

Parameter Space Exploration Using Simulations for Inspection Design and Qualification

Paul Wilcox, Nachman Malkiel, Anthony Croxford, Josh Tyler

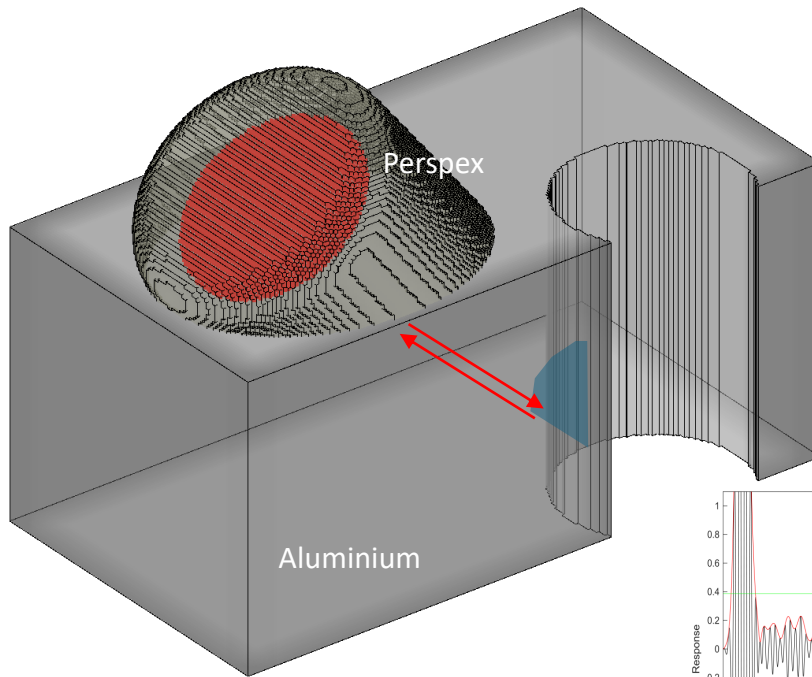
Ultrasonics and Non-Destructive Testing Group



Context

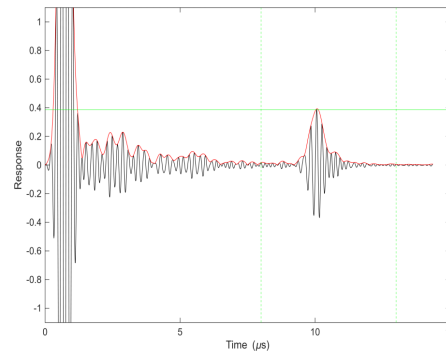
- Full 3D FE simulations (e.g. Pogo) capturing all relevant physics are becoming viable

- Assuming we have a validated, physics-based model (e.g. FE) that can accurately simulate any ultrasonic inspection, how do we use that model to design and qualify an inspection?



pogo.
www.pogo.software

~5mins on PC with
standard GPU; main
limitation on model size
is GPU memory



- How do we know which cases to run?
- How do we know when we have run enough?
- How do we visualise and interpret the output?
- How do we quantify uncertainty?

Context

- ***Fast, efficient and reliable: digital qualification of ultrasonic inspection for safety-critical components*** – EPSRC/RCNDE-funded collaborative project between Imperial College and University of Bristol (Project Lead: Peter Huthwaite, Imperial)
 - WP1 – Bottom up – improving speed and accuracy of simulations (Imperial)
 - WP2 – Top down – making effective use of simulation results (Bristol)
 - WP3 – Integration and application (Imperial/Bristol)

IMPERIAL

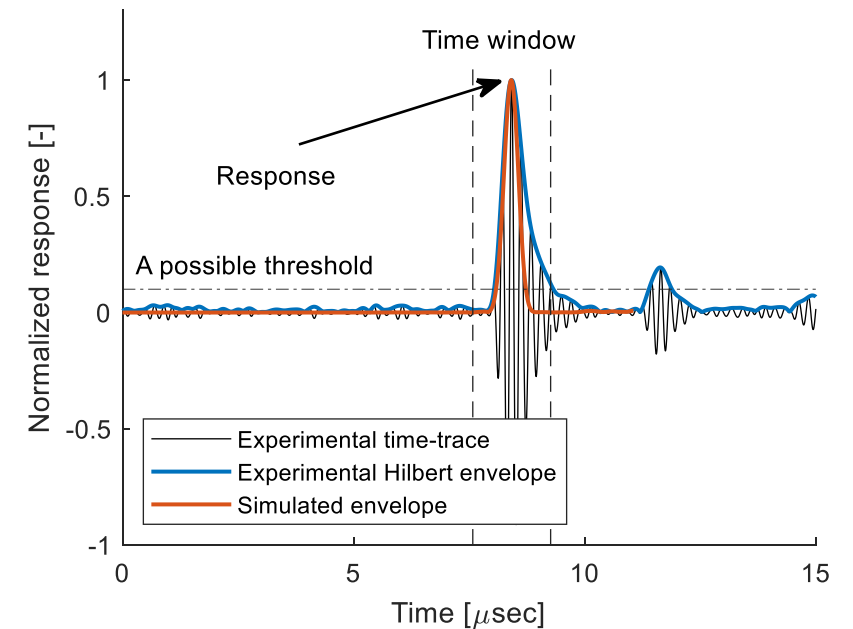
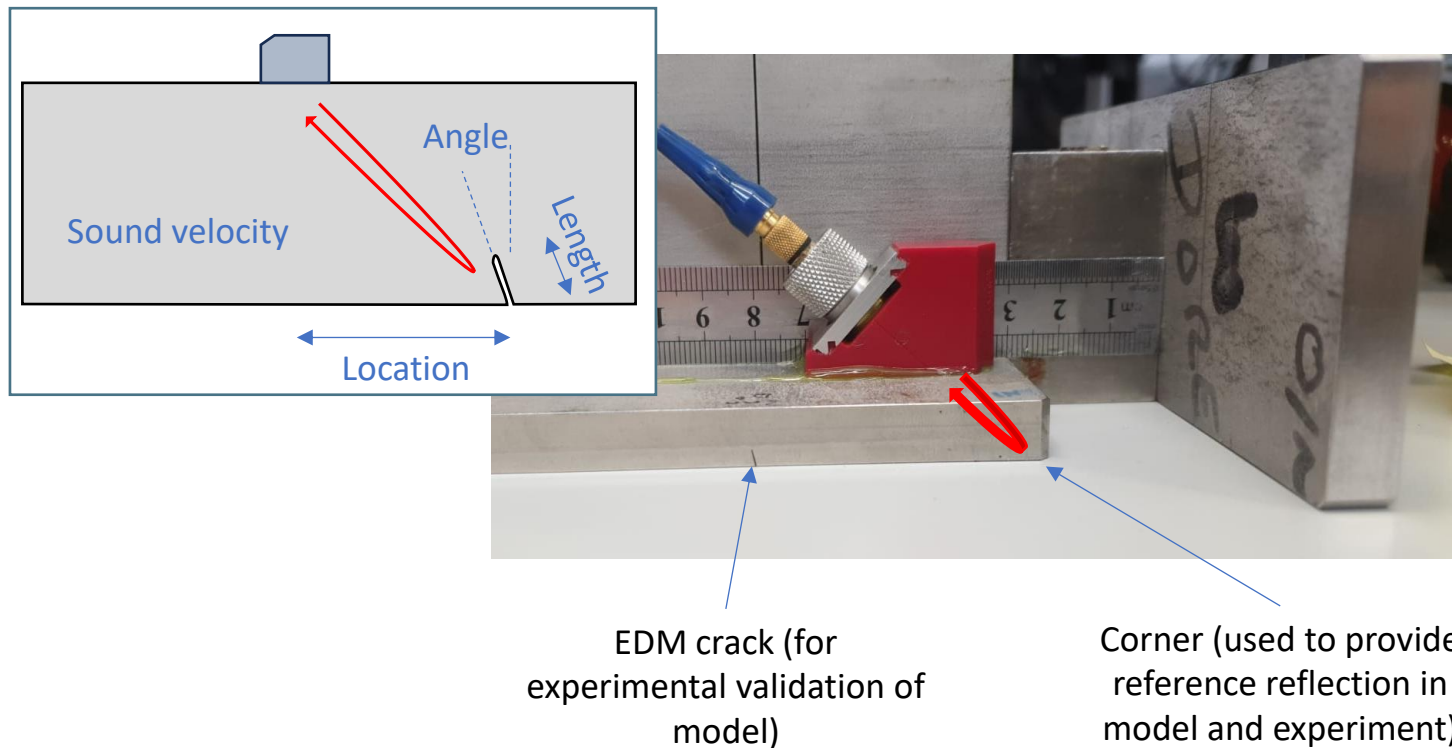


Outline

- Inspection example
 - FE model validation
- Generalised $\hat{a}$ vs. a approach – support for inspection qualification
 - Limitations of standard $\hat{a}$ vs. a approach
 - Methodology
 - Benefits of generalised approach
- Parameter space visualisation – support for inspection design
 - Parameter types
 - Methodology
 - Example
- DigiQual toolkit – software in progress

