

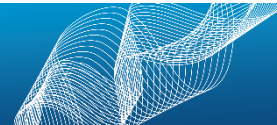


Model Validation in the UK Nuclear Industry: A Probabilistic Metric

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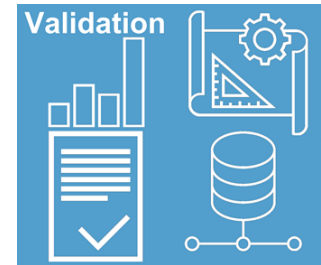
- Accurate modelling and simulation processes in the nuclear industry are crucial for the safe operation of nuclear plants and processes
- Confidence in model-based inputs to safety cases is usually claimed through a model validation exercise
- Success is demonstrated by convincing the nuclear regulator that the model outputs are 'credible' as a result of a validation process



- ONR: Validation of Computer Codes and Calculation Methods (NS-TAST-GD-042):

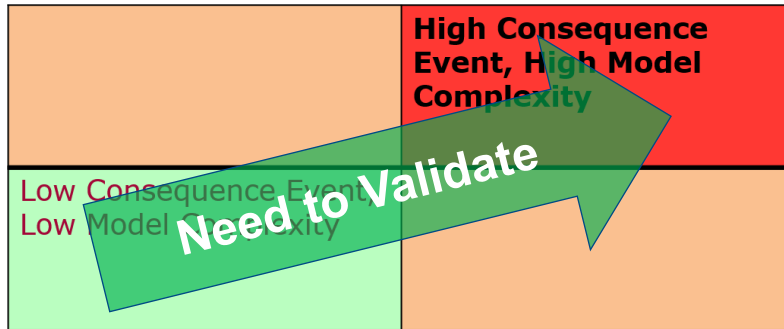
“Statements such as ‘the model has been validated’ are misleading, and betray overconfidence, and lack of understanding, since in theory only lack of validation can be demonstrated - in much the same way as physical ‘laws’ are repeatedly tested for differing situations.”

- Note that the regulator is necessarily ‘remote’ from the validation process
- Usually, the key stakeholders who need to be convinced are not close to the process



How do we validate a model?

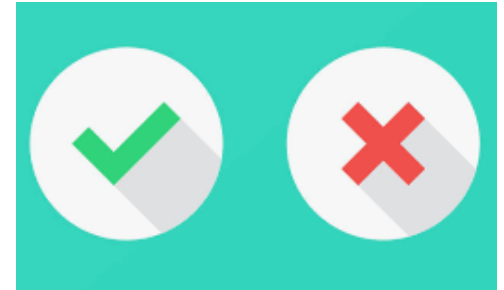
First of all, perhaps the question should be: do we really need to?



PRACTICALITIES

Important considerations for model validation:

- Exercise usually performed by comparing model results against a controlled experiment that represents the key physical processes in the model (the experiment does not need to look like the plant!!)
- It is not usually obvious whether the model has been validated for use given the absence of clear metrics
- It is advisable to **avoid** comparing against plant measurements:
 - The system is probably more complicated with a wider spectrum of physics/chemistry coming into play
 - The instrumentation may not be of sufficient fidelity for validation
- The model is only validated for use within the limits of a 'validation space'.
- The model is **not** validated for use outside this implied range of investigation.

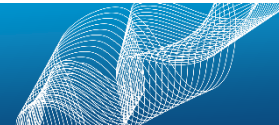


NNL-sponsored research at the University of Liverpool:

- Development of a new validation metric for the validation of computational models*
- Preliminary research with structural analysis
- Outcome is a clear criterion to show if a model is validated or not

