BAYESIAN REGRESSION OVER SPARSE FATIGUE CRACK GROWTH DATA FOR NUCLEAR PIPING

Adolphus Lye [1,*], Marco de Angelis [1], Edoardo Patelli [1,2]

[1] Institute for Risk and Uncertainty, University of Liverpool

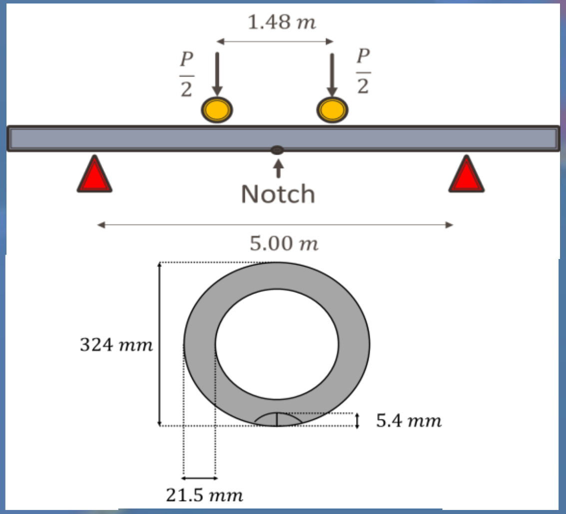
[2] Centre for Intelligent Infrastructure, University of Strathclyde

[*] Email: adolphus.lye@liverpool.ac.uk

UNIVERSITY OF LIVERPOOL | Institute for Risk and Uncertainty

INTRODUCTION

- Research objectives: To perform probabilistic model calibration and quantify the uncertainty over the sparse data;
- A set of crack data obtained via a 4-point bending test on a Carbon-Steel nuclear piping [1];
- Test was conducted over 40000 periodic stress cycles, N_{cycles};
- Each stress cycle has stress range: $\Delta P = 156\ MPa$;
- 24 readings of crack depth, z, obtained for 24 distinct N_{cycles}.



PROBLEM

- Crack growth assumed to follow Paris-Erdogan Law [2]:

$$\frac{dz}{dN_{cycles}} = C\,(\Delta K)^m \qquad (1)$$

- This can be linearized to:

$$\log\left[\frac{dz}{dN_{cycles}}\right] = m \cdot \log[\Delta K] + \log[C] \qquad (2)$$

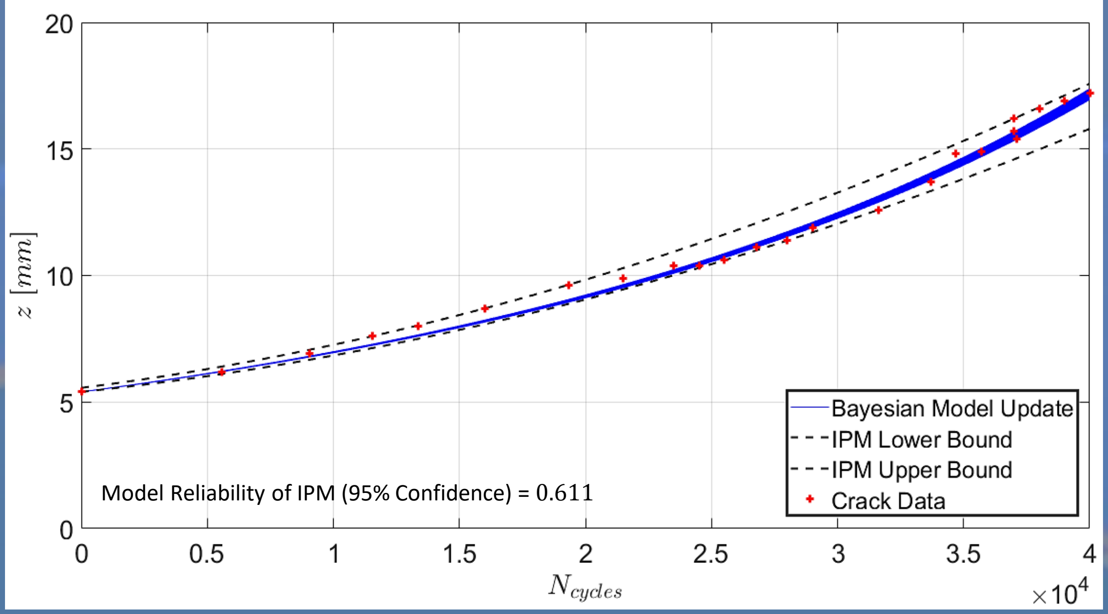
where:

$$\Delta K = \left(\frac{z}{\sqrt{r_m \cdot t}}\right)^{\frac{1}{8}} \cdot \Delta P \cdot \sqrt{\pi \cdot z} \qquad (3)$$

METHODOLOGY

- Bayesian regression technique for uncertainty quantification over the sparse data in log-space;
- Epistemic parameters to be inferred: $\boldsymbol{\theta} = \{\log[C], m\}$;
  - Prior PDF: 2D Uniform distribution with correlation coefficient of -0.999 defined by a Gaussian Copula. $\log[C]$ has bounds $[-50, 0]$ while m has bounds $[0, 10]$;
  - Likelihood function is Gaussian with standard deviation: $\sigma = 0.0191$;
  - Model used for Bayesian updating is defined by Eq. (2) ;
  - 1000 samples generated via TMCMC [3].
- Compare the results with 2nd-order polynomial Interval Predictor Model [4] in the original real space.

RESULTS



CONCLUSION

- Bayesian regression / model updating results showed that all possible trajectories lie within IPM;
- Bayesian model updating results yield tighter bounds and this is attributed to the choice of σ in the Likelihood function;
- Further works: To compare the results from Bayesian regression using different models of ΔK and to also include Kriging as a form of validation.

REFERENCES

[1] R. Rastogi, S. Ghosh, A. K. Ghosh, K. K. Vaze, and P. K. Singh (2016). Fatigue crack growth prediction in nuclear piping using Markov chain Monte Carlo simulation. *Fatigue and Fracture of Engineering Materials and Structures*, **40**(1), 145–156. doi: 10.1111/ffe.12486

[2] P. Paris and F. Erdogan (1963). A Critical Analysis of Crack Propagation Laws. *Journal of Basic Engineering*, **85**(4), 528–533. doi: 10.1115/1.3656900

[3] J. Ching and Y. C. Chen (2007). Transitional Markov Chain Monte Carlo Method for Bayesian Model Updating, Model Class Selection, and Model Averaging. *Journal of Engineering Mechanics*, 133(7). doi: 10.1061/(ASCE)0733-9399(2007)133:7(816)

[4] M. Campi, G. Calafiore, and S. Garatti (2009). Interval predictor models: Identification and reliability. *Automatica*, **45**(2), 382-392. doi: 10.1016/j.automatica.2008.09.004

NUCLEAR MODELLING SCIENCES AND ENGINEERING SEMINAR 2020, University of Bangor, 4th to 5th-November-2020