Inspection example

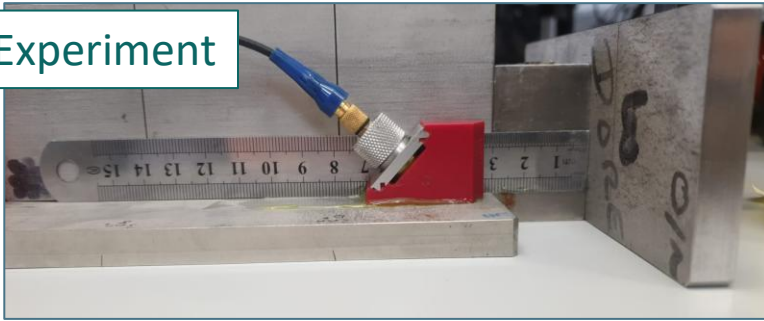
- Oblique incident shear wave inspection of surface-breaking cracks
 - 5MHz, 45° wedge, aluminium samples with s/breaking EDM notches



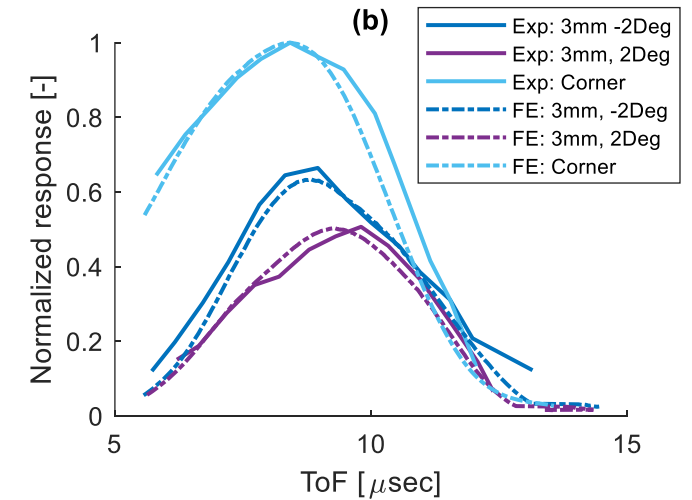
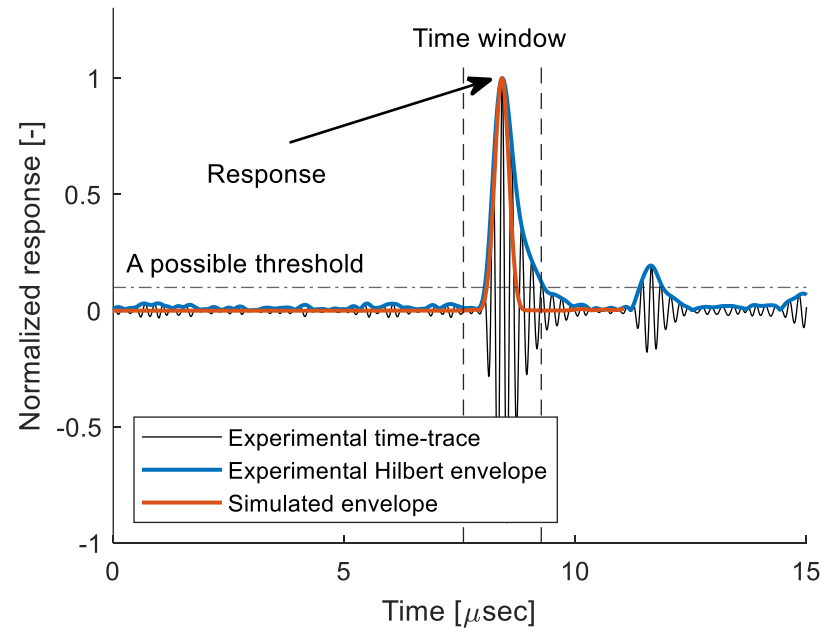
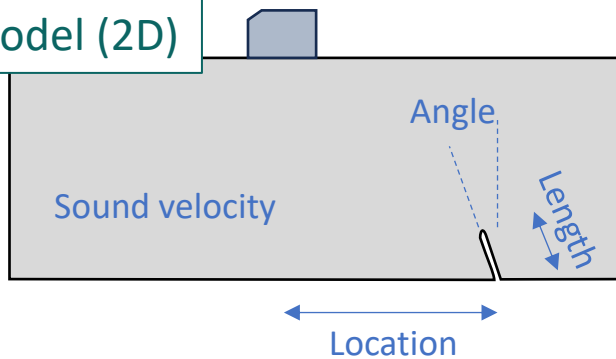
Inspection example – FE model validation

- Comparison of FE and experimental predictions of response from corner and two inclined cracks

Experiment

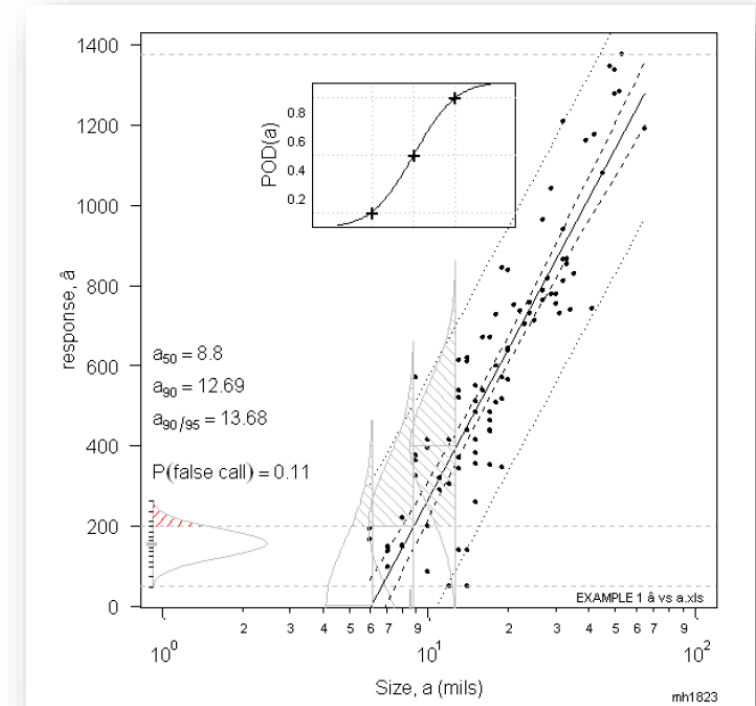


FE model (2D)



Generalised $\hat{a}$ vs. a approach

- Concept and limitations of standard $\hat{a}$ vs. a approach
 - Obtain responses ($\hat{a}$) for various defect sizes (a)
 - Transform one or both (e.g. $\hat{a} \rightarrow \log \hat{a}$) so relationship between $\hat{a}$ and a is as close to linear as possible
 - Assume points normally distributed about line of best fit with constant variance (due to other parameters)
 - Enables prediction of PoD vs. a with quantified uncertainty
 - Good for
 - Limited amount of data (typically ~100 experimental points)
 - Well-behaved inspection
 - Well-chosen representative data points
 - Data that satisfies assumptions!



Generalised $\hat{a}$ vs. a approach

- Physical models (e.g. FE) can efficiently provide many more data points than experiments
- Many examples of model-assisted PoD studies and surrogate modelling
- However, final PoD calculation and uncertainty quantification almost always based on standard $\hat{a}$ vs. a approach

Annis *et al.*, *Nucl. Eng. Des.* 2013

Aldrin *et al.*, *QNDE*, 2009

Bao, *Research in NDE*, 2023

Du & Leifsson, *J. NDE*, 2020

Gandossi & Annis, *ENIQ Technical Document*, 2010

Jarvis *et al.*, *NDT&E Int.*, 2017

Dobson *et al.*, *QNDE*, 2016

Knott *et al.*, *Proc. SPIE*, 2023

Le Gratiet *et al.*, *J. NDE*, 2017

Lei *et al.*, *J. NDE*, 2022

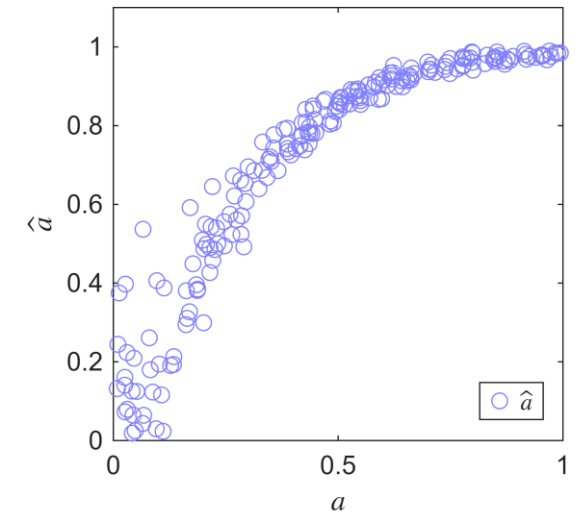
MIL-HDBK-1823A, 2009

Syed Akbar Ali & Rajagopal, *J. NDE*, 2018

Wirdelius & Persson, *Int. J. Fatigue*, 2012

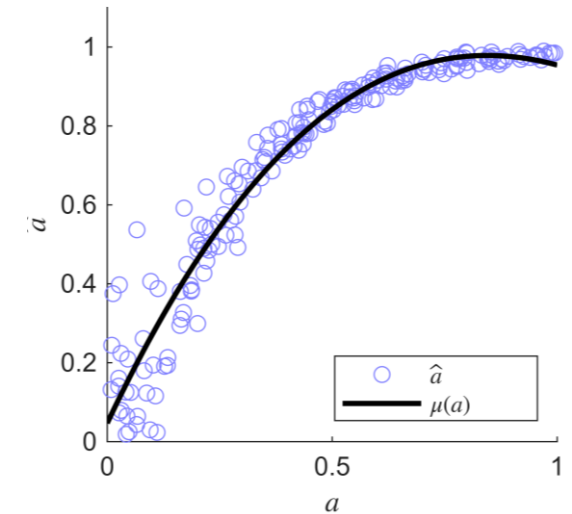
Generalised $\hat{a}$ vs. a approach

- Methodology – two-stage statistics
 - Fit first function (e.g. polynomial) to data points to describe mean, $\mu(a)$



