Enhancing the Accuracy of Embrittlement Trend Curves for Nuclear Power Plants through Group Bias Estimation with a Multilevel Model

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1. Introduction

The RPV material's irradiation embrittlement is critical for the safe operation of a nuclear power plant (NPP). The RPV is evaluated through a surveillance test program to quantify the embrittlement. The embrittlement trend curve (ETC) predicts the transition temperature shift (TTS) of RPV materials over the NPP's lifetime, considering initial material properties and operating conditions. However, there is a need to account for heat-based prediction of TTS and the effect of unirradiated Charpy transition temperature on subsequent TTS measurements. This study proposes a grouping variable to estimate biases of the global trend ETC in individual NPPs using a Bayesian multilevel model. The model's performance is compared with E900-15 ETC [1].

2. Methods and Results

2.1 Dataset

This study uses Baseline22, a dataset in Plotter-22, to group RPV surveillance test results and calculate bias for each NPP. Baseline22 corrects data from Plotter-15 and contains information to group data based on NPP, material product forms, and notch orientation of Charpy specimens. A new column combining material lookup and notch orientation was created, and group IDs were assigned based on country. The total number of groups was 677.

2.2 Modelling

The E900-15 ETC was used to represent the global trend. Residuals were calculated by taking the difference between measured and predicted TTS. A multilevel model was then fitted using the Markov Chain Monte Carlo method (MCMC) [4] to reduce the residuals through group bias. The multilevel model estimated three parameters: group bias mean, group bias SD, and within-group SD. The model was fitted using R [2] and the brms [3] package, which generated 20,000 samples in approximately 2 minutes. The size of the model was approximately 200 MB, and the model parameters were calculated to two decimal places.

2.3 Comparison with E900-15 ETC

The multilevel model was fitted using Markov Chain Monte Carlo method (MCMC) [4]. The comparison of prediction accuracy between E900-15 and E900-15 with group bias is shown in Fig. 1. Introducing group bias resulted in significant improvements in R-squared and root mean SD (RMSD) values. The E900-15 model had significant errors when the measured TTS was negative since it did not contain negative values. However, group bias in E900-15 with negative values significantly relaxed the restriction in such cases.

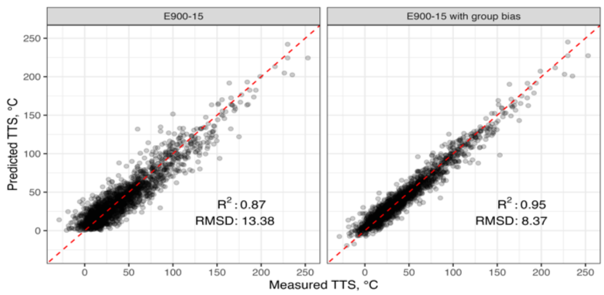

Fig. 1. Measured vs predicted TTS plots of E900-15 and E900-15 with group bias.

In Fig. 2, the Korean surveillance test data's group bias is displayed. The red points indicate the no pooling bias calculated for each group, and the blue points are the group bias means calculated by the multilevel model. The histograms above the blue dots represent the distribution of the group bias. Typically, the multilevel model's bias moves closer to the overall average than the no pooling bias, a phenomenon known as shrinkage [5]. The amount of shrinkage depends on the number of data points in each group. A group with more than four data points approaches no pooling bias, while a group with fewer data points approaches the overall average. Additionally, the bias distribution's width is influenced by the amount of data. With only one datum in a group, the bias's position can vary widely, but it becomes more reliable with increasing data points. Unlike the frequentist approach, MCMC enables the calculation of the group bias distribution, which is one of its advantages.

