

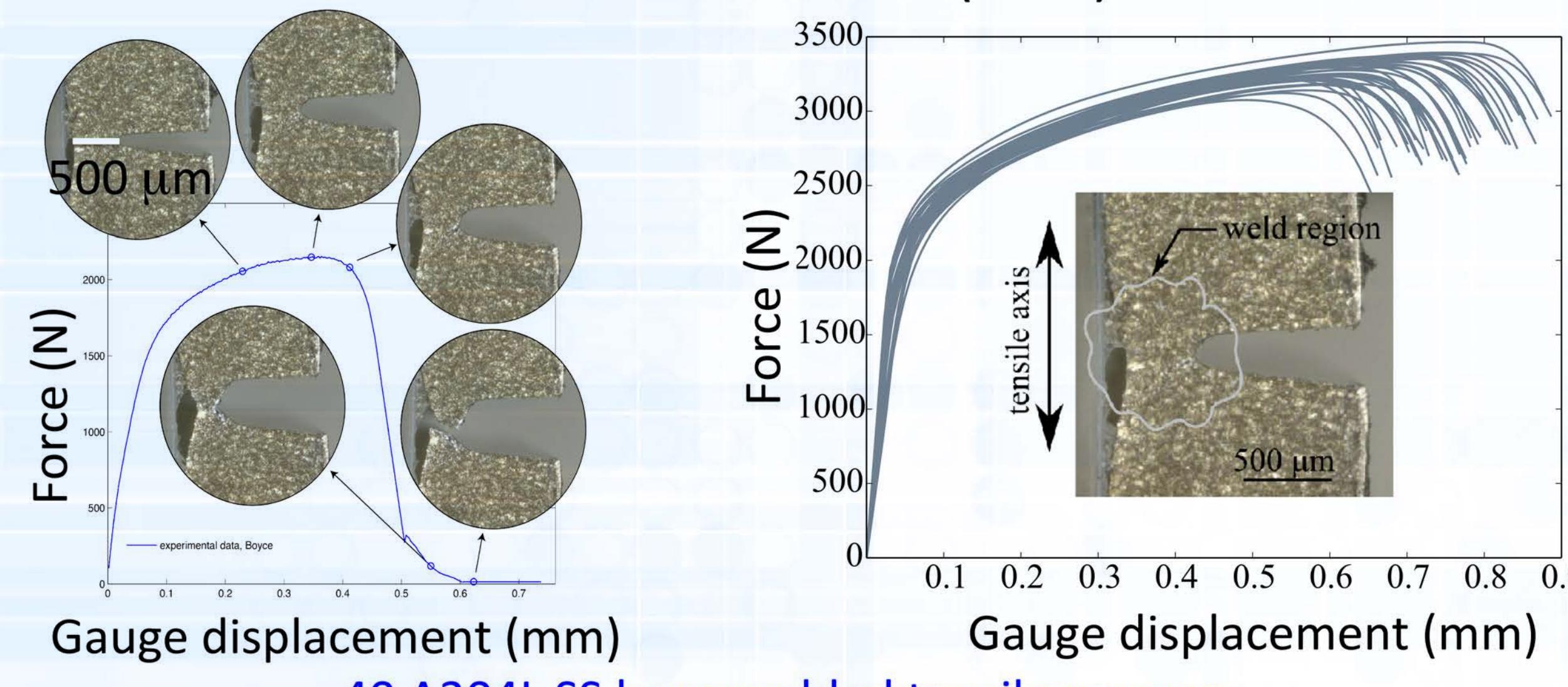
Reliability calculations for A304L SS laser welds with stochastic reduced-order model