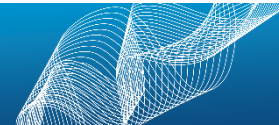


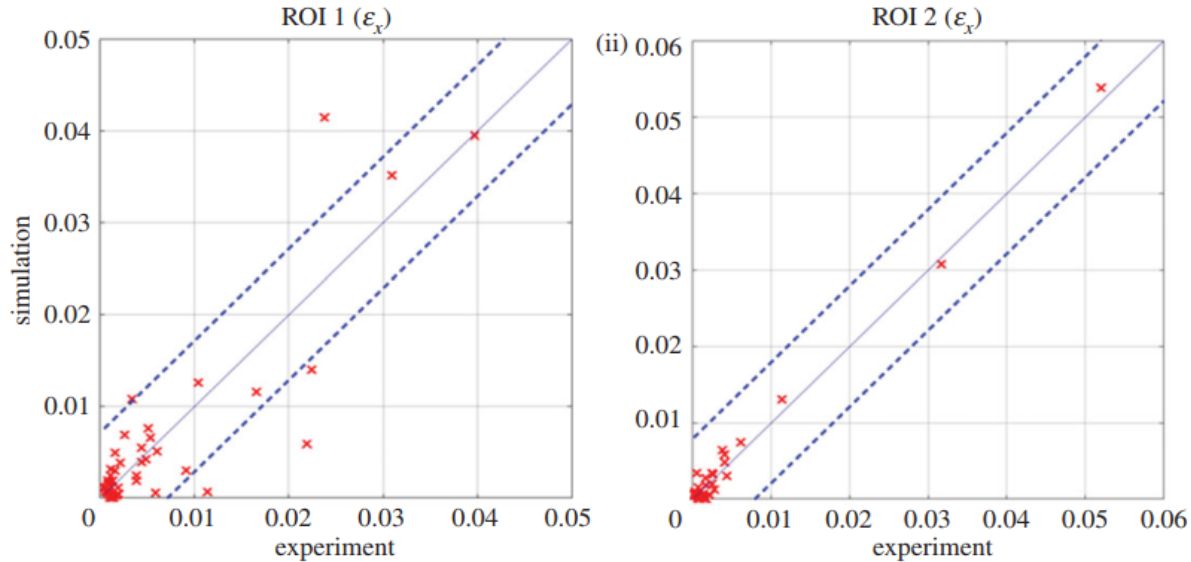
*Dvurecenska K., Graham S., Patelli E., Patterson E. A. *A Probabilistic Metric for the Validation of Computational Models*
R. Soc. open sci **5**, 2019



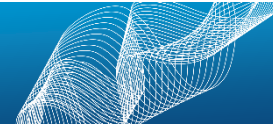
SCENE SETTING

- Validation concept emerged in the 1980s
- Embodied in AIAA guides, one for CFD and one for structural analysis
- Provide a concise frameworks for verification and validation but definitive step-by-step procedures are absent
- Some studies have divided empirical datasets into a calibration subset and validation subset; using the calibration subset to ‘tune’ the model and the validation subset to test (double counting?)
 - This approach has been argued to be legitimate within a Bayesian framework
- Quality of data is absolutely key. Optical measurement techniques have recently been developed for the whole domain
- Orthogonal decomposition techniques for validation can be applied to images of experimental and model data





- The CEN guide framework provides a means to evaluate the acceptability of model predictions (plots of longitudinal strain from I-beam three point loading case). The model is validated when all the points lie within the zone, whose extent is based on the measurement uncertainty



NEW VALIDATION METRICS

- Build on the approach recommended in the CEN guide. In terms feature vectors, obtained by image decomposition, we have: $S_P = S_M \pm 2u_{\text{exp}}$ Steps are:

1. Compute normalised relative error for each pair of vector components:
$$e_k = \left| \frac{S_{P_k} - S_{M_k}}{\max_{m \in S_M} |S_{M_m}|} \right|$$

