STUDY ON BEST ESTIMATE OF FUEL ROD FRACTURE DURING LOCA INCLUDING UNCERTAINTY IN STRESS-STRENGTH MODEL

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ABSTRACT

Probabilistic risk assessments of nuclear power plants have relied on conservative deterministic criteria for core damage determination, despite advancements in plant response and system analyses, including the best-estimate plus uncertainty (BEPU) methodology. To achieve more rational and realistic assessments, we previously proposed a probabilistic approach for estimating fuel rod fracture during loss-of-coolant accidents (LOCAs) in light-water reactors by developing a fracture probability estimation model that integrates BEPU analysis. In this framework, fracture probabilities are estimated using a stress-strength model, in which stress and strength are represented as probability distributions modeled as functions of the equivalent cladding reacted (ECR)—a key indicator of fuel cladding oxidation under LOCA conditions. The stress distribution is represented by a log-normal model derived through Bayesian inference of BEPU analysis results, while the strength distribution is modeled with a log-probit model based on Bayesian inference applied to LOCA-simulated test data. A Monte Carlo simulation samples and compares random values from these distributions to calculate probabilities. However, this approach requires substantial computational resources. To address this, we explored a numerical integration method that replaces the full propagation of uncertainty with representative curves constructed from posterior distributions, aiming to approximate the fracture probabilities calculated by Monte Carlo simulation with reduced cost. This study investigates how representative curves—based on pointwise means or medians computed from sampled distributions at each ECR value—affect the accuracy of the numerical integration results compared to full Monte Carlo simulations. By analyzing four combinations of normal and log-normal distributions for stress and strength, we found that using the pointwise mean curve yields highly accurate results, with relative errors below 1%, while the use of the pointwise median curve causes larger discrepancies. This approach improves computational efficiency in rare fracture probability estimation while retaining compatibility with uncertainty-aware modeling.

Keywords: Fuel rod fracture, LOCA, BEPU, Stress-strength model, Bayesian inference, Monte Carlo simulation, Numerical integration

I. INTRODUCTION

In the field of nuclear power plant safety assessment, recent advancements have been made toward more realistic and rational evaluation methods, including best-estimate plus uncertainty (BEPU) [1] and probabilistic risk assessment (PRA). These methods have been primarily applied to estimate stress-side parameters, such as peak cladding temperature (PCT) and equivalent cladding reacted (ECR), which indicate the degree of oxidation in fuel cladding tubes. On the other hand, strength-side criteria used for core damage determination, such as regulatory ECR limits, remain highly conservative and deterministic, as they are based on conditions that ensure fuel rods (fuel cladding tubes) do not fracture during loss-of-coolant accidents (LOCAs) [2]. Importantly, fuel rod fracture itself does not directly lead to core damage; rather, core damage arises when fractured rods reduce the core's cooling capability. This imbalance—where stress is estimated using best-estimated methods with uncertainty consideration, while strength is estimated deterministically—can result in excessive conservatism in safety evaluation, as shown in Figure 1 [3].

To resolve this inconsistency, a previous study proposed a probabilistic model for estimating the fracture probability of fuel rods under LOCA conditions of light-water reactors (LWRs), incorporating uncertainties and using ECR [4]. This model serves as a best-estimate representation of the strength-side characteristics. Building on this model, we have previously developed a probabilistic framework for determining fuel rod fracture under LOCA conditions by integrating BEPU-based plant response analysis with the probabilistic fracture model [3].

Our proposed approach has provided a probabilistic fuel rod fracture determination method using the stress-strength model and Monte Carlo simulations. Furthermore, we have explored numerical integration to enhance the accuracy of the estimation for rare fracture probabilities, offering an alternative to Monte Carlo simulations, which might not effectively handle these events.