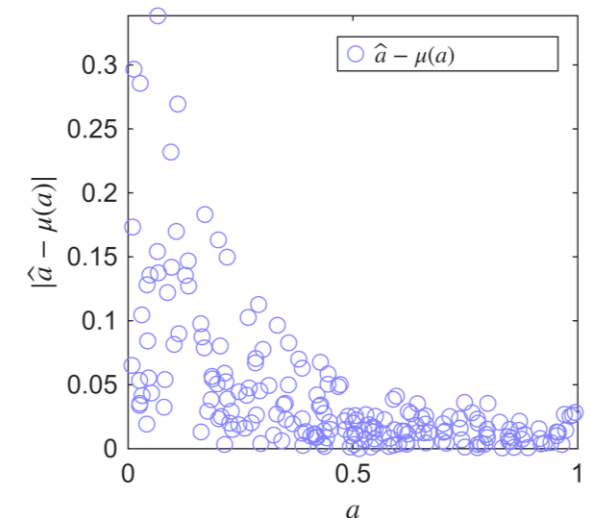
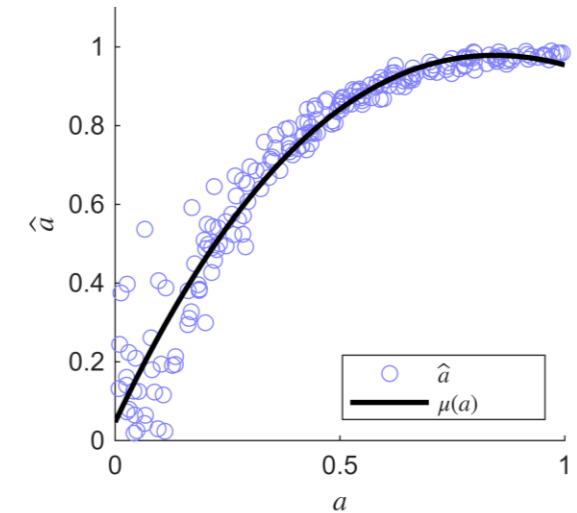
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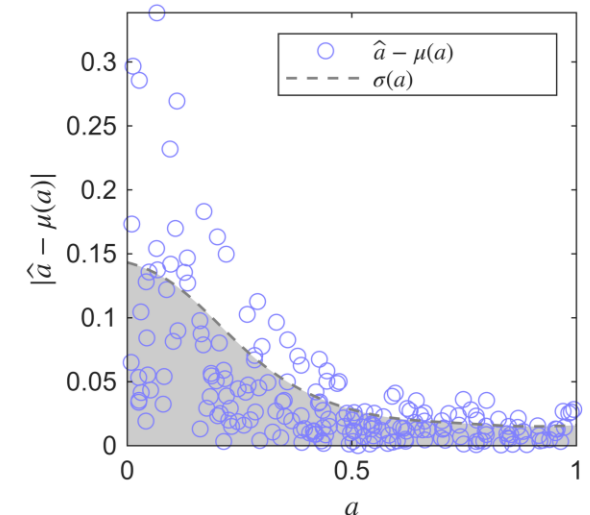
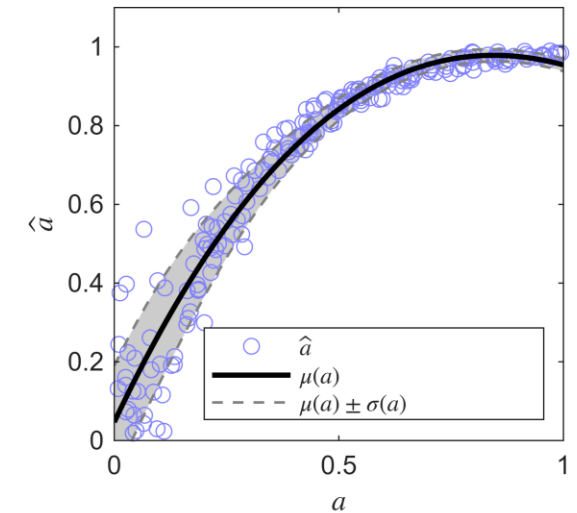
Generalised $\hat{a}$ vs. a approach

- Methodology – two-stage statistics
 - Fit first function (e.g. polynomial) to data points to describe mean, $\mu(a)$
 - Compute error $|\hat{a} - \mu(a)|$ between each data point and mean



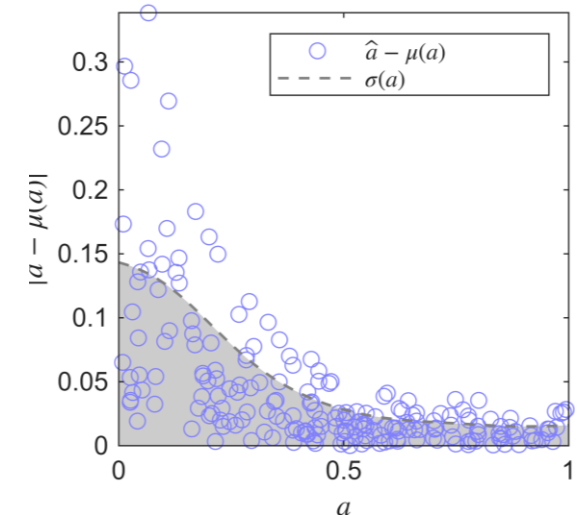
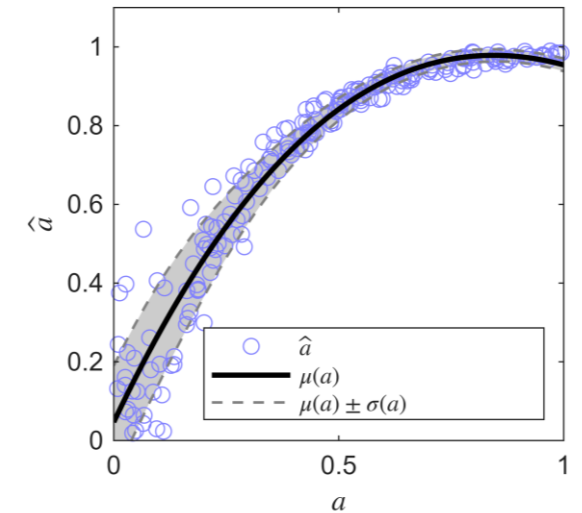
Generalised $\hat{a}$ vs. a approach

- Methodology – two-stage statistics
 - Fit first function (e.g. polynomial) to data points to describe mean, $\mu(a)$
 - Compute error $|\hat{a} - \mu(a)|$ between each data point and mean
 - Fit second function to $|\hat{a} - \mu(a)|$ to get standard deviation, $\sigma(a)$



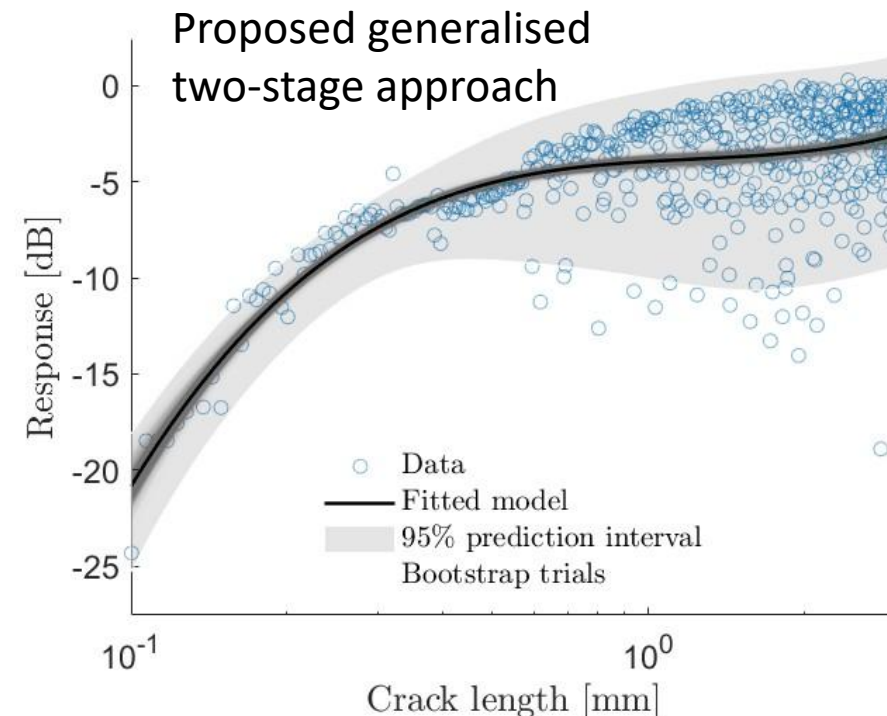
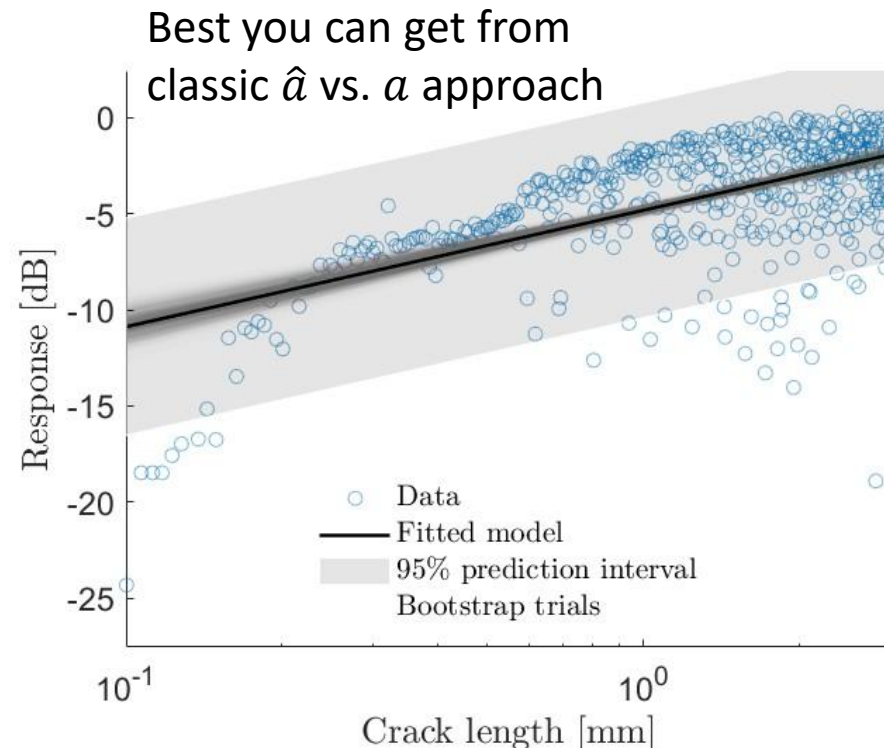
Generalised $\hat{a}$ vs. a approach

