Development of Probabilistic Environmental Fatigue Lifetime Model for Ni-Base Alloys Using End-of-Life Data

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1. Introduction

The fatigue life of nuclear power plant components is estimated based on the fatigue design curve described in the ASME Boiler & Pressure Vessel Code Section III [1, 2]. The design curve is based on the best fitting curve of fatigue life for a given stress/strain amplitude data, and after, conservatively corrected to consider the associated uncertainties (e.g., surface finish, material grade).

However, there is a limitation that the fatigue design curve is basically estimated based on fatigue test data performed in an in-air environment. Decades ago, when the initial nuclear power plant was designed, it was considered that there was no problem in the use of the fatigue design curve. However, as the nuclear power plant aged, it has been reported that the environmental effect of corrosion greatly shortened the fatigue life (i.e., environmental fatigue). Thus, Reg. Guide 1.207 requires the fatigue life to be corrected by the existing design curve by an additional *environmental correction factor* to account for these environmental effects for nuclear components in LWR(Light Water Reactor) coolant environments [3].

In this work, the objective is to extend the above fatigue life prediction approach from deterministic to probabilistic. The probabilistic approach has the following two advantages: 1) The probabilistic model can quantify the safety margin as a level of failure probability. 2) In the model estimation step, the probabilistic approach can account for the censored data in the test, which are usually neglected in the deterministic approach.

2. Literature Survey and Data Extraction

For Ni-based alloys and weldments except for Alloy 718, the ASME fatigue design curve is specified to follow the fatigue design curve of AuSS (Austenitic Stainless Steel) material [1, 2]. The best fit S-N(stress/strain amplitude vs. fatigue life) curve for AuSS and Ni-based Alloys is

$$\ln N_{f,\mathrm{Air}} = 6.891 - 1.920\ln(\varepsilon_a - 0.112) \qquad (1)$$

where, $N_{f,\mathrm{Air}}$ is the in-air fatigue life (cycles), and ε_a is the strain amplitude (%). The fatigue design curve is then calculated using an adjustment life factor of 12 and stress/strain factor of 2 based on the best fit S-N curve (Eq. 1).

The environmental correction factors for nickel-based alloys and welding materials covered in this study are presented as a function of temperature, strain rate, and dissolved oxygen (DO) values as follows [2].

$$F_{\mathrm{en}} = \frac{N_{f,\mathrm{air}}}{N_{f,\mathrm{water}}} = \exp(-T^*\dot{\varepsilon}^*O^*) \qquad (2a)$$

$$T^* = \begin{cases} 0 & (T < 50\ ℃) \\ \dfrac{T-50}{275} & (50\ ℃ \le T \le 325\ ℃) \end{cases} \qquad (2b)$$

$$\dot{\varepsilon}^* = \begin{cases} 0 & (\dot{\varepsilon} > 5.0\%/s) \\ \ln\dfrac{\dot{\varepsilon}}{5} & (0.0004\ \%/s \le \dot{\varepsilon} \le 5.0\ \%/s) \\ \ln\dfrac{0.0004}{5} & (\dot{\varepsilon} < 0.0004\ \%/s) \end{cases} \qquad (2c)$$

$$O^* = \begin{cases} 0.06 & (\text{BWR water, DO} \ge 0.1\ \text{ppm}) \\ 0.14 & (\text{PWR water, DO} < 0.1\ \text{ppm}) \end{cases} \qquad (2d)$$

where, F_{en} is the environmental correction factor, and $N_{f,\mathrm{water}}$ is the LWR-water fatigue life, T is the temperature (°C), $\dot{\varepsilon}$ is the strain rate (%/s), $T^*, \dot{\varepsilon}^*, O^*$ are the effect terms of temperature, strain rate, and DO, respectively. The NUREG/CR-6909 report, which provides above formula for calculating environmental correction factors through Eq. 2, collects environmental fatigue test data that have been conducted worldwide so far, and the database results are presented in the form of graphs in the report. In this study, the in-air and environmental fatigue test data given in NUREG/CR-6909 was extracted using a graph digitizer program. The results are as follows.