However, this issue remains, as numerical integration cannot directly handle uncertainties in their distributions. To address this limitation, we consider an approach in which uncertainty in the distribution parameters is replaced with representative curves—such as those based on pointwise means or medians, computed from sampled distributions at each ECR value—thereby enabling integration without repeated stochastic sampling. This study aims to explore how representative curves can be used effectively to ensure the reliability and accuracy of fracture probability estimation using numerical integration.

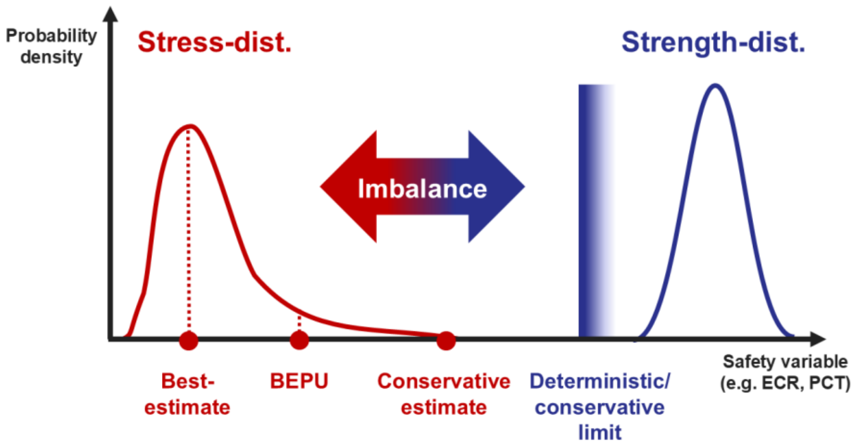

FIGURE 1. Imbalance Between Stress-side and Strength-side Estimations in Safety Assessments [3]

II. PROBABILISTIC FRACTURE DETERMINATION METHOD

II.A. Fracture Determination Using the Stress-Strength Model

In our previous study [3], we have proposed a fracture determination method utilizing the stress–strength model and Monte Carlo simulations. In this chapter, we present a detailed explanation of the method. The model employs probability distributions on both the stress side (representing plant response) and the strength side (representing the fracture threshold of fuel rods). These distributions are constructed using the ECR as the explanatory variable under LOCA conditions. The use of ECR is supported by previous studies indicating that it is a dominant factor in the fracture of fuel cladding tubes during LOCAs [4].

We present herein the complete methodology of the probabilistic fracture determination approach. First, distributions for ECR on both the strength and stress sides are estimated, including uncertainty. Then, values are randomly sampled from both distributions and compared. If the ECR value drawn from the stress distribution exceeds the corresponding value from the strength distribution, a fracture is considered to have occurred. Otherwise, no fracture is assumed. This process is repeated multiple times, and the fracture probability is calculated as the proportion of trials resulting in fracture.

II.B. Estimation of Stress Distribution

To estimate the stress distribution, we use ECR data obtained under specific accident conditions. In the study, we employ the BEPU analysis results for a pressurized water reactor (PWR) large break LOCA scenario conducted by Zugazagoitia et al. [5]. The analysis, performed using the TRACE5 code (Patch 4) [6], assumes a guillotine break at both ends of a reactor coolant system pipe. A total of 1021 simulations are performed to estimate parameters such as peak cladding temperature (PCT) and local maximum oxidation (LMO), where LMO is defined identically to ECR. This number of simulations is adopted directly from the dataset provided by Zugazagoitia et al. [5], as it is designed to ensure sufficient coverage of parameter variability while maintaining computational feasibility. We adopt the ECR values from this analysis because our estimation focuses on the relationship between ECR and fuel rod fracture.

Using this dataset, we estimate the stress distribution while incorporating uncertainty. For this purpose, we assume that the ECR follows a log-normal distribution. This choice reflects the distribution's ability to capture rare but high ECR values due to its long right tail and the fact that it is defined only for positive values. These features make the log-normal distribution well-suited for representing the probabilistic characteristics of the stress side ECR data. For the parametric estimation of the distribution using the log-normal distribution, we use Bayesian inference with Markov chain Monte Carlo (MCMC) methods as follows:

$$X_{stress} \sim LogNormal(\mu, \sigma) \tag{1}$$

where X_{stress} represents the literature value of ECR (-), and μ and σ represent the mean and standard deviation of the log-normal distribution.

