Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 22-23, 2025

Refinement of Reactor Pressure Vessel Embrittlement Trend Curves Using a Mixed-Effects Model

Gyeong-Geun LEE [a*], Bong-Sang LEE [a], Min-Chul KIM [a], Junhyun Kwon[a], Jong-Min KIM[a]
[a]*Materials Safety Technology Research Division, Korea Atomic Energy Research Institute,*
111 Daedeok-daero 989Beon-gil, Yuseong-gu, Daejeon, 34057
[*]*Corresponding author: gglee@kaeri.re.kr*

***Keywords :** reactor pressure vessel, irradiation embrittlement, embrittlement trend curve, adjustment, Markov Chain Monte Carlo

1. Introduction

The long-term operation of nuclear power plants leads to neutron irradiation embrittlement in reactor pressure vessels (RPVs), resulting in a shift in the Charpy transition temperature and a reduction in impact toughness. Surveillance test programs are implemented to monitor RPV material properties over time. Various embrittlement trend curves (ETCs) have been developed using accumulated surveillance data, such as ASTM E900-15 [1], which provides a generic nonlinear regression model for predicting the transition temperature shift (TTS). However, many nuclear power plants exhibit systematic deviations from this generic curve due to variations in production heats, notch orientation, or initial unirradiated properties. This study proposes a mixed-effects modeling approach to better account for plant-specific deviations and reduce prediction errors by distinguishing group-level biases from within-group measurement errors.

2. Methodology

A large surveillance dataset (Baseline22), comprising over 2,000 Charpy test data points from various nuclear power plants worldwide, was grouped based on material type and notch orientation, resulting in over 600 distinct groups [5]. The generic ETC (E900-15) served as the baseline trend function.

The adjustment model can be expressed as:

$$TTS_{ij} = \eta_i + \mu_i \cdot ETC(x_{ij}) + e_{ij}$$
$$\eta_i \sim N(\eta_0, \sigma_b)$$
$$\mu_i \sim N(\mu_0, \sigma_m)$$
$$e_{ij} \sim N(0, \sigma)$$

Bayesian Markov Chain Monte Carlo (MCMC) methods were then used to fit mixed-effects models, incorporating group-specific intercepts and, in some cases, slopes to adjust baseline predictions [3-5]. An intercept-only model introduced a unique vertical shift for each group, while a more complex model allowed both intercept and slope deviations. Model performance was evaluated using root mean squared deviation (RMSD) and leave-one-out cross-validation (LOO-CV).

3. Results

Figure 1 presents residual plots for various adjustment models. AM1 and AM2, which do not incorporate group-specific intercepts, exhibit an RMSD of approximately 13.35°C, similar to the unadjusted E900-15, with a broad residual distribution. AM2, which applies a slope adjustment to the entire dataset, corrects the residual trend to near zero. AM3, incorporating group-specific intercepts, reduces RMSD by approximately 37%, with a noticeably narrower residual spread. AM4, which includes a fixed-effect slope, offers slight additional improvement. AM5 and AM6 introduce group-specific slopes, further reducing RMSD, but with marginal benefits compared to AM3 and increased computational complexity.

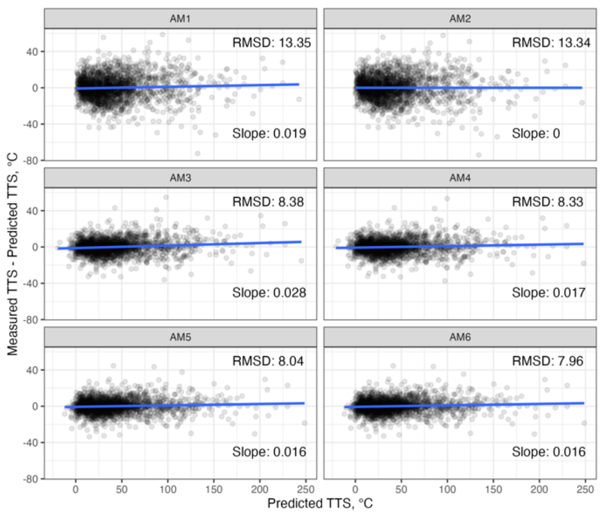

Fig. 1. Residual plots for each adjustment model based on Baseline22g data.