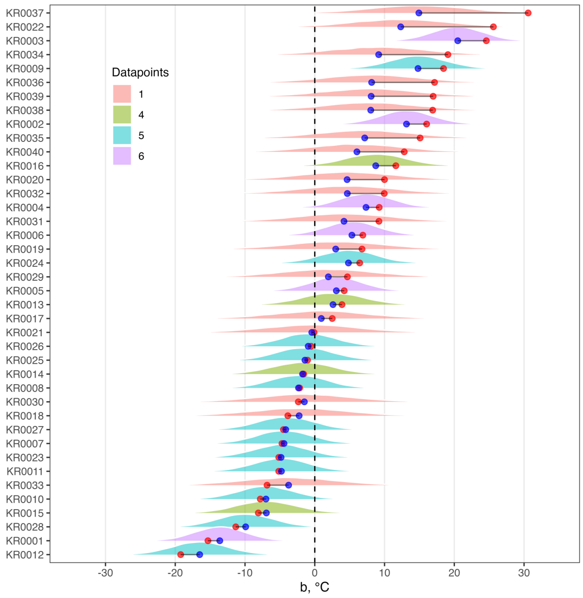

Fig. 2. Distribution and mean value of the bias from the multilevel model in grouped Korean surveillance data. Blue points represent the biases from the multilevel model. Red points represent the no pooling biases.

2.4 Calculation of prediction intervals

The multilevel model can estimate the prediction interval of a model with new data added. An experimental model was created, and Fig. 3 shows the bias and prediction intervals based on the model update. The prediction interval of the multilevel model was wider during the early stages of neutron irradiation, but it decreased as more data were added. The multilevel model can quantify the group bias and prediction interval according to the addition of data, and it can be appropriately applied to evaluate plant units for regulatory purposes. Even with just one data point, the multilevel model suggests a reduced SD compared with E900-15, and the prediction interval continued to decrease as data were added.

3. Conclusions

This study developed a Bayesian multilevel model with group bias to improve the applicability of the global trend E900-15 to nuclear power plants (NPPs). The model divided the error of E900-15 into between- and within-group errors and assumed that the group bias was normally distributed. The MCMC method estimated the distribution of model parameters and the bias of each group. Changes in the bias and prediction interval due to the addition of surveillance test data could be quantitatively estimated. The multilevel model provided an appropriate bias without overfitting, even with less than three surveillance test data points.

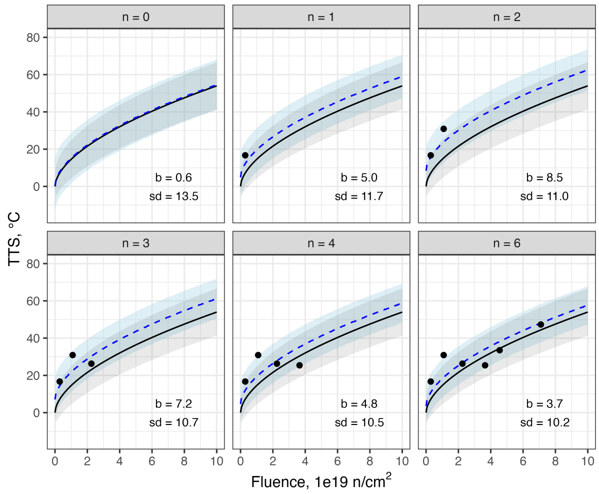

Fig. 3. Evolution of the bias and prediction interval of the multilevel model with increasing data points and refitting of the multilevel model.

REFERENCES

[1] E10 Committee, Guide for Predicting Radiation-Induced Transition Temperature Shift in Reactor Vessel Materials, ASTM International, ASTM E900-15e2.
[2] R Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria, 2020. https://www.R-project.org/.
[3] P.-C. Bürkner, brms: An R Package for Bayesian Multilevel Models Using Stan, Journal of Statistical Software. 80 (2017).
[4] W.R. Gilks, S. Richardson, David Spiegelhalter, eds., Markov Chain Monte Carlo in Practice, Chapman; Hall/CRC, 1995.
[5] R. McElreath, Statistical rethinking: A Bayesian course with examples in r and stan, CRC Press/Taylor & Francis Group, Boca Raton, 2016.