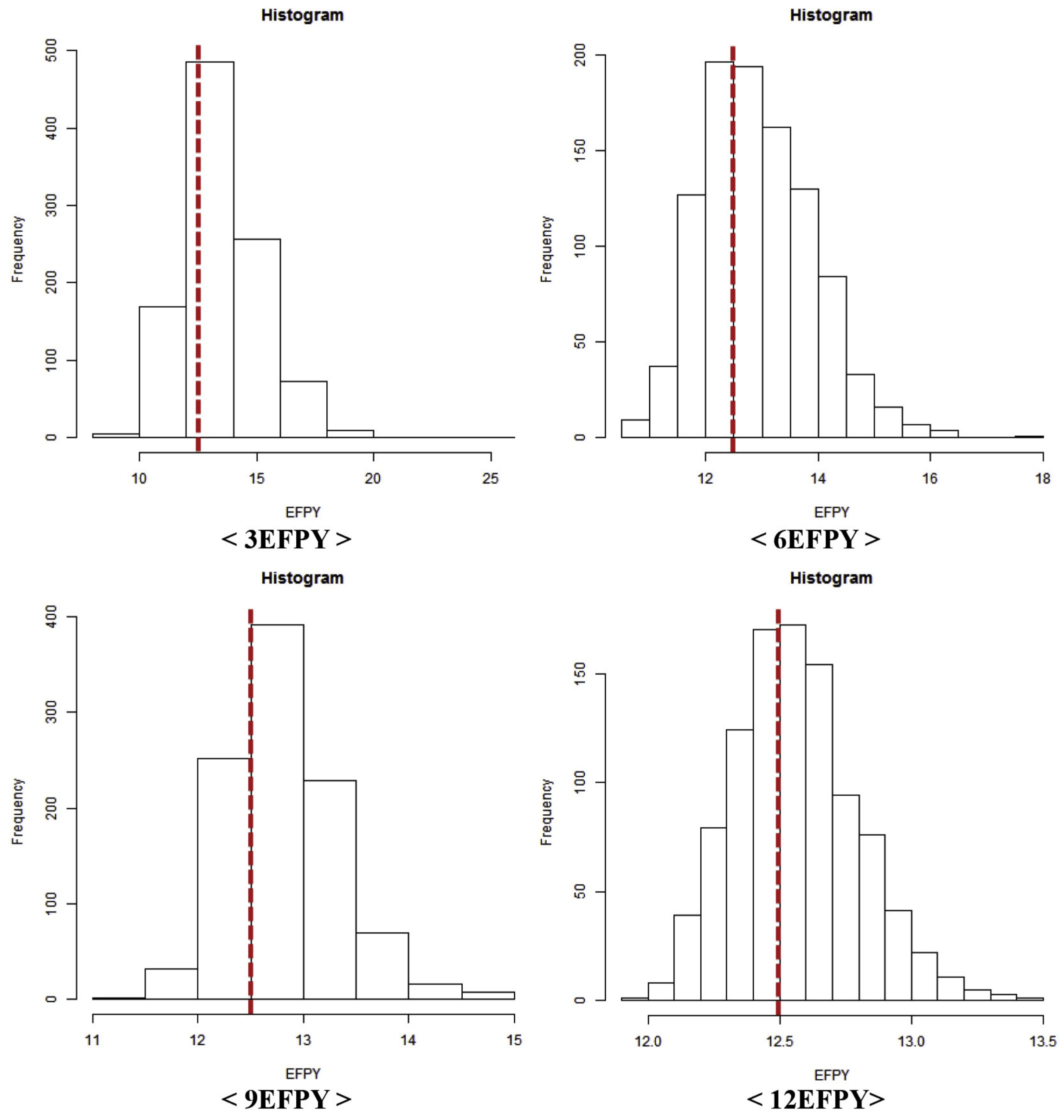

Fig. 8. The histogram of GPM/Bayes for each part.
EFPY, effective full power years; GPM, general path model.

For using GPM/Bayes, the parameters of each failure data were determined by regressing failure data. The threshold value is found using failure data. By multiplying the last value of failure data with the parameter found during fitting, where a user determines quantile values conservatively, the 95% quantile value is determined in this paper. After determining the fitting function and the threshold value of the failure data, the prior parameter should be identified.

The GPM/Bayes was performed by using training data and the results are summarized in Table 1. In Table 1, as previously mentioned, the degradation path assumes a monotonically increasing equation and steam generator tube aging data were optimized with a quadratic equation. In addition, the prior was calculated using Eq. (3) in Chapter 2. The variance was residual from fitted data and training data, and the threshold value is calculated by the lower 5%.