Using the posterior distribution of the parameters estimated from Eq. (1), the posterior predictive distribution of the stress side's ECR can be expressed as follows:

$$p_{pred}(x \mid X_{stress}) = \int \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\log x - \mu)^2}{2\sigma^2}\right) p_{post}\left(\mu, \sigma \mid X_{stress}\right) d\mu d\sigma \tag{2}$$

where $p_{pred}(x \mid X_{stress})$ represents the posterior predictive distribution of the stress side's ECR, x represents ECR, and $p_{post}\left(\mu, \sigma \mid X_{stress}\right)$ represents the joint posterior distribution of the parameters.

The estimation involved running four chains with 2,000 iterations each, discarding the first 1,000 iterations in each chain as warm-up, resulting in 4,000 posterior samples in total. For the marginal prior distributions of the parameters, non-informative distributions are used, employing a normal distribution with a mean of 0 and a variance of 10^4 [7]. The convergence of MCMC sampling is confirmed by examining the $\hat{R}$ statistics [8] for all parameters, which are found to be sufficiently close to 1.0, indicating good mixing across chains. In addition, trace plots of all four chains are visually inspected to confirm that the samples have reached stationary distributions after the warm-up. These non-informative priors are selected to avoid imposing prior bias, allowing the data to drive the inferences while minimizing potential bias from weakly supported prior beliefs. The sampling is performed using the No-U-Turn Sampler (NUTS), an adaptive variant of Hamiltonian Monte Carlo (HMC), as implemented in the rstan package. NUTS is chosen over traditional because it adaptively tunes step sizes and trajectory lengths, offering faster convergence and more efficient exploration of the posterior distribution in low-dimensional models without requiring manual tuning of proposal distributions.

The results are shown in Figure 2 [3], where the blue histogram represents the ECR dataset from the simulation results of the previous study. The black line and shaded regions correspond to the median, 50% interval, and 95% interval of the posterior predictive distribution, respectively.

II.C. Estimation of Strength Distribution

The strength distribution is estimated based on a fracture probability model developed in a previous study [4]. In that study, LOCA-simulated tests were carried out under conditions designed to eliminate conservatism. The resulting data, including both fractured and unfractured outcomes of Zircaloy-4 cladding tubes, were used to construct a probabilistic model of the relationship between ECR and fracture probability using Bayesian inference. Assuming the binary fracture outcomes follow a Bernoulli distribution [8], a log-probit model was adopted to estimate the fracture probability curve [9]. In this model, ECR is calculated using the Baker–Just equation [10]. However, because the ECR values on the stress side are obtained using the Cathcart–Pawel equation [11], we recalculate the strength-side ECR values using the same equation to ensure consistency across both sides. The fracture probability estimation model is expressed as:

$$Y \sim Bernoulli(P(Y=1 \mid X_{strength})) \tag{3}$$

$$P(Y=1 \mid X_{strength}) = \Phi\left[\alpha + \beta \log X_{strength}\right] \tag{4}$$

$$p_{pred}(y=1 \mid X_{strength}, Y) = \int \Phi\left[\alpha + \beta \log X_{strength}\right] p_{post}(\alpha, \beta \mid Y) d\alpha d\beta \tag{5}$$

where Y represents binary coded LOCA-simulated test data, where 1 indicates a fracture and 0 indicates no fracture. $X_{strength}$ is the ECR (-). $P(Y=1 \mid X_{strength})$ is a fracture probability given $X_{strength}$. $p_{pred}(y=1 \mid X_{strength}, Y)$ represents the posterior predictive distribution of the fracture probability, the link function Φ employs the cumulative distribution function (CDF) of the standard normal distribution, α and β represent the scalars of unknown parameters to be estimated, and $p_{post}(\alpha, \beta \mid Y)$ represents the joint posterior distribution of the parameters.