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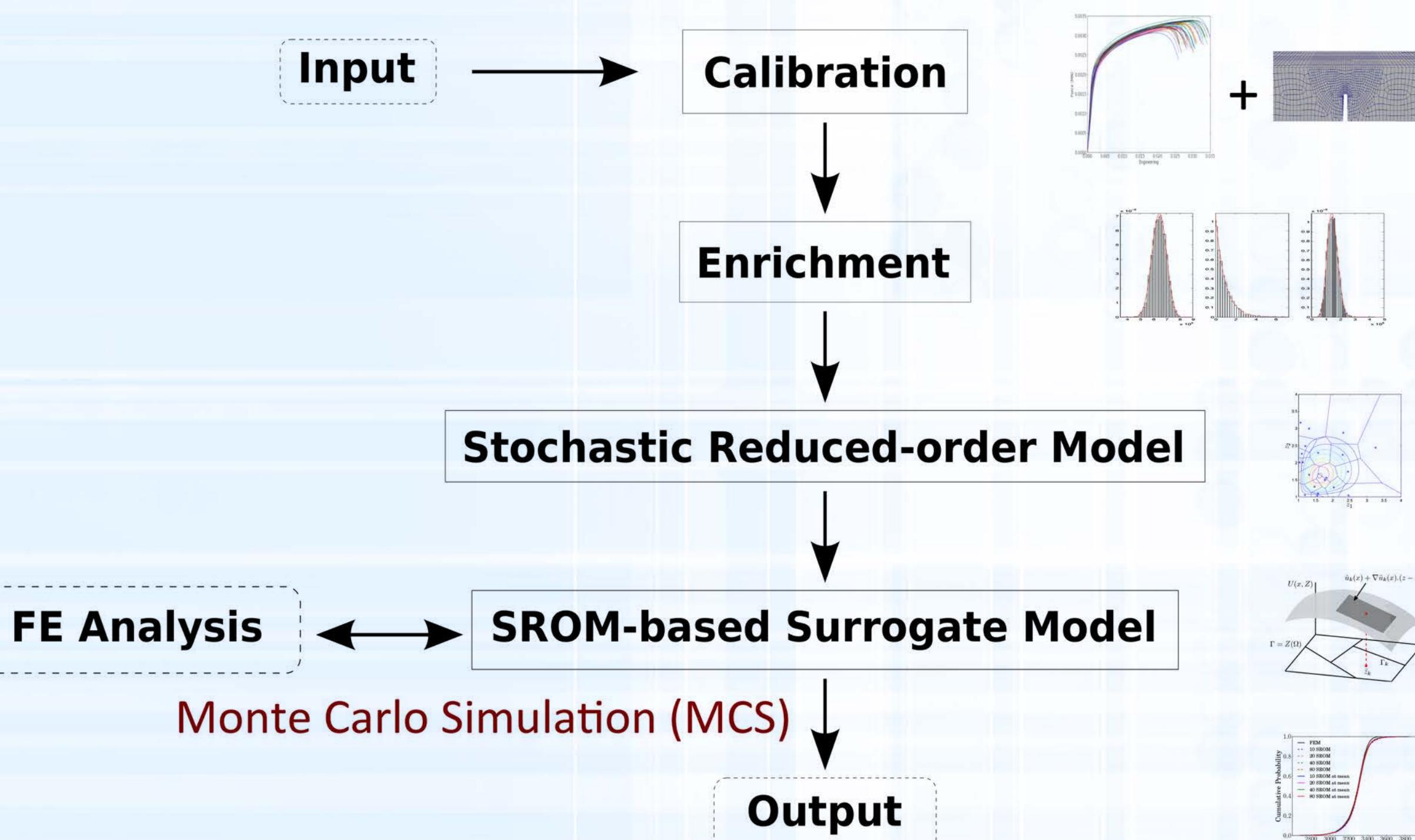
Introduction

Laser welding is an imprecise joining method that results in variability in weld performance. We propose a methodology to propagate the observed randomness through large computational models for prediction of component reliability. We use stochastic reduced-order models (SROMs) to develop a surrogate model for component response that provides efficient calculations and enables robust Monte Carlo simulation (MCS).



A304L SS is extraordinarily ductile and hardens at 400% applied shear strain (Kawahara, '80). Weld failure is dominated by geometric instability and weld performance is highly variable.