To show how to update RUL and improve the reliability using the monitoring data, the test set is classified into four parts. Each part was calculated based on EFPY, and 1 EFPY was 18 months. Part 1 was 3 EFPY, Part 2 was 6 EFPY, Part 3 was 9 EFPY, and Part 4 was 12 EFPY. An uncertainty analysis was also performed. There are many types of uncertainty, such as uncertainty in parameters, measurement noise, and failure threshold. In this paper, only the parameter uncertainty is considered. Although the measurement noise is handled in preprocessing to calculate the burst probability to reduce its effect, the parameter uncertainty includes information of the measurement noise because the parameter is calculated using measurement values. We assume that the uncertainty can be combined. Eq. (9) was used to quantify the uncertainty, where the parameters were assumed to follow a normal distribution with a 95% confidence interval.

$$\beta \in \left[\widehat{\beta}_{\mu} - t_{n-1,\alpha/2}\widehat{\beta}_{\sigma}\sqrt{1+1/n}\,,\, \widehat{\beta}_{\mu} + t_{n-1,\alpha/2}\widehat{\beta}_{\sigma}\sqrt{1+1/n}\right] \tag{9}$$

Fig. 7 shows the results of GPM/Bayes for one case at each part. In Fig. 7, the circles and the solid line connecting those circles are test data (measured data): the horizontal line at 0.33 shows the threshold value, and the dashed lines are predicted values and uncertainty bands determined using the GPM/Bayes method. The uncertainty of data combined into an uncertainty band using the GPM/Bayes method is expressed as the difference between data and predicted values from training data. Part 1 had

Table 2
RUL error mean and standard deviation of each part.

-	EFPY3	EFPY6	EFPY9	EFPY 12
Mean	5.15	4.026	1.782	0.335
Standard deviation	3.084	3.173	1.366	0.256

EFPY, effective full power years; RUL, remaining useful lifetime.

lower accurate RUL with high uncertainty compared with others because the size of the initial crack was not large, which means less predictable.

For providing the different view of the concept of prognostics, a histogram is constructed depending on the monitoring data in Fig. 8. To make the histogram, 1,000 simulations were performed; they represented the same tube as that shown in Fig. 7. The threshold value was 12.5 EFPY, and is indicated as a dashed vertical line. In addition, Table 2 shows the RUL error mean and standard deviation for each part based on Eq. (10). As previously explained and shown in Fig. 8 and Table 2, as more observation data become available, better predictions can be achieved. The error ε is defined as follows:

$$\varepsilon = \frac{t_r - t_p}{t_r} \times 100 \tag{10}$$

where t_r is the measured data and t_p is the predicted data.

The root mean square (RMS) is obtained for each crack and each part. The RMS results are shown in Fig. 9. In addition, the RMS is defined as follows:

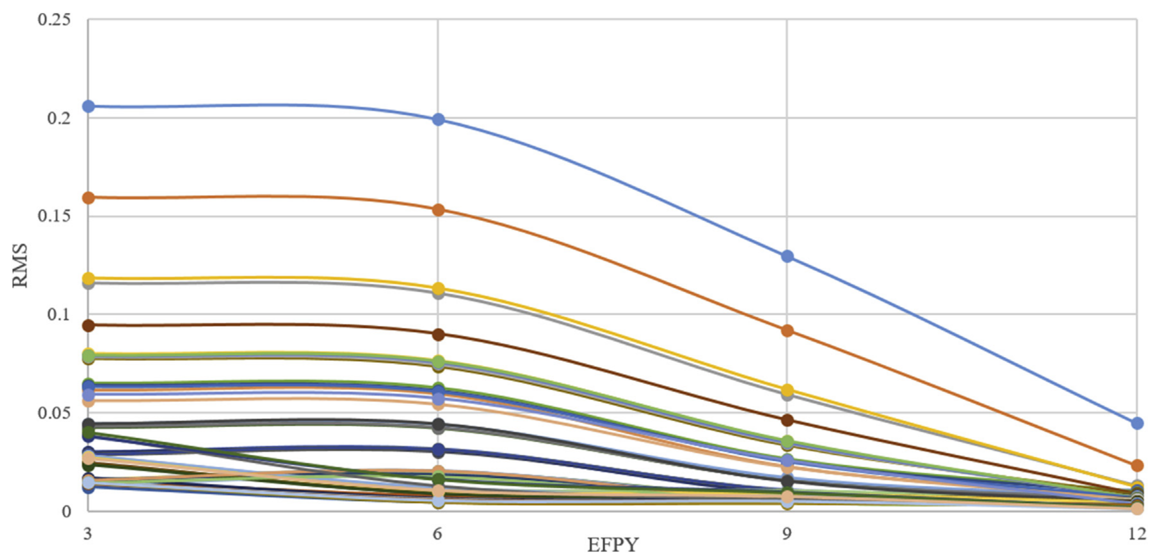

Fig. 9. RMS results for each crack.
EFPY, effective full power years; RMS, root mean square.