While the stress distribution is represented by a probability density function (PDF), the strength distribution is initially given as a CDF. Therefore, we apply the inverse function method to derive the corresponding ECR probability density function from the CDF.

In this model, the parameters α and β are estimated using Bayesian inference with the MCMC method. The Bayesian estimation conditions are set identically to those used for the stress side. The convergence of MCMC sampling was confirmed in the same manner as for the stress side, through the examination of $\hat{R}$ statistics [8] and trace plots.

The results are shown in Figure 3 [3], where the red points represent the binary data concerning fracture and non-fracture of the test rods obtained from the LOCA-simulated test. The black line and shaded regions indicate the median, 50% interval, and 95% interval of the posterior predictive distribution of the fracture probability, respectively.

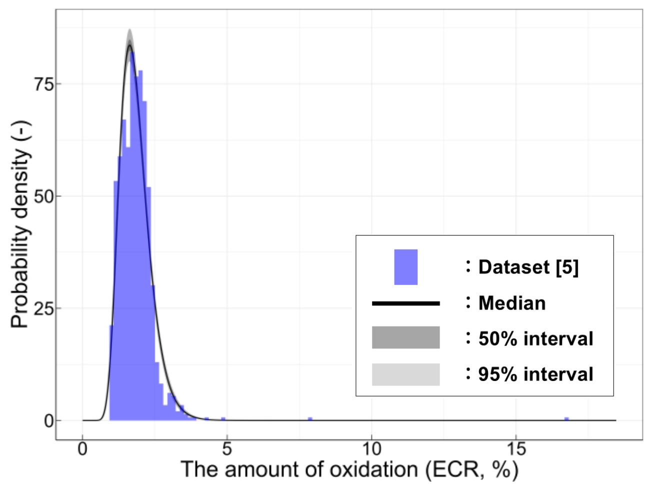

FIGURE 2. Probability Density Distribution of ECR Estimated Using Log-normal Distribution [3]

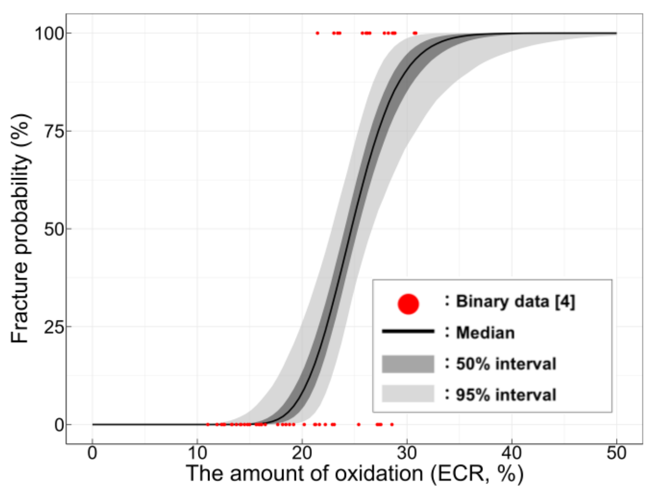

FIGURE 3. Fracture Probability Curve Estimated Using the Log-probit Model [3]

III. IMPROVING COMPUTATIONAL EFFICIENCY OF RARE FRACTURE PROBABILITIES

III.A. Fracture Probability Calculation Using Numerical Integration

According to Zugazagoitia et al. [5] and Nissley et al. [12], actual ECR values from BEPU analysis of large break LOCA scenarios are typically only a few percent. For such low ECR values, the corresponding fracture probabilities become extremely small, presenting challenges for Monte Carlo simulation-based estimation. This is because Monte Carlo methods require sample sizes proportional to the inverse of the target probability to achieve reasonable accuracy, meaning extremely large numbers of trials are needed for rare events with very low probabilities. To address this issue, we have introduced a numerical integration approach as an alternative to Monte Carlo simulations for estimating rare fracture probabilities [3]. In this section, we outline the numerical integration approach introduced in our previous study [3].

