Bayesian Statistical Analysis on the In-reactor Diametral Creep of Pressure Tubes in Wolsong Units

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1. Introduction

The pressure tubes are the primary pressure boundary within the core of the CANDU reactor. During the operation, neutron irradiation results in the diametral expansion of a pressure tube, and it causes a reduction of fuel cooling due to the increased bypass flow. A CANDU unit measures dimensions of pressure tubes periodically, and examine the results of in-service inspection.

In order to estimate the diameter expansion in a pressure tube, a mechanistic model was developed by Canadian researchers [1]. The model is used in various CANDU units all over the world. Recently, the in-service inspection data has been accumulated substantially, and various statistical models are developed using the data [2].

In this study, Bayesian statistics were applied to develop a statistical model for predicting the diametral creep of the pressure tubes in Korean CANDU reactors. Bayesian statistics is useful even when there is not enough data, and it can be applied to complex multilevel modeling. In our model, the bundle position effect was integrated within the existing statistical model.

2. Methodology

The data used in this study were the in-service data collected in Wolsung units. This data includes diameter changes with bundle location measured on selected channels in the CANDU unit at various temperatures and neutron fluxes.

In order to determine the effect of time on the model, we have plotted the change in diameter over time. The pressure tube diameter at the same bundle position increased linearly with operating time, and the correlation coefficient shows a perfect linearity. We assumed that each channel has its own model parameter, because a channel is a basic unit for the inspection and the bundles in a channel are correlated. The model is described below:

$$\epsilon^{creep} = \beta_1 + f(\phi,\ T,\ bundle)\ t + \delta$$

$$f(\phi,\ T,\ bundle) = \beta_2\phi + \beta_3 T + \beta_4\phi + f(\boldsymbol{\beta}, bundle)$$

$$f(\boldsymbol{\beta},\ bundle) \sim polynomial(bundle)$$

ϵ^{creep}: $creep\ strain$, ϕ: $flux$, T: $temperature$,
$bundle$: $position\ in\ a\ channel$, t: $EFPH$,
δ: $error$, β: $parameter$

There are three ways to fit a statistical model with correlated data of channels. First, complete pooling of data; All channel data are pooled together. The method ignores any variation among channels. It's a basic statistical method. Second, no pooling method, it fits individually at each channel. It needs too many parameters, and only weak statistical inference of channels can be acquired. Third, partial pooling method which assumes that there exists hyper-parameter of channels. The parameters of the channels are sampled from the hyper-parameter. It is also known as mixed-effect model or multilevel model.

In order to find hyper-parameter of Bayesian model, Markov Chain Monte Carlo (MCMC) calculation were introduced. MCMC method eliminates difficulties of analytic calculation of Bayesian method and provides accurate statistical inference. In this study, R and STAN package were used to establish a model for diametral expansion [3,4].

3. Results and Discussion

Fig. 1 shows the hyper-parameter estimation from chains of the MCMC calculation. The shape of chains is uniformly distributed along the trials (x-axis), and it represents the stable procedure of MCMC. The tn1, tn2, tn3, and tn4 are hyper-parameters of the model. The model in this study needs 8 hyper-parameters and covariance matrix, however only four MCMC procedures were shown in this figure. Fig. 2 represents the distribution of hyper-parameters of the model. The trial number was 5000, and it showed a Gaussian-like shape. From Fig. 1 and Fig.2, we were able to estimate the hyper-parameter of the model adequately.

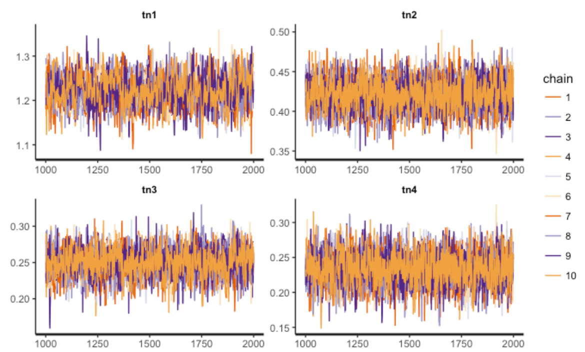

Fig. 1. MCMC procedure of 4 major hyper-parameters of the model.