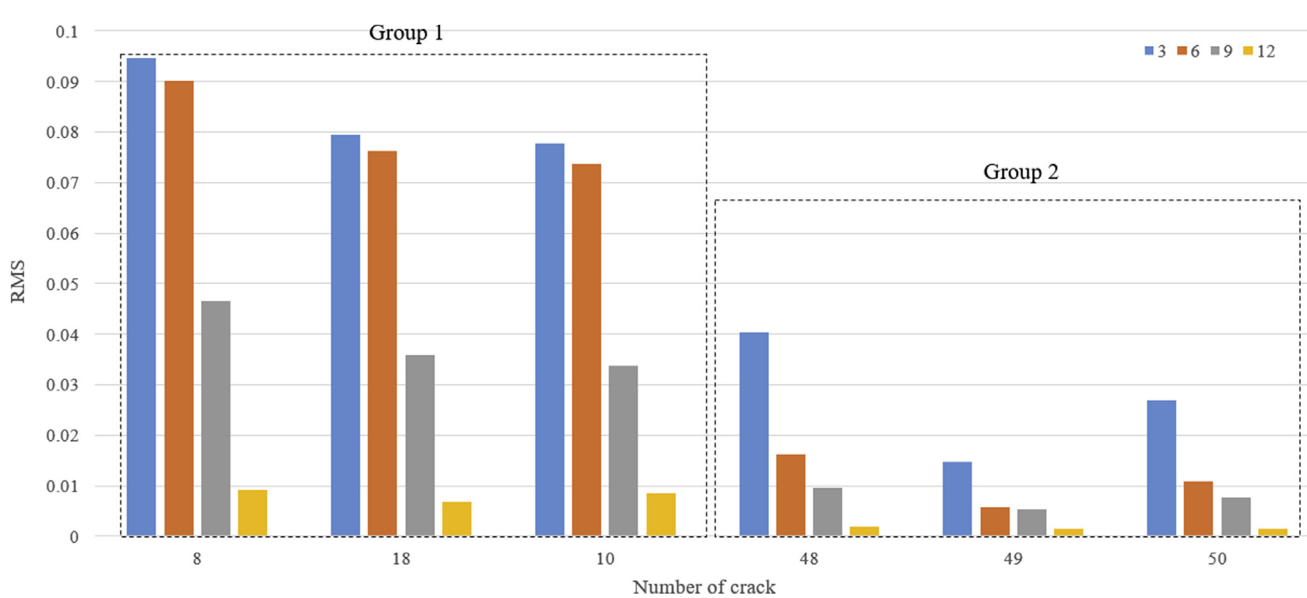

Fig. 10. Representative cases for grouping of RMS results.
RMS, root mean square.

$$RMS = \sqrt{\frac{\sum_{i}^{n} \left(t_{r,i} - t_{p,i}\right)^2}{n}} \tag{11}$$

where $t_{r,i}$ is the i^{th} measured data and $t_{p,i}$ is the i^{th} predicted data.

As previously mentioned, because the GPM/Bayes method uses the monitoring method, the RMS results decrease as shown in Fig. 9. However, there are two graph trends in Fig. 9; in addition, Fig. 10 shows representative cases that indicate the two trends for grouping of RMS results. One trend is the decrease between 6 EFPY and 9 EFPY, and the other trend is the decrease between 3 EFPY and 6 EFPY. The two trends are not different from each other because they are decided by the initial crack condition. If the crack growth condition is satisfied at 3 EFPY, the decreasing trend between 3 EFPY and 6 EFPY appears. If the crack growth condition is not satisfied at 3 EFPY, the crack growth propagates to 6 EFPY to mature crack growth condition. Thus, the trend appears almost flat between 3 EFPY and 6 EFPY and decreasing between 6 EFPY and 9 EFPY.

5. Conclusions

In this paper, using the data-based GPM/Bayes, a prognostic method was used to predict the integrity of a steam generator tube. Most NPPs have been operating in Korea for a long time, and it can be predicted that NPPs operating for the same number of years would undergo a varying extent of aging and degradation. It is thus essential to reflect aging as a characteristic of each NPP, and this is performed through prognostics. The suggested method is supplementary to a conventional assessment using experimental correlations under general conditions, and it is able to reflect aging by calculating plant-specific data for the reliability assessment by virtue of prognostic method characteristics. The main characteristic of the suggested method is that the model accuracy is increased by gathering monitoring data.

From this research, some practical issues arise. The first is the absence of data. In the case of NPPs, it is difficult to obtain real-time and on-line monitoring data because of the harsh environment. Furthermore, the level of difficulty in observing fault symptoms is comparatively higher for passive components than for active components comparatively because of the nature of the fault mechanism. Thus, obtaining of real-time data should be performed for better health management of NPPs. The second limitation is how to find the best parametric model. In this paper, the degradation path assumed a monotonically increasing function, such as a quadratic, linear, or exponential function. Third, there is a problem of determining the failure threshold from data. Because, to prevent accidents, NPPs operate with high conservatism, it is difficult to determine an accurate threshold value. Also, there may be some machines or systems that do not have an accurate failure threshold. Finally, there is an issue of how to quantify uncertainty. As mentioned earlier, there are many types of uncertainty such as that regarding measurement noise, parameters, and failure threshold. However, in this paper, only parameter uncertainty is considered. For further study, and more accurate estimation, all sources of uncertainty should be quantified.

This research shows the possibility of application to prognostics for NPPs. For further study, a methodology may be suggested using the present results. It would be helpful to estimate the RUL for components and systems by considering the characteristics of each. Moreover, these results are applicable to PSA.

Conflicts of interest

No conflict of interest.

Acknowledgments

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