This approach involves integrating the overlapping areas of the stress and strength distributions. Due to the complexity of deriving an analytical solution, the ECR domain from 0 to 1 is divided into sufficiently small intervals, and numerical integration using the trapezoidal rule is applied to find an approximate solution.

This method could estimate rare fracture probabilities with lower computational loads than the Monte Carlo simulation. However, using numerical integration, it is not possible to directly handle distributions that include uncertainties. Therefore, representative curves corresponding to specific credible levels are used, effectively removing the uncertainty in advance. The calculation of fracture probability using numerical integration is expressed as follows:

$$P_{\text{int}} = \int_0^1 [f_{stress}(x|\mu,\sigma) \times F_{strength}(x|\alpha,\beta)]dx \tag{6}$$

where $f_{stress}(x|\mu,\sigma)$ represents the probability density function of ECR for the stress side, $F_{strength}(x|\alpha,\beta)$ represents the cumulative probability distribution function of ECR for the strength side, x represents ECR, and other parameters represent those estimated via Bayesian inference, set to a specific credible level.

III.B. Consideration of Uncertainty in Numerical Integration

As mentioned in Section III.A, numerical integration offers a computationally efficient alternative to Monte Carlo simulation for estimating rare fracture probabilities. However, because numerical integration cannot directly incorporate parameter uncertainty, it requires the use of representative distributions or curves in which uncertainty is removed, which presents a methodological challenge.

As one approach to addressing this challenge, we have investigated whether using representative curves corresponding to specific credible levels could produce results comparable to Monte Carlo methods [3]. To conduct this investigation, we have created a virtual dataset by increasing the ECR values from a BEPU analysis [5] for a PWR large break LOCA scenario tenfold, resulting in 1020 data points after excluding one entry where ECR exceeded 100%. This modification was necessary as the original ECR values were too low to demonstrate significant fracture phenomena.

We then have examined how fracture probability estimates from numerical integration using curves corresponding to various credible levels compared to those from a Monte Carlo simulation. Our analysis has revealed that when curves corresponding to approximately a 55% credible level, the numerical integration produced fracture probability estimates (15.1%) that matched those from the Monte Carlo simulation. This finding suggests that by appropriately replacing parameter uncertainty with representative curves, it is possible to calculate fracture probabilities that consider uncertainties using numerical integration. This approach allows for estimating rare fracture probabilities with high computational accuracy and low computational load while considering uncertainties.

IV. EVALUATING THE APPLICABILITY OF NUMERICAL INTEGRATION UNDER VARIOUS UNCERTAINTY CONDITIONS

IV.A. Analytical Conditions

As described in the previous section, our previous study demonstrated that numerical integration using a representative curve corresponding to approximately the 55% credible level produces results comparable to a Monte Carlo simulation that evaluates overall uncertainties. However, this result was specific to the dataset used in our previous study [3], and may not necessarily generalize to other distribution types or uncertainty structures. Therefore, we investigate how representative curves—constructed by removing parameter uncertainty—can be used in numerical integration to ensure broad applicability under various combinations of stress and strength distributions and their associated uncertainties.