- Methodology – two-stage statistics
 - Fit first function (e.g. polynomial) to data points to describe mean, $\mu(a)$
 - Compute error $|\hat{a} - \mu(a)|$ between each data point and mean
 - Fit second function to $|\hat{a} - \mu(a)|$ to get standard deviation, $\sigma(a)$
 - Test candidate statistical distributions (e.g. Gaussian, Gumbel-min) and select most-likely, $f(a; \mu(a), \sigma(a))$
 - PoD(a) curve for given threshold computed analytically from $f(a; \mu(a), \sigma(a))$
 - PoD(a) confidence interval computed by bootstrapping



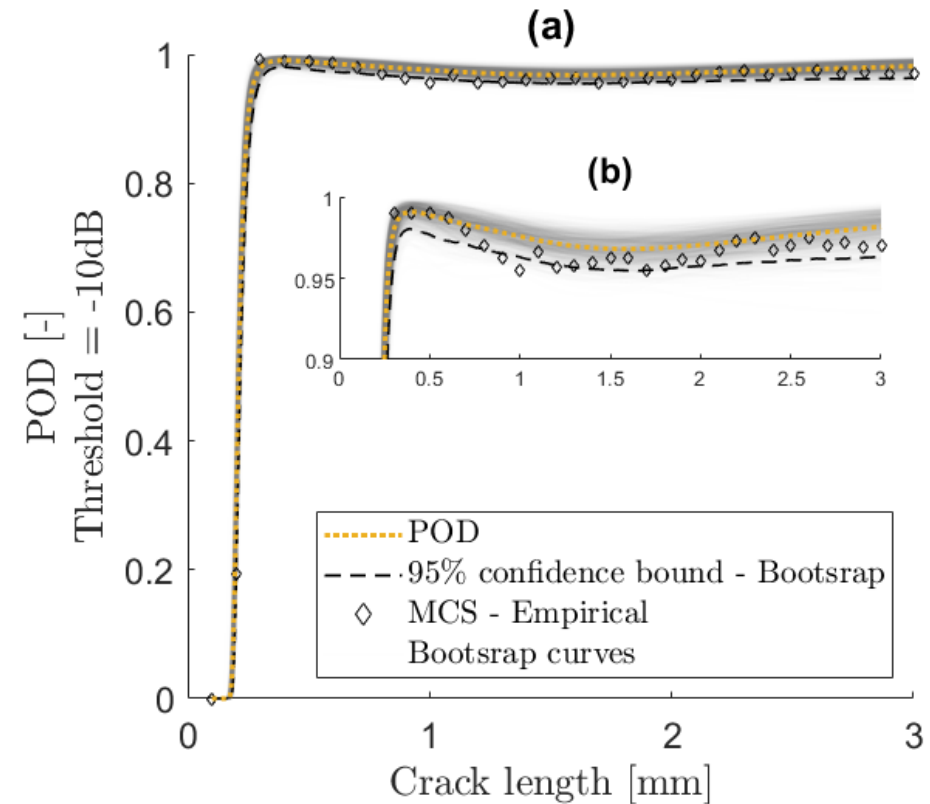
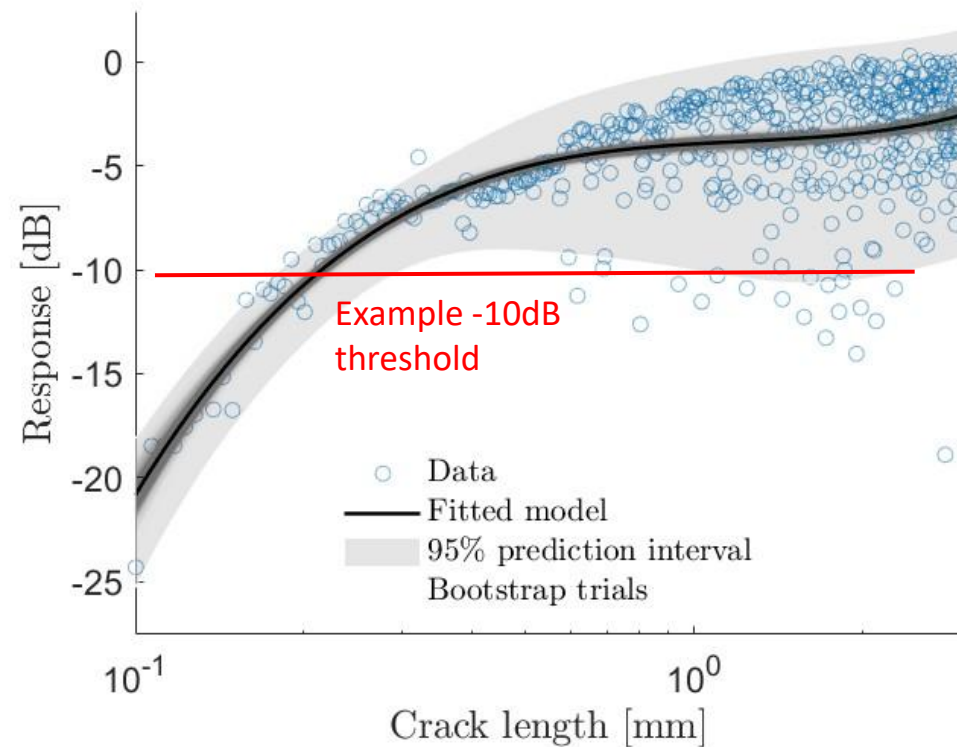
Generalised $\hat{a}$ vs. a approach

- Avoids limiting assumptions of standard $\hat{a}$ vs. a approach
 - Handles non-linear response with non-uniform variance
 - Two-stage statistics enabled by increased number of data points (500 here)



Generalised $\hat{a}$ vs. a approach

- Example output: response curve and PoD curve with uncertainty

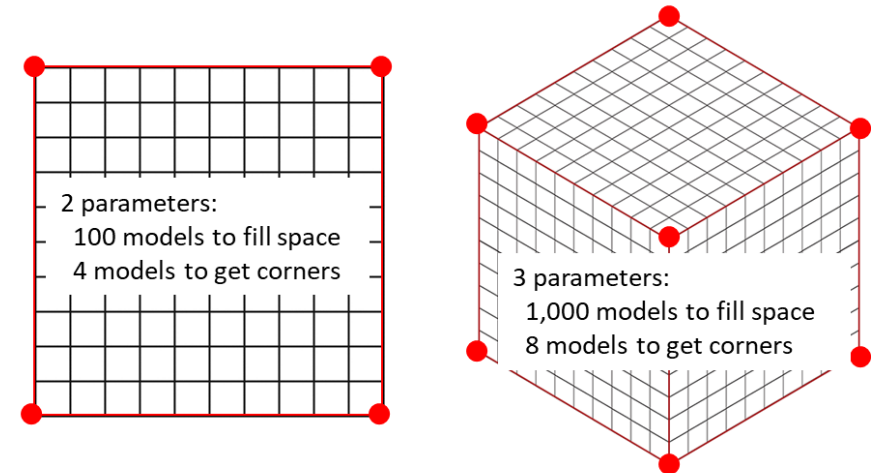


Parameter space visualisation

- Generalised $\hat{a}$ vs. a approach can deal with many parameters, but response is presented as stochastic function of one parameter
- Why visualise effect of multiple parameters?
 - Better understanding of inspection / improved design
 - Identification of worst-case scenarios (e.g. for experimental trials)

Challenges

- Efficiently obtaining response functions of multiple parameters from limited simulations



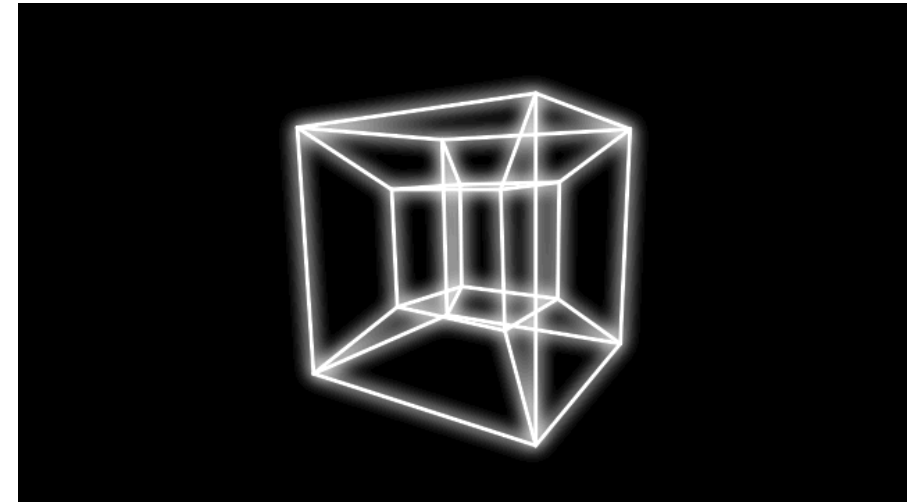
10 parameters:

$10^{10} = 10,000,000,000$ models to fill space!