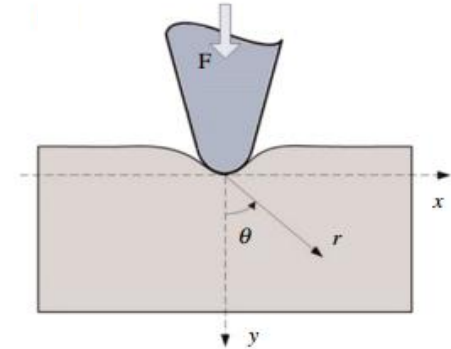
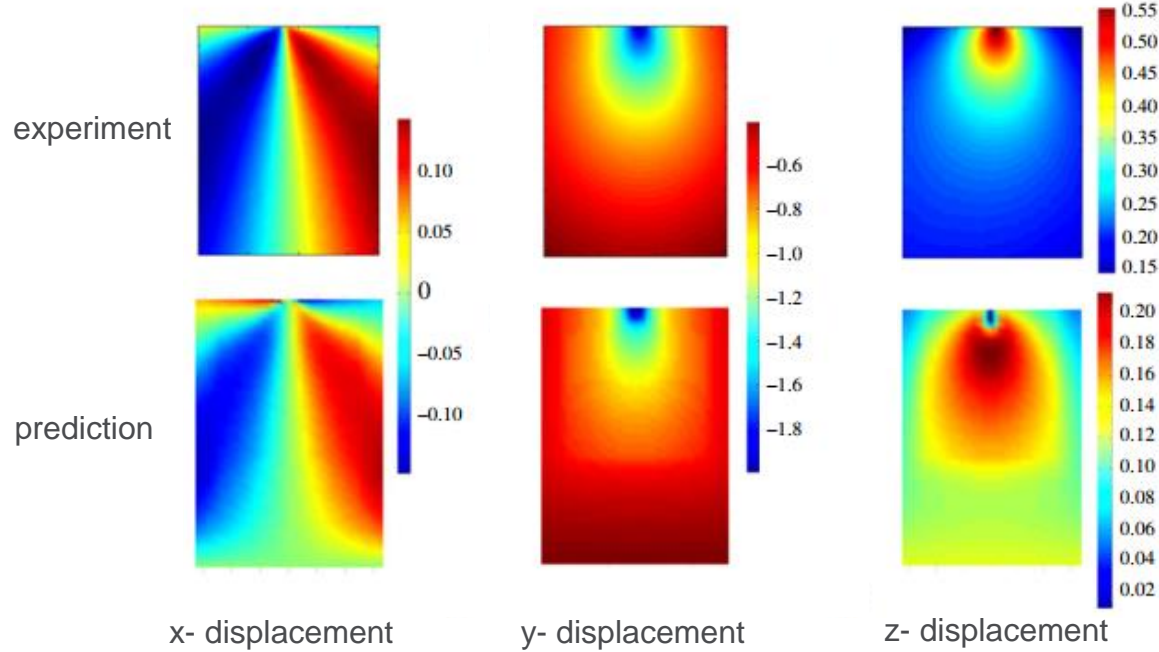
2. Compute a weight factor for each error:
$$w_k = \frac{e_k}{\sum_{k=1}^n e_k} \times 100$$

3. Define an error threshold:
$$e_{th} = \frac{2u_{\text{exp}}}{\max_{m \in S_M} |S_{M_m}|} \times 100.$$

4. Calculate the validation metric:
$$VM = \sum_i w_i \mathbb{1}_{e_k < e_{th}}$$

i.e. the probability that model is representative of reality for a specified intended use

CASE STUDY: INDENTATION OF RUBBER BLOCK



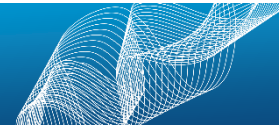
VM = 82.48% for the x- displacement
VM = 62.42% for the y- displacement
VM = 34.3% for the z- displacement

Poor performance for the z- displacement prediction; differences quantified by the methodology

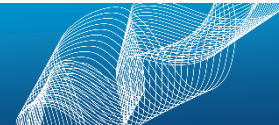
- For the rubber block indentation study we can now state:

There is an 83% probability that the model is representative of reality, when simulating x-direction displacements, induced by a 2 mm indentation, based on experimental data with 10% relative uncertainty

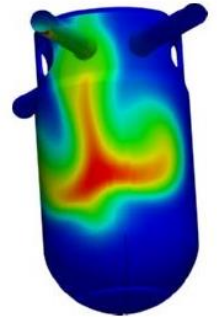
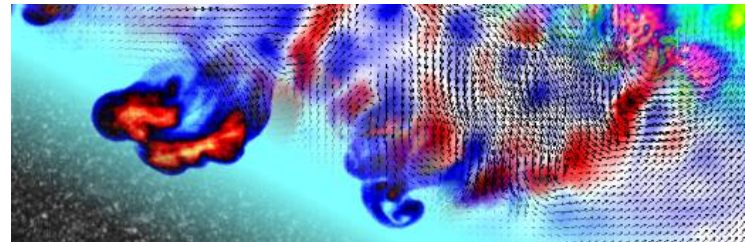
- A validation metric has been developed to deliver the outcome of the validation process to be expressed in a clear quantitative statement, which can contain:
 - The probability of the model's predictions being representative of reality
 - for the intended use and conditions for which the comparison was performed
 - including the uncertainty in the measurement data
- The implementation of this type of statement would represent a significant advance on current practice



- A new validation metric is proposed that can handle datasets with large variations in data values, together with the uncertainty in the measured data
- The validation metric allows a statement to be constructed about the probability that predictions from a model represent reality based on experimental data with a given relative uncertainty for specified intended use
- The validation statement enables decision makers to judge whether a model has been validated or not over the range of investigation, where the decision makers can be remote from the validation process



- Extension of the methodology to isothermal fluid flow
- Extension of the methodology to thermal-hydraulics (including development of robust validation domains)
- Implementation of the methodology in nuclear power applications



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