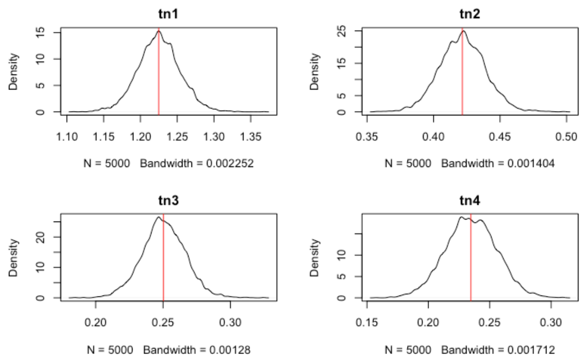

Fig. 2. The distribution of 4 major hyper-parameters of the model.

From the model, posterior prediction was sampled, and the prediction intervals can be counted from the distribution. Fig. 3 shows the measured and predicted diametral expansion of an inspected channel O08 in a CANDU unit. Red cross shows the in-service inspection results, and the black circle shows the predicted from the model. The grey shade represents the 95% credible intervals. In case of inspected channels, the individual parameter of the channel was fixed from the measured data. Thus, the predicted results are very similar to measured results. The range of the predicted intervals are really narrow.

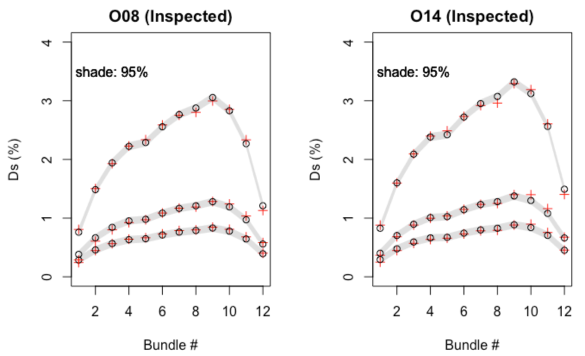

Fig. 3. Posterior predication of inspected channels.

Fig. 4 shows the case of imaginary channel with the same flux and temperature without in-service inspection data. There is no data to fix the parameters of the specific channel, and the prediction intervals are large compared to inspected results. Similarly, the diameter change of uninspected channels can be calculated quantitatively. In other words, an arbitrary channel in a CANDU unit can be calculated from the hyper-parameters of the model. One more thing to note is that bundles closed to the outlet showed large prediction intervals consistently. It is thought that the temperature calculation affected the statistical variance of the model.

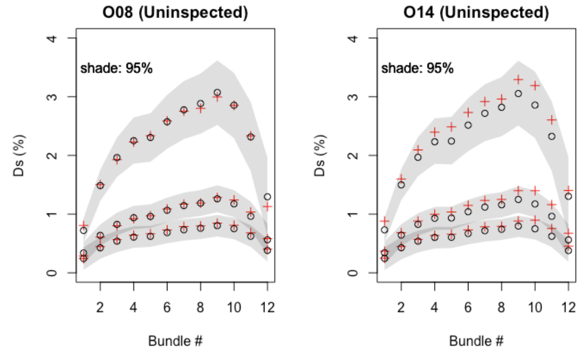

Fig. 4. Posterior prediction of uninspected channels.

4. Summary

In this study, Bayesian statistical model for diametral expansion of pressure tubes CANDU units in Korea has been introduced. Multilevel modeling with partial pooling has been applied to the model. The channel-based model with bundle term calculated he predicted means and prediction intervals quantitatively, and it showed excellent prediction performance. The additional adjustment and improvement of the model is going to be conducted.

REFERENCE

[1] R.A. Holt, J. Nucl. Mater. Vol 372, pp. 182-214, 2008.
[2] M.I. Jyrkama, G.A. Bickel, M.D. Pandey, Nucl. Eng. Design. Vol. 300, pp. 241-248, 2016.
[3] R Development Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, 2018.
[4] Stan Development Team, RStan: the R interface to Stan, R package version 2.17.3, http://mc-stan.org, 2018.