$2^{10} = 1,024$ models needed just to get corners of parameter space

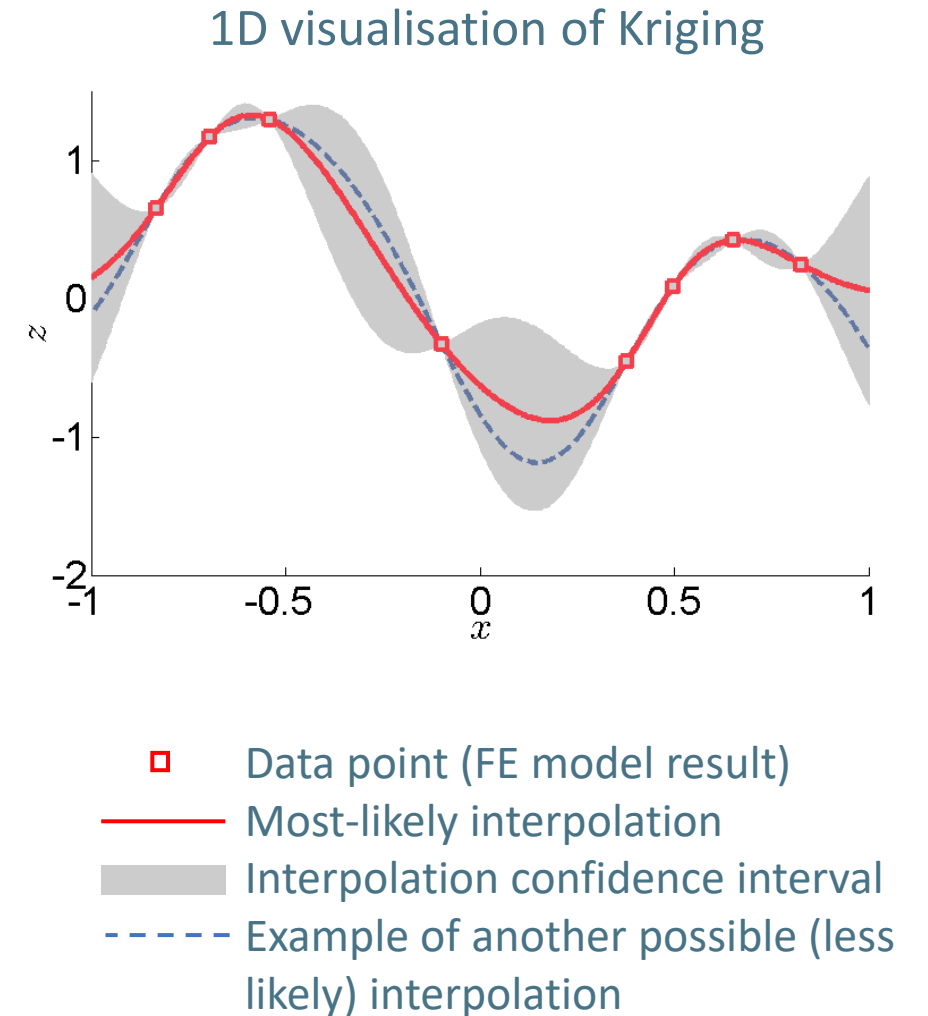
Parameter space visualisation

- Generalised $\hat{a}$ vs. a approach can deal with many parameters, but response is presented as stochastic function of one parameter
- Why visualise effect of multiple parameters?
 - Better understanding of inspection / improved design
 - Identification of worst-case scenarios (e.g. for experimental trials)
- Challenges
 - Visualisation of response functions of $n > 2$ parameters



Parameter space visualisation

- Methodology – Kriging surrogate model
 - Interpolates (multi-dimensional) response function between FE data points
 - Provides mean and variance of interpolation at all points
 - Space-filling algorithm to decide parameters for FE model executions
 - Iterative scheme to do FE simulations until surrogate model achieves desired interpolation accuracy



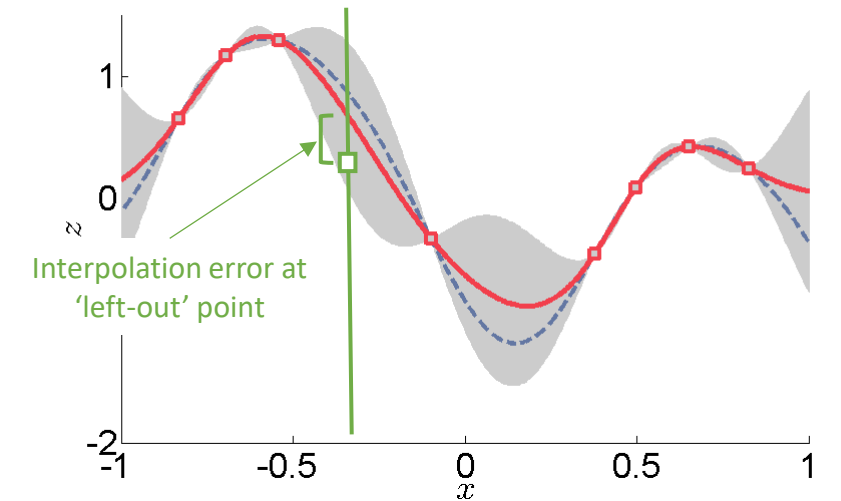
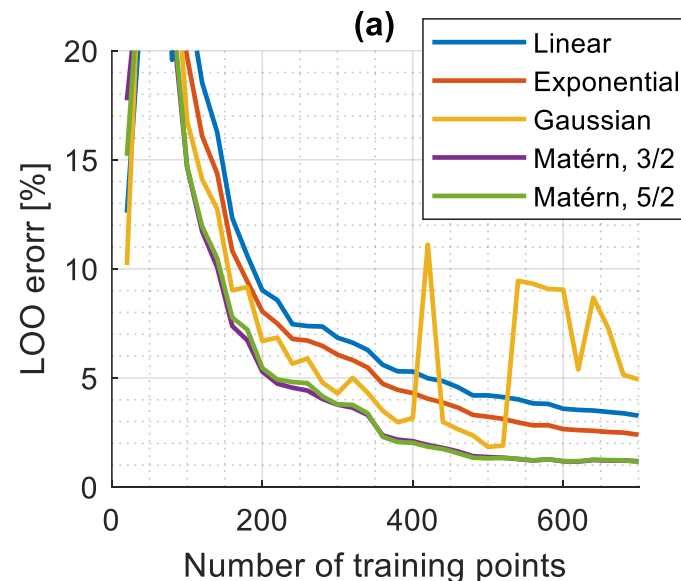
[Wikipedia graphic]

Parameter space visualisation

- Methodology – Fast Kriging surrogate model enables:
 - Quick ‘slicing’ of high-dimensional response function for visualisation and inspection design
 - Quick numerical integration of response function over nuisance dimensions to obtain PoD curves as functions of parameter(s) of interest
 - Uncertainty quantification of response function and PoD curves

Parameter space visualisation

- Methodology – tracking convergence
 - Leave-one-out (LOO) – perform fitting missing out one data point ($\square$) and compare fitted value to actual value at missing point; repeat with every point missed out in turn