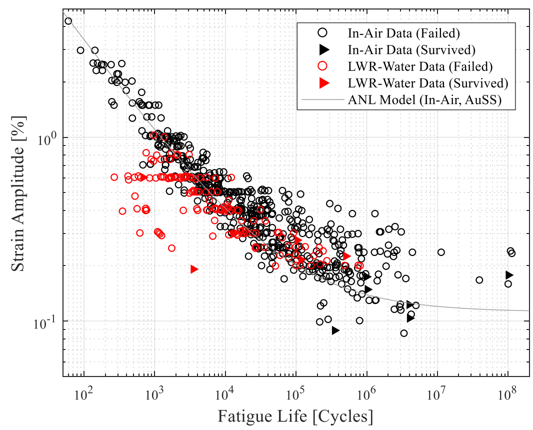

Figure 1 All fatigue data of Ni-base Alloys and welding materials extracted from NUREG/CR-6909, classified according to in-air/LWR-water environment and exact/right-censoring data.

- The number of fatigue data for nickel-based alloys published in the NUREG/CR-6909 report is 559 in in-air and 162 in LWR-water conditions. Among these, the number of fatigue data extracted by the graph digitizer program in this study is 529 in-air data and 137 LWR-water data. The data mentioned below all refer to the data that were extracted in this study.

- The 529 in-air data consisted of 522 exact (failed at the time) data and 7 right-censored (survived at the time) data. The 137 LWR-water data consisted of 131 exact data and 6 right-censored data (see Fig. 1). The solid gray line in Fig. 1 is the reference model equation that corresponds to the in-air best fit curve of the AuSS material (Eq. 1).
- When 529 in-air data are classified according to base/weld metal, 397 are base metal data and the remaining 132 are weld metal data. The 397 in-air base metal data consist of 191 Alloy 600 data, 17 Alloy 690 data, 196 Alloy 718 data, and 23 Alloy 800 data. The fatigue resistance of Alloy 718 material is superior to that of the other nickel-based alloy materials. Meanwhile, 132 in-air weld metal data include 10 Alloy 52 data, 50 Alloy 82 data, 6 Alloy 132 data, 6 Alloy 152 data, 26 Alloy 182 data, 6 Alloy 690 weld data, and 28 unclassified as other NiCrFe weld data.
- When 529 in-air data are classified according to experimental temperature, they can be divided into 432 400 °C and below data and 97 427 °C data. The 97 data performed at 427 °C consisted of 81 Alloy 718 data and 16 Alloy 800 data. The 427 °C data appear to have longer fatigue life than the data below 400 °C, because the fatigue resistance of Alloy 718 material itself, which makes up the majority of the 427 °C data, is much higher than that of other nickel-based alloy materials. The NUREG/CR-6909 report states that the in-air environmental fatigue life of AuSS materials has little effect on the temperature below 400 ° C. However, also the report states that the data given are not sufficient to investigate the effect of fatigue life above 400 ° C.
- When 137 LWR-water data are classified according to base/weld metal, 83 are base metal data and the remaining 54 are weld metal data. The 83 LWR-water base metal data consist of 67 Alloy 600 data and 16 Alloy 690 data. Meanwhile, 54 LWR-water weld metal data consist of 8 Alloy 82 data, 9 Alloy 132 data, 10 Alloy 152 data, 26 Alloy 182 data and 1 Alloy 690 weld data.
- The 137 LWR-water data can be classified by temperature into 6 100 °C data, 5 200 °C data, 73 288 °C data and 53 325 °C data.
- 137 LWR-water data can be classified by strain rate: 7 0.0001%/s data, 19 0.001%/s data, 1 0.004%/s data, 3 0.01%/s data, 16 0.04%/s data, 8 0.1%/s data, and 83 0.4%/s data.
- 137 LWR-water data can be classified by DO level: 54 0.005 ppm data, 5 0.007 ppm data, 5 0.01 ppm data, 69 0.2 ppm data, and 4 8 ppm data.

The next step is to estimate a probabilistic fatigue life prediction model using the above nickel-based alloy in-air and LWR-water data. However, we only considered Alloy 600/690 base/weld metal data for the following reasons:

- All in-air Alloy 600/690 base/weld metal data were conducted at temperatures below 400 °C. Therefore, it is possible to neglect in-air temperature effects on fatigue life. In the in-air condition, at temperatures above 400 °C, the temperature effect has not been clearly identified yet [2].
- Alloy 718 has a significantly higher fatigue resistance than other nickel-based alloys. When included those data in a one data set, the conservatism of estimated model could be decreased.
- All materials tested in the LWR-water environment are Alloy 600/690, base/weld metal data. Therefore, it is possible to exclude material grade effect when we consider only in-air Alloy 600/690 base/weld metal data.