Methodology



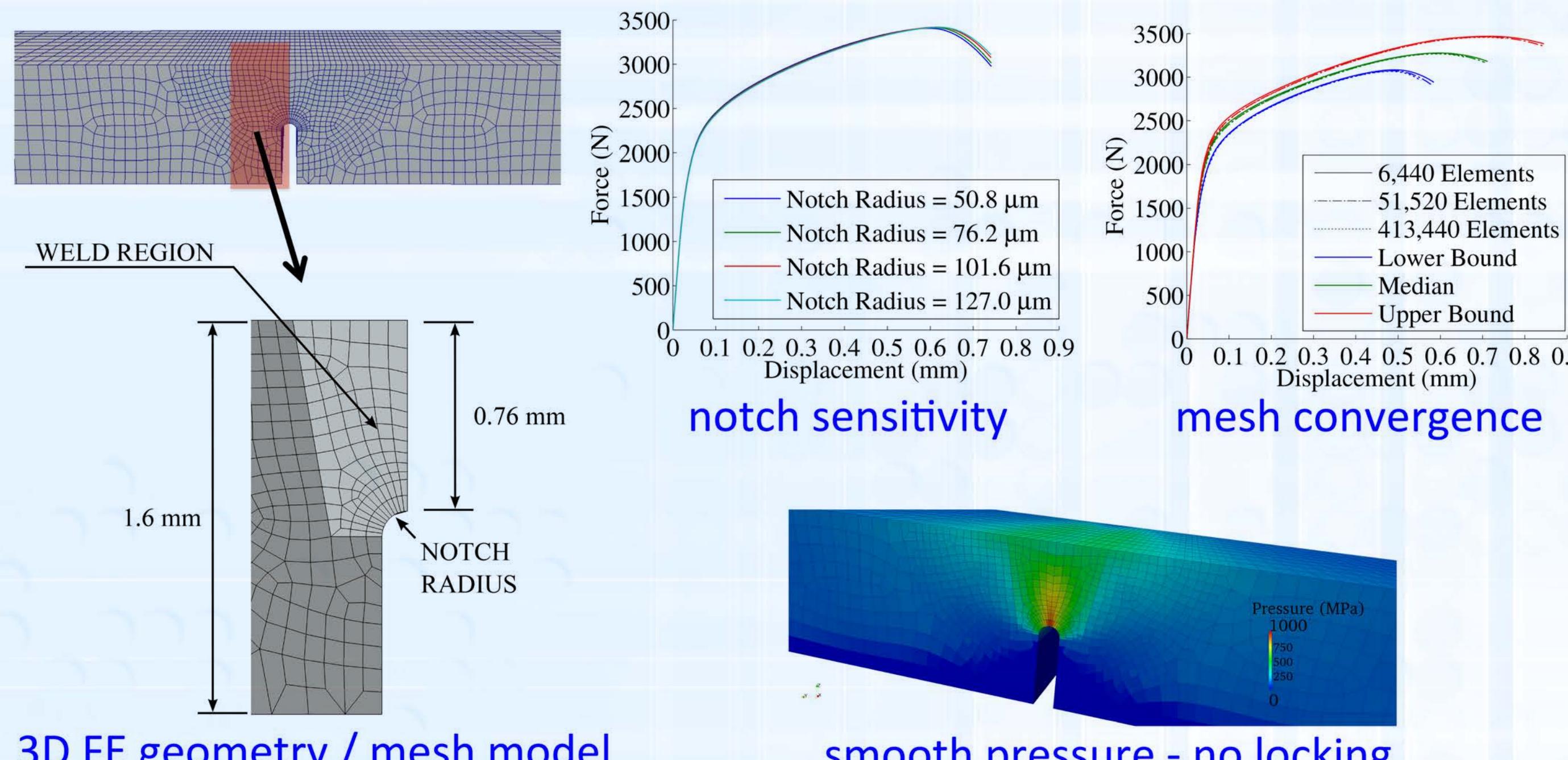
Calibration

A model is calibrated to the 40 available experiments using DAKOTA and includes choices for the geometry, mesh and material.

$$\begin{aligned} \sigma_y &= Y + \kappa & \dot{\kappa} &= [H - R\kappa] \dot{\epsilon}_p \\ \kappa(\epsilon_p) &= \frac{H}{R} [1 - \exp(-R\epsilon_p)] & \Theta &= \begin{bmatrix} Y \\ H \\ R \end{bmatrix} \end{aligned}$$

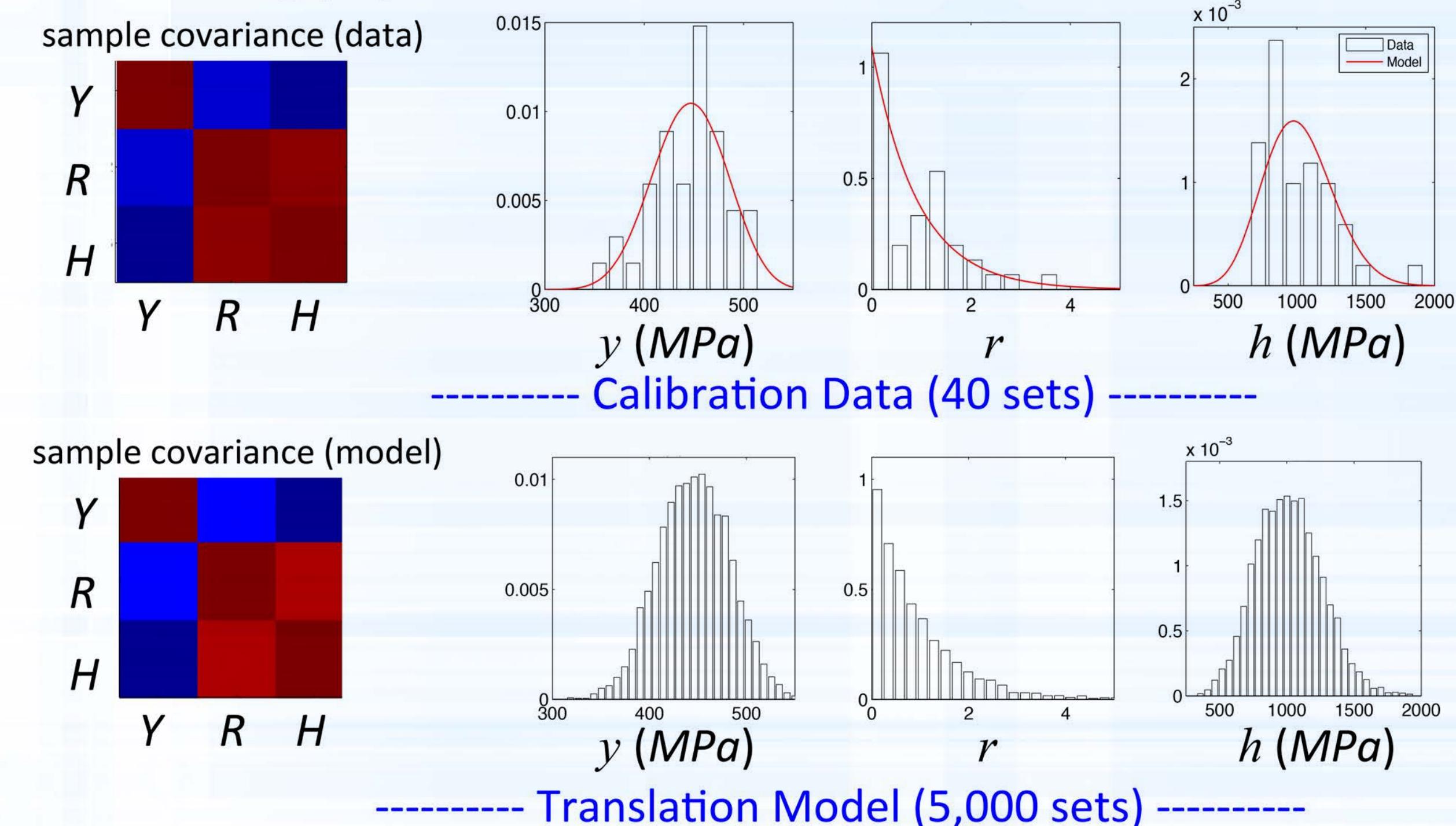
initial yield stress
hardening (linear)
recovery coefficient
stochastic dimension = 3