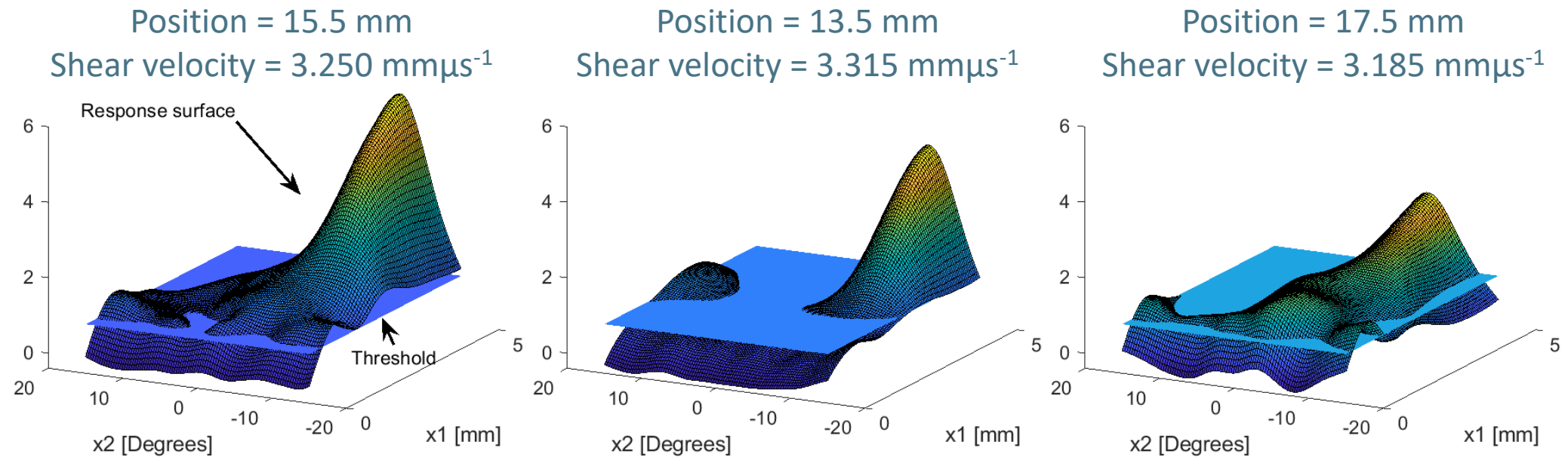


- $\square$ Data points used for interpolation
- Most-likely interpolation through $\square$
- $\square$ 'Left-out' data point

[Wikipedia graphic]

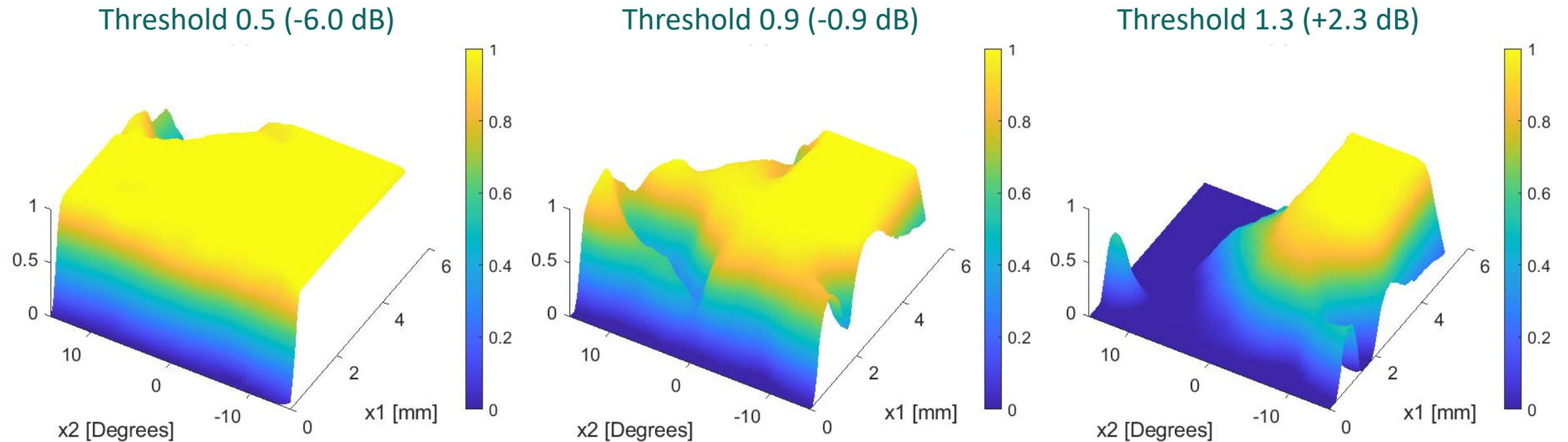
Parameter space visualisation – Slicing example

- 2D depth-angle slices through 4D response function for various arbitrary fixed values of crack position and shear velocity



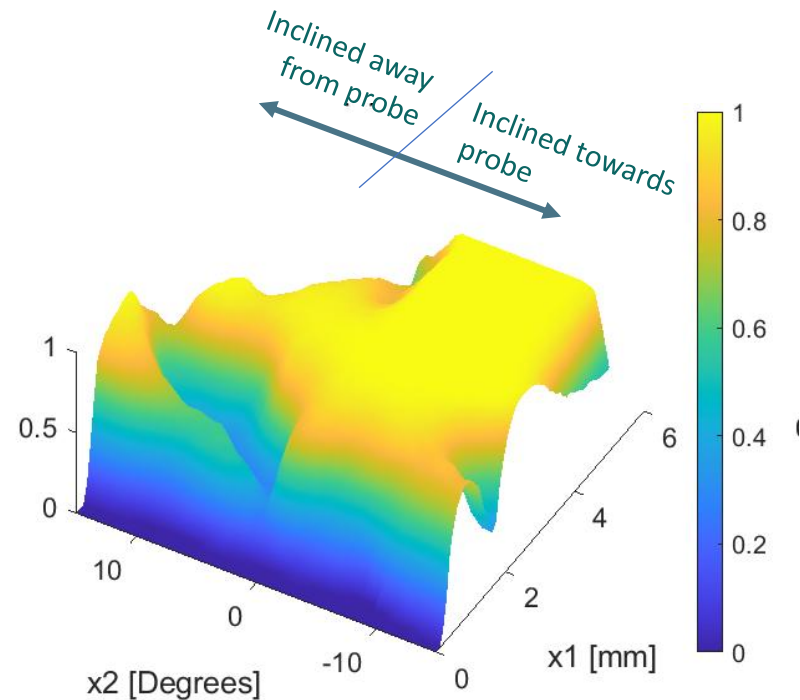
Parameter space visualisation – Integration example

- Integration over other dimensions (crack position and shear velocity) of fraction of response > threshold gives PoD curve (2D surface)

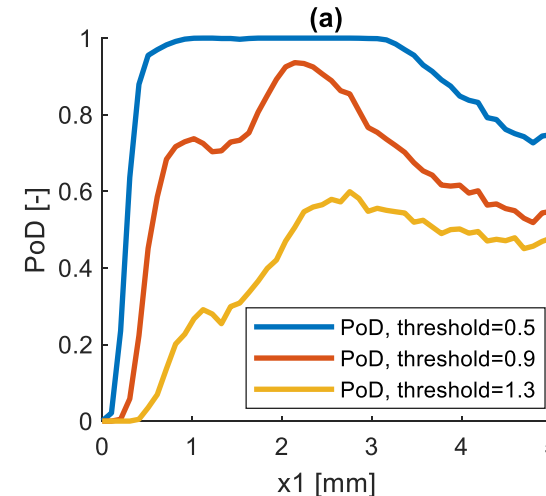


Parameter space visualisation – Integration example

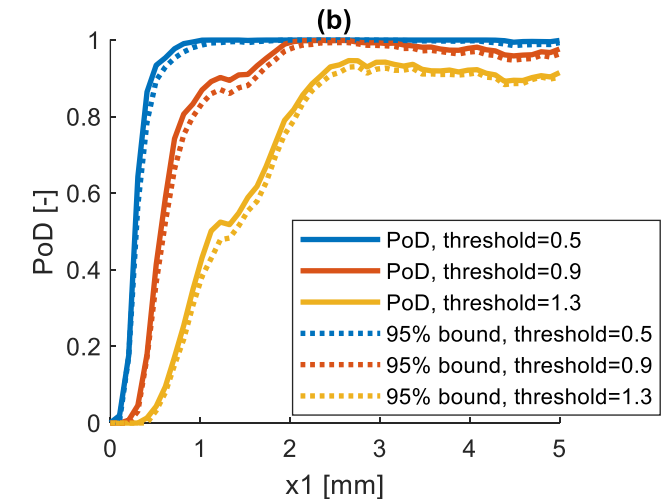
- Further integration to 1D PoD function of crack length
 - Shows effect of single- vs. double-sided access



Angle range $[-15^\circ, 15^\circ]$
(single-sided access)



Angle range $[-15^\circ, 0^\circ]$
(double-sided access)