Therefore, a total of 283 in-air data were selected from the original 529 in-air data set, which consists of 176 Alloy 600 base metal data, 82 Alloy 600 weld metal (i.e., Alloy 82/182/132) data, 13 Alloy 690 base metal data, 12 Alloy 690 weld metal (i.e., Alloy 152/52) data. Meanwhile, a total of 137 LWR-water data are all used, which consists of 67 Alloy 600 base metal data, 43 Alloy 600 weld metal data, 16 Alloy 690 base metal data, and 11 Alloy 690 weld metal data.

3. Probabilistic Model Development

We assumed the Weibull distribution as the basic functional form of the fatigue life model [4]. The Weibull distribution is one of the most widely used distributions for probabilistic modeling of material lifetime. It is applicable when the size of the considered components is macroscopic and the failure mechanism follows the weakest link behavior [5]. In this study, the following two parameter Weibull distribution is adopted.

$$F\left(N_f;\beta,\eta\right) = 1 - \exp\left[-\left(\frac{N_f}{\eta}\right)^{\beta}\right] \tag{3a}$$

$$f\left(N_f;\beta,\eta\right) = \frac{\beta}{\eta}\left(\frac{N_f}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{N_f}{\eta}\right)^{\beta}\right] \tag{3b}$$

where, F and f correspond to the Cumulative Distribution Function (CDF) and the Probability Density Function (PDF) of the Weibull distribution, N_f is the fatigue life, β is the shape parameter, and η is the scale parameter. The shape parameter is a parameter related to the time-dependent degradation behavior of the material and is generally considered a material constant. On the other hand, the scale parameter corresponds to the quartile when the CDF value is about 0.632. If the shape parameter is 1, the scale parameter is equal to the expectation of the probability distribution. Therefore, the scale parameter is often used as a representative value for the corresponding probability distribution.

In this work, we assumed the following environmental fatigue life model based on the Eq. 2.

$$\eta(\eta_{\text{air}}, F_{\text{en}}) = \frac{\eta_{\text{air}}}{F_{\text{en}}} \tag{4a}$$

$$\eta_{\text{air}}(\varepsilon_a; \theta_1, \theta_2, \theta_3) = \left(\frac{\varepsilon_a - \theta_3}{\theta_1}\right)^{\frac{1}{\theta_2}} \tag{4b}$$

$$F_{\text{en}}(T^*, \dot{\varepsilon}^*, O^*) = \begin{cases} 1 & (\text{In} - \text{air}) \\ \exp(-T^* \dot{\varepsilon}^* O^*) & (\text{LWR} - \text{water}) \end{cases} \tag{4c}$$

$$T^*(T; a_T, b_T) = \frac{T - a_T}{b_T} \tag{4d}$$

$$\dot{\varepsilon}^*(\dot{\varepsilon}; a_{\dot{\varepsilon}}) = \ln\left(\frac{\dot{\varepsilon}}{a_{\dot{\varepsilon}}}\right) \tag{4e}$$

$$O^*(\text{DO}) = 1 + (a_{\text{DO}} - 1)H(\text{DO} - 0.1) = \begin{cases} 1 & (\text{PWR water, DO} < 0.1 \text{ ppm}) \\ a_{\text{DO}} & (\text{BWR water, DO} \geq 0.1 \text{ ppm}) \end{cases} \tag{4f}$$

where, η_{air} is the in-air Weibull scale parameter, $\theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}$ are the parameters which should be estimated from the data, and H is the Heaviside step function. From Eqs. 3 and 4, it can be seen that the total number of parameters to be estimated is eight. In this study, MLE (Maximum Likelihood Estimation) method is used to estimate the parameters. The MLE method has the advantage that the most reliable estimate can be obtained when the number of data is large enough, and that the bias of the estimated Weibull scale parameter is small compared to the median rank regression method, which is another Weibull parameter estimation method [5, 6]. The likelihood function for the MLE method can be calculated as follows.