Considering how Monte Carlo simulation handles uncertainties, each trial involves fixing distribution parameters through random sampling, with the fracture probability calculated by repeating these trials sufficiently. Consequently, a Monte Carlo simulation with adequate trials should converge to numerical integration results using curves representing the mean of uncertainty distributions. To verify this approach, we prepared stress and strength distributions with uncertainties and performed numerical integration using pointwise mean curves, validating accuracy by calculating errors against true values. The pointwise mean curve refers to a line connecting mean probability density values calculated for each small interval across the ECR range. For comparison, we also computed errors for pointwise median curves derived through the same methods. The verification included all combinations of normal and log-normal distributions for both stress and strength distributions. When both the stress and strength distributions are assumed to follow normal distributions, the fracture probability can be calculated analytically. The fracture probability under this assumption is given by the following expression:

$$P_f = \int_0^{\infty} \left\{ \int_0^x f_R\left(x\right) dx \right\} f_S(x) dx = 1 - \Phi\left(\frac{\mu_R - \mu_S}{\sqrt{\sigma_R^2 + \sigma_S^2}} \right) \tag{7}$$

where P_f represents the fracture probability, $f_R\left(x\right)$ and $f_S(x)$ represent the PDFs of the strength and stress distributions, respectively, x represents the ECR, μ_R and μ_S represent the mean values of strength and stress distributions, respectively, σ_R and σ_S represent the standard deviations of strength and stress distributions, respectively.

For the log-normal×log-normal case, logarithmic transformation of stress and strength values enables derivation of analytical solutions as same to the normal distribution case. For cases with different distribution types (normal×log-normal, log-normal×normal), Monte Carlo simulation results with 10^8 trials were used as true values. For numerical integration, the integration range was set to cover at least 99.99% of the total cumulative probability, with 10^3 divisions.

For each case, we assigned prior distributions to the parameters (mean μ, standard deviation σ), and used prior predictive distributions created from 4,000 extracted samples as stress and strength distributions. To ensure uniform parameter variation, normal distributions were used for μ priors, while log-normal distributions with small standard deviations were used for σ priors, since these parameter settings assume a symmetric uncertainty structure where the mean and median of the distributions are nearly equal. The specific prior settings for all four cases (Normal × Normal, Lognormal × Lognormal, Normal × Lognormal, and Lognormal × Normal) are summarized in Table I. The prior predictive distributions $p(x)$ can be expressed by the following equations:

$$p(x) = \iint p(x \mid \mu, \sigma) p(\mu) p(\sigma) d\mu d\sigma \tag{8}$$

The parameters were adjusted to ensure final fracture probabilities fell within a 0.1%–2.0% range, allowing meaningful comparison with Monte Carlo simulations. This range was selected because it corresponds to a level at which the true values can be accurately estimated using 10^8 Monte Carlo simulation trials, which were used in cases where analytical solutions were not available. Figure 4 shows an example of the predictive distributions for the normal×normal case, where the red dotted line represents the pointwise mean curve, the black solid line indicates the median curve, and the shaded regions show the 50% interval and 95% interval of the distribution.

IV.B. Results and Discussion

Table II summarizes the relative errors obtained using pointwise mean and median curves for each stress–strength distribution pairing. Numerical integration with the pointwise mean curve resulted in relative errors of 0.29%, 0.08%, 0.04%, and 0.06% across the four distributional combinations. In contrast, using the pointwise median curve yielded higher errors of 19%, 11%, 9.2%, and 8.6%, respectively. These findings indicate that numerical integration using the pointwise mean curve yields fracture probabilities that closely match analytical solutions and Monte Carlo simulation results, with relative errors below 1%. This approach outperforms the use of pointwise median curves, which leads to noticeably larger deviations.

While this chapter has focused on evaluating the applicability of numerical integration across different distributional combinations of stress and strength, it does not consider variations in the shape of the parameter uncertainty distributions. Addressing this limitation by incorporating a wider range of uncertainty characteristics remains an important direction for future research.