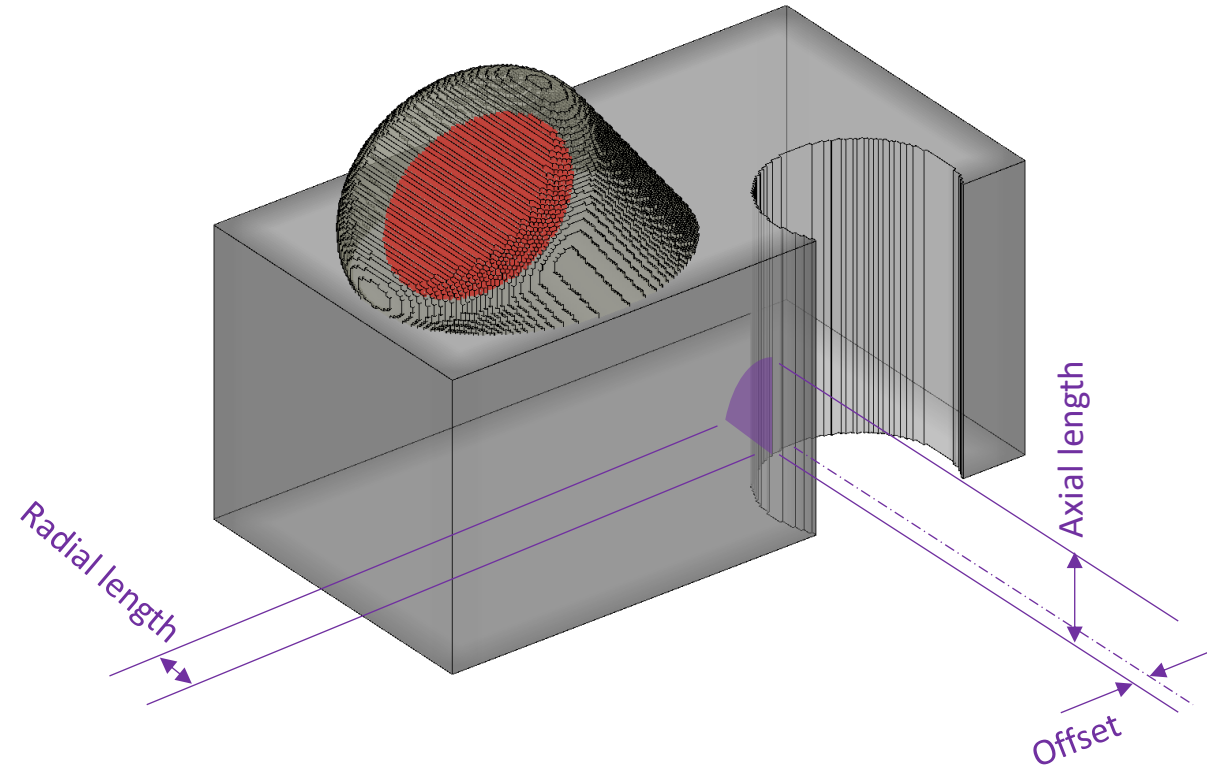
DigiQual toolkit – work in progress

- Concept
 - Python library for expert users to fully automate simulation workflow
 - Automatically select parameters for simulations
 - Automatically execute simulation using user's simulation tool*
 - Extract response of interest from simulation output*
 - Iteratively execute simulations and to achieved desired level of accuracy
 - Analyse responses and produce results with quantified uncertainty
 - GUI wrapper to inform simulations and analyse results
 - Produce table of parameters for simulation executions
 - *[User executes simulations and extracts responses of interest]*
 - Analyse responses and produce results with quantified uncertainty

*requires user to write script that runs simulation tool with given parameters and processes output

DigiQual toolkit – work in progress

- Example – radial crack at fastener hole



DigiQual toolkit – work in progress

Current GUI front end

Experimental Design

Experimental Design Variables

Variable Name	Min Value	Max Value
Radial length (mm)	0.1	4
Axial length (mm)	0.1	4
Offset (mm)	-0.25	0.25

+ Add Variable

Framework Preview

Radial length (mm)	Axial length (mm)	Offset (mm)
2.668162223074526	0.16535293833939474	0.052415141710339286
0.3519099150739664	1.027070766423413	0.21053280362883764
3.239670046158741	2.433638792965782	0.057388011514
0.9724260562389544	3.7491840587266556	0.08837657798
1.5577602545387101	3.15971790425097	0.13292167479
0.2920758024804838	1.641849130957671	-0.2477848916
1.0322196092329807	0.7579279227230495	0.13772485444

Viewing rows 1 through 7 of 400

Generation Settings

Number of samples
400

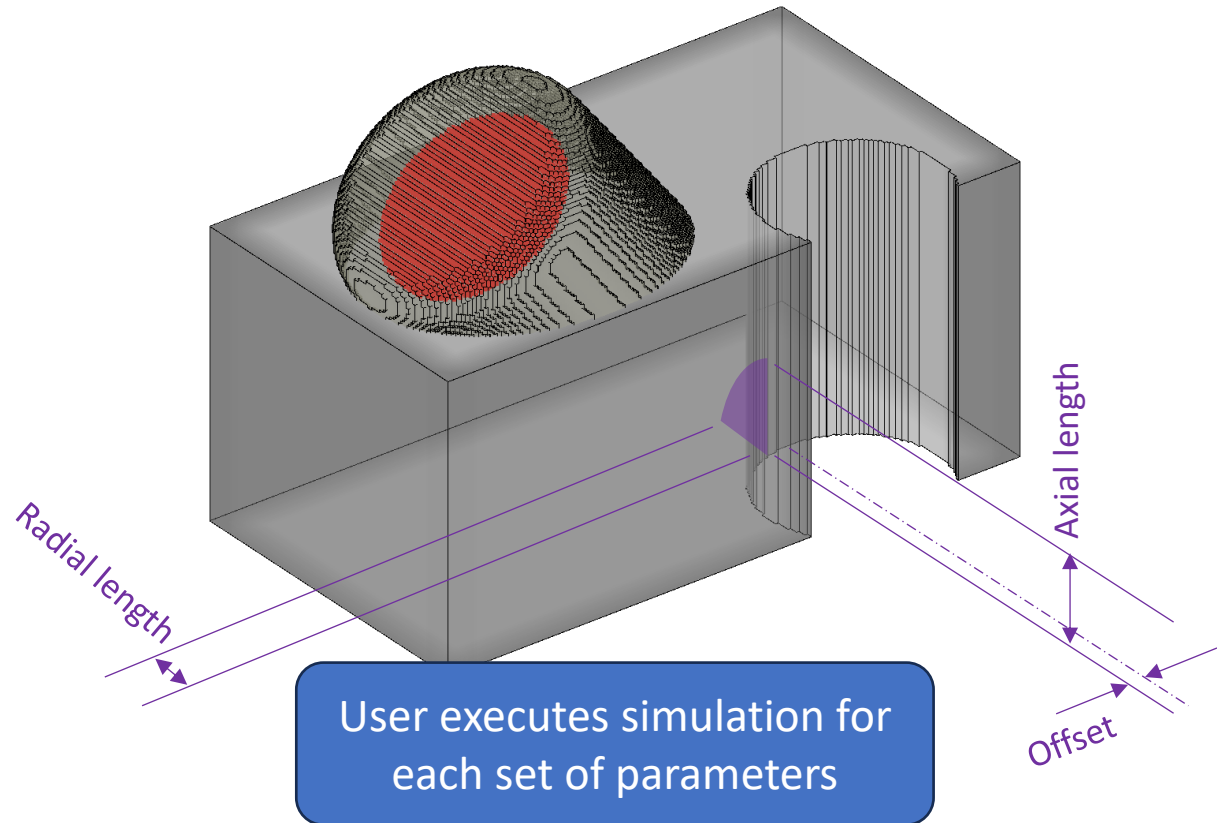
Generate Framework

Download CSV

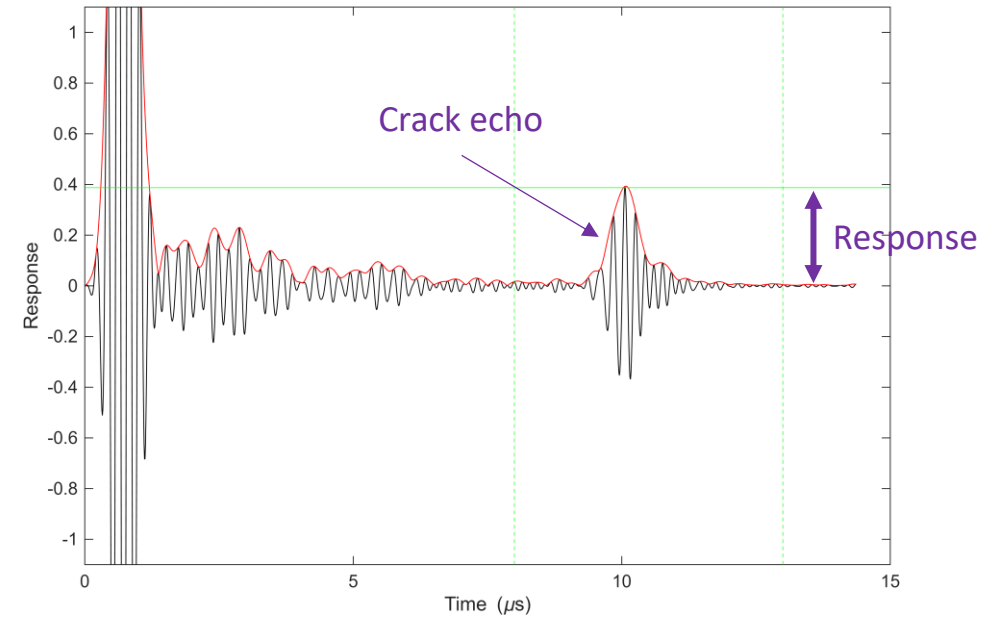
User inputs parameters of interest and their ranges

Software outputs table of parameters with specified number of samples (one sample = one simulation execution)

DigiQual toolkit – work in progress



pogo.
www.pogo.software



User extracts defect response from each simulation

DigiQual toolkit – work in progress

Current GUI front end

DigiQual [Home](#) [Experimental Design](#) [Simulation Diagnostics](#) [Data Visualisation](#) [PoD Analysis](#)

Simulation Diagnostics

Diagnostic Configuration

Upload CSV file

[Browse...](#)

output_reduced.csv

Upload complete

Select Input Variables

Radial length (mm) × Axial length (mm) × Offset (mm) ×

Select Outcome Variable

Response

User uploads results from simulations

Uploaded Data Preview

Radial length (mm)	Axial length (mm)	Offset (mm)	Area (mm^2)	Response
1.726	2.909	-0.25	4.134	0.392
1.8	0.201	0.025	0.365	0.03
2.248	2.862	-0.105	5.3	0.426
3.871	2.234	0.236	7.084	0.441
0.966	3.496	-0.147	2.85	0.285

Validation Report

Test	Variable	Metric	Value	Threshold	Pass
Input Coverage	Radial length (mm)	Max Gap Ratio	0.0091	< 0.20	true
Input Coverage	Axial length (mm)	Max Gap Ratio	0.0078	< 0.20	true
Input Coverage	Offset (mm)	Max Gap Ratio	0.006	< 0.20	true
Model Fit (CV)	Response	Mean R2 Score	0.9915	> 0.50	true
Bootstrap	Response	Avg CV (Rel Std Dev)	0.1428	< 0.15	true

Input Space Coverage Overview

Distribution of each input variable. Green title = coverage passed. Red title + orange shading = gap detected.