The AM3 model, using only three parameters, achieves lower RMSD than E900-15, enabling effective bias adjustment with minimal data. Bayesian MCMC analysis shows that intercept values converge with increased data, aligning with the "shrinkage" effect. AM3 allows a closed-form solution using the Best Linear Unbiased Prediction (BLUP) method. Figure 2 illustrates the shrinkage effect of slope and intercept in AM3 models according to group size.

Since between-group and within-group variances are nearly equal in AM3, its adjustment formula aligns with MRP-462. While incorporating group-specific random slopes requires matrix-based computations, increasing complexity, AM3's simplicity makes it suitable for regulatory applications by balancing accuracy and computational efficiency.

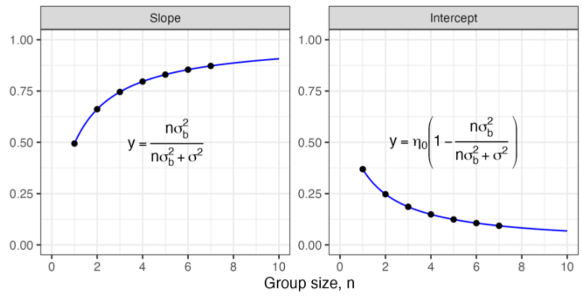

Fig. 2. Relationship between group size n and the slope and intercept in the AM3 model.

Figure 3 highlights the predictive interval standard deviation as more surveillance data become available. In the early stages, with only one or two irradiation data points per group, the model's prediction interval remains relatively large. As additional measurements are incorporated, the intercept and its uncertainty converge to more stable values, reducing the overall prediction interval. Using AM3 model parameters, the standard deviation of the prediction interval can be quantitatively computed through a closed-form equation.

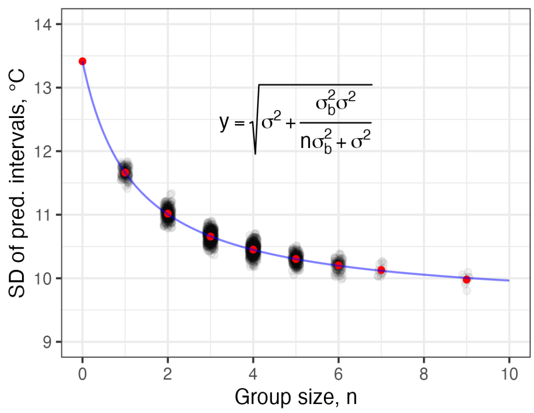

Fig. 3. Standard deviation of prediction interval as a function of group size.

4. Conclusion

This study demonstrates that incorporating a mixed-effects model into the E900-15 ETC framework significantly improves the prediction accuracy of RPV embrittlement. Even a simple intercept-only adjustment model (AM3) effectively separates group-specific biases from measurement errors and substantially reduces RMSD. While including group-specific slope terms provides further improvements, regulatory clarity and practical simplicity may favor the intercept-only approach. Closed-form approximations for intercept correction can be implemented without extensive MCMC calculations, making this method particularly promising for regulatory and field applications in aging nuclear power plants.

REFERENCES

[1] E10 Committee, ASTM E900-15e2: Guide for Predicting Radiation-Induced Transition Temperature Shift in Reactor Vessel Materials, ASTM International, 2021.
[2] G.-G. Lee et al., Determining the adjusting bias in reactor pressure vessel embrittlement trend curve using Bayesian multilevel modelling, Nuclear Engineering and Technology 55 (2023) 2844–2853.
[3] R Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, 2020.
[4] P.-C. Bürkner, brms: An R Package for Bayesian Multilevel Models Using Stan, Journal of Statistical Software 80 (2017).
[5] W.R. Gilks, S. Richardson, and D. Spiegelhalter, Markov Chain Monte Carlo in Practice, Chapman & Hall/CRC, 1995.