TABLE I. Prior Distribution Settings for Stress and Strength Parameters Across All Cases

		Normal × Normal	Lognormal × Lognormal	Normal × Lognormal	Lognormal × Normal
Stress Distribution	μ	Normal (1, 0.05^2)	Normal (0, 0.05^2)	Normal (1, 0.05^2)	Normal(0, 0.05^2)
	σ	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)
Strength Distribution	μ	Normal(3, 0.05^2)	Normal(1.6, 0.05^2)	N(1.4, 0.05^2)	N(3, 0.05^2)
	σ	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)	LogNormal(log0.5, 0.1^2)

TABLE II. Relative Errors in Fracture Probability Estimation Accuracy for Each Distribution Combination

	Relative errors (%)			
	Normal × Normal	Lognormal × Lognormal	Normal × Lognormal	Lognormal × Normal
Mean Curve	0.29	0.08	0.04	0.06
Median Curve	19	11	9.2	8.6

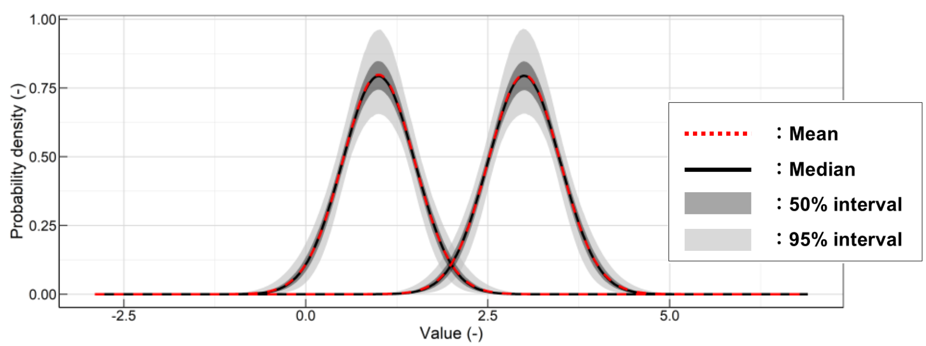

FIGURE 4. Prior Predictive Distributions for the Normal×Normal Case

V. CONCLUSIONS

In our previous study, we have proposed a probabilistic fracture determination method based on a stress–strength framework and Bayesian inference, aiming to efficiently estimate fuel rod fracture probabilities under LOCA conditions while accounting for parameter uncertainties. In this method, both stress and strength distributions are modeled as functions of ECR. As part of this method, we introduced numerical integration as an alternative to Monte Carlo simulation to estimate rare fracture probabilities with reduced computational cost. However, since numerical integration cannot be directly applied to distributions that retain parameter uncertainty, representative curves—constructed by summarizing the uncertainty (e.g., via pointwise means or medians computed from sampled distributions at each ECR value)—are required. Building on this framework, the present study investigated how representative curves derived from stress and strength distributions can be used in the numerical integration process to reproduce fracture probabilities consistent with those obtained from Monte Carlo simulations with full uncertainty propagation.

We evaluated the effect of different distributional combinations (normal and log-normal) and compared the accuracy of two approaches—using pointwise mean curves and pointwise median curves. The results showed that using the pointwise mean curve consistently achieved high accuracy, with relative errors below 1% in all cases, whereas using pointwise median curves resulted in larger errors ranging from 8% to 20%. These findings indicate that the performance of numerical integration is highly sensitive to the choice of statistical summary, and that using pointwise mean curves is robust across typical distribution types.

While the current study focused on symmetric uncertainty structures in which the mean and median are approximately aligned, future work should extend the applicability of the method to more general cases involving skewed or heavy-tailed uncertainty distributions.

Furthermore, generalizing our findings into a mathematical model that includes margins could be considered. Our current approach represents a best estimate method aimed at accurately understanding phenomena. By generalizing this into a mathematical model that incorporates margins, the method could produce outputs corresponding to required credible levels, making it more suitable for engineering applications.

While this study modeled fuel fracture, future efforts could model the entire process from fuel fracture to core damage. This would shift from the conservative evaluation of "fuel fracture equals core damage" to a more realistic evaluation. Potential applications could include using the integrity of the reactor pressure vessel to determine core damage.

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