$$L = L_{\text{air}} L_{\text{water}} \tag{5a}$$

$$L_{\text{air}}(\beta, \theta_1, \theta_2, \theta_3) = \prod_{i=1}^{N_{E,\text{air}}} \left[f(N_{f,i}, \varepsilon_{a,i})\right] \cdot \prod_{j=1}^{N_{R,\text{air}}} \left[1 - F(N_{f,j}, \varepsilon_{a,j})\right] \tag{5b}$$

$$L_{\text{water}}(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = \prod_{i=1}^{N_{E,\text{water}}} \left[f(N_{f,i}, \varepsilon_{a,i}, T_i, \dot{\varepsilon}_i, \text{DO}_i)\right] \cdot \prod_{j=1}^{N_{R,\text{water}}} \left[1 - F(N_{f,j}, \varepsilon_{a,j}, T_j, \dot{\varepsilon}_j, \text{DO}_j)\right] \tag{5c}$$

$$l = \ln L = \ln L_{\text{air}} + \ln L_{\text{water}} \tag{5d}$$

where, L is the total likelihood function, $L_{\text{air}}, L_{\text{water}}$ are the partial likelihood functions for in-air and LWR-water data, $N_{E,\text{air}}, N_{R,\text{air}}, N_{E,\text{water}}, N_{R,\text{water}}$ are the number of exact/right-censored in-air/LWR-water data, i, j are the data indexes, l is the log-likelihood function.

The goal of the MLE method is to find a combination of parameters that maximizes the log-likelihood function. This is similar to the unbounded optimization problem, except that you need to find the maximum value of the log-likelihood function, not the minimum value of the objective function. The solution to this problem is the same as the solution of the system of simultaneous differential equations in Eq. 6. Because Eq. 6 is a nonlinear and its form is very complex, it is truly difficult to solve analytically. Therefore, in this study, the solution was solved using the numerical method, conjugate gradient method [7]. The convergence criterion is when the L2 norm of the relative difference becomes less than 1e-6.

$$\begin{cases} \dfrac{\partial}{\partial \beta} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial \theta_1} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial \theta_2} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial \theta_3} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial a_T} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial b_T} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial a_{\dot{\varepsilon}}} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \\ \dfrac{\partial}{\partial a_{\text{DO}}} l(\beta, \theta_1, \theta_2, \theta_3, a_T, b_T, a_{\dot{\varepsilon}}, a_{\text{DO}}) = 0 \end{cases} \tag{6}$$

Table 1 shows the parameter estimates obtained using the in-air/LWR-water Alloy 600/690 base/weld metal data and the MLE method above, and Figure 2 shows the estimated Weibull model. Most of the in-air data are well contained within the 90% confidence bounds of the in-air condition Weibull model. Therefore, the fatigue life model estimated in this study was judged to be appropriate.

Table 1 Results of MLE parameter estimation.

$\hat{\beta}$	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_3$
1.2361	9.1842	-0.3267	0.0444
$\hat{a}_T$	$\hat{b}_T$	$\hat{a}_{\dot{\varepsilon}}$	$\hat{a}_{\text{DO}}$
-39.8713	2651.1	6.4886	0.6563

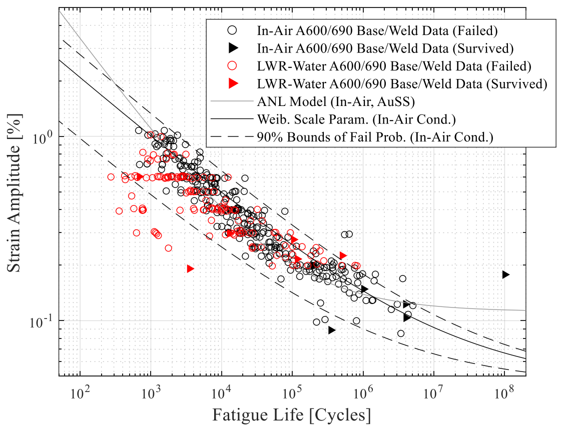

Figure 2 Result of Weibull-based probabilistic environmental fatigue life model.

4. Conclusions

In this study, the NUREG/CR-6909 report was reviewed and the data in the report was extracted. We estimated the Weibull-based probabilistic life prediction model of the environmental fatigue using those end-of-life data. The resulting probabilistic model considering environmental effect well fits the original raw data set.

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