Radial length (mm) ✓

Axial length (mm) ✓

Offset (mm) ✓

Data check and visualisation of parameter space coverage

DigiQual toolkit – work in progress

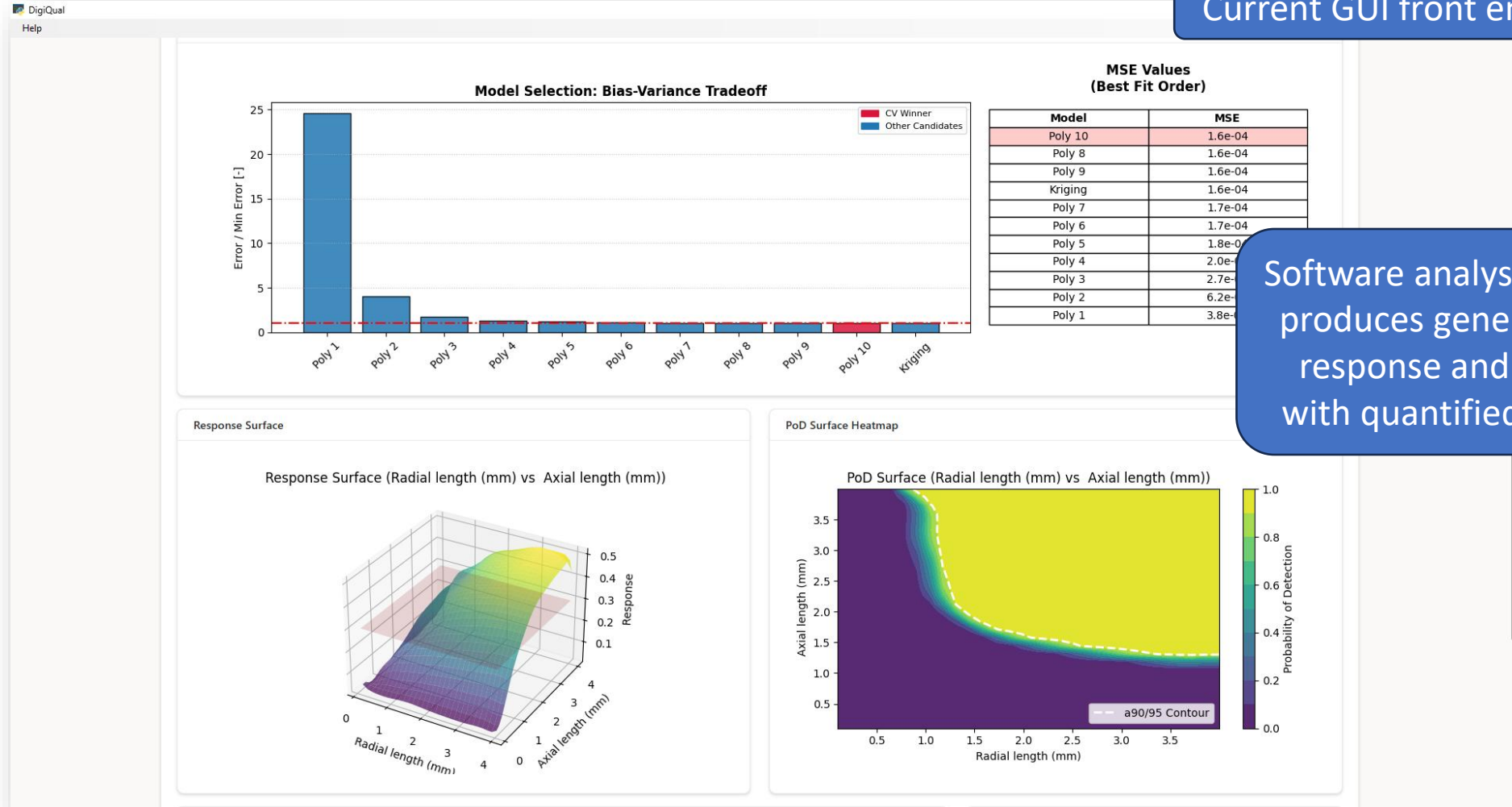
Current GUI front end



Software analyses results and produces generalised signal response and PoD curves with quantified uncertainty

Response model and PoD as function of 1 parameter

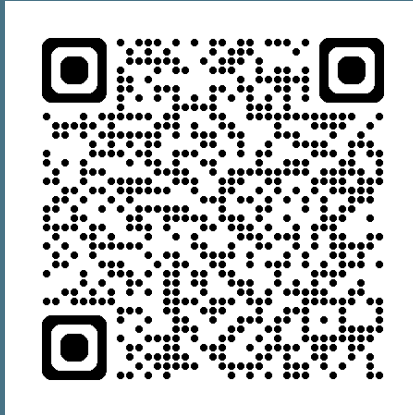
DigiQual toolkit – work in progress



Response model and PoD as function of 2 parameters

DigiQual toolkit – work in progress

<https://forms.office.com/e/pFDGgqpuJ8>



DigiQual software survey

Background

The project *Fast, efficient and reliable: digital qualification of ultrasonic inspection for safety-critical components (DigiQual)* is a collaboration between Imperial College (PI Peter Huthwaite) and University of Bristol funded by EPSRC and RCNDE. Imperial's work has been on the "bottom-up" task of making high-fidelity numerical simulations more efficient while the Bristol work has been "top-down" on making effective use of simulations for Inspection Qualification (IQ).

Purpose of this survey

As part of the Bristol work, we have published two papers that show how the classic *ahat-vs-a* approach to generate PoD curves can be generalised to cases where the standard assumptions cannot be satisfied [1] and how surrogate modelling and adaptive sampling can enable rapid visualisation of inspection performance for multiple parameters of interest [2]. The latter approach can be used as a tool to improve inspection design and also to identify worst-case scenarios, for example, to inform experimental test piece design. We have employed a Research Software Engineer to make these tools available as open-source software for industrial use to enable them to be trialled on real inspections. In broad terms, we envisage software that wraps around a user's preferred inspection simulation tool (e.g. a finite element package) that will:

1. provide a list of parameters for the inspection cases to simulate initially,
2. analyse the simulation outputs to produce, for example, PoD curves with quantified uncertainty, inspection performance visualisations,
3. provide a list of parameters for further cases to simulate to increase accuracy and reduce uncertainty,
4. the option to automatically iterate through (1-3) until a desired level of accuracy is obtained.

The anticipated software is likely to be offered in two forms: (a) a documented Python library that Python users can access directly, and (b) a graphical user interface that non-experts can use.

We are now at the point where we would like to get some input from potential users and would appreciate your input to whatever questions below you are able to answer. There are 13 questions and it should not take longer than 5 minutes to complete.

The survey is anonymous unless you provide contact details in response to the final question.

References

- [1] N. Malkiel, A. J. Croxford, and P. D. Wilcox, 'A generalized method for the reliability assessment of safety-critical inspection', *Proc. Roy. Soc. A*, vol. 481, no. 2312, 2025, doi: 10.1098/rspa.2024.0654.
- [2] N. Malkiel, A. J. Croxford, and P. D. Wilcox, 'A comprehensive investigation of flexible and multi-dimensional simulation-based PoD analysis', *NDT and E International*, vol. 159, 2026, doi: 10.1016/j.ndteint.2025.103596.

When you submit this form, it will not automatically collect your details like name and email address unless you provide it yourself.

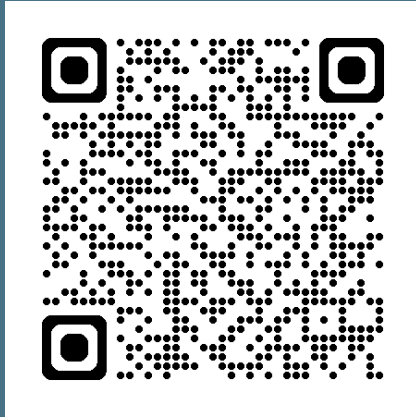
1. Your sector (tick all that apply) ☐

☐ Aerospace

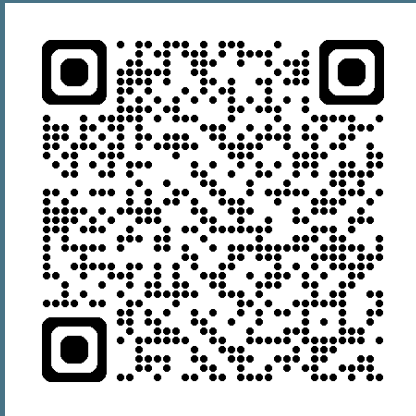
☐ Non-nuclear power generation

Summary

<https://forms.office.com/e/pFDGgqpuJ8>



<https://pypi.org/project/digiqua>



- 3D direct numerical simulation via FE is increasingly viable – 1000s simulations can be run in a few days
- Generalisation of $\hat{a}$ vs. a approach
- Exploration of multi-dimensional parameter space
 - Better understanding of inspection
 - Identification of worst-case scenarios
 - Optimisation of inspection design

• Try the Python version of DigiQual software (under development)!