Rate-/Temperature independence (assumed) with BCJ_MEM material model



Enrichment

We use translation random vectors to enrich the data while maintaining physical bounds and correlations.



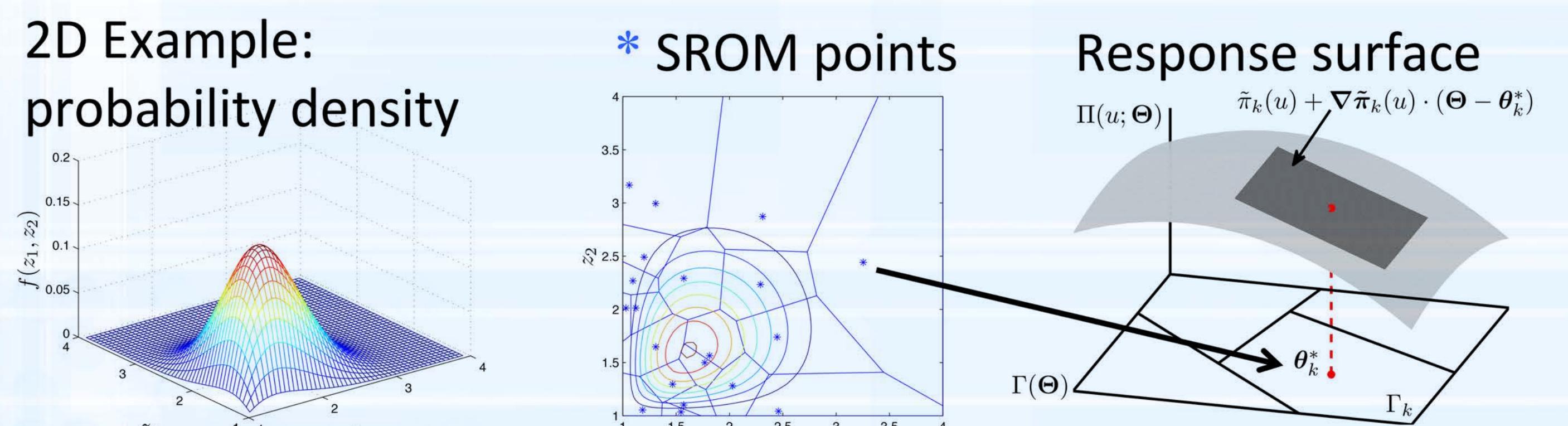
Stochastic Reduced-order Model

We choose to represent the uncertain input with a discrete random variable $\tilde{\Theta}$. The SROM is defined by the collection $(\tilde{\theta}_k, \tilde{p}_k)$ $k = 1, \dots, m$ that minimizes an objective function of the form:

$$\max_{1 \leq r \leq \bar{r}} \max_{1 \leq s \leq d} \underbrace{\alpha_{s,r} |\tilde{\mu}_s(r) - \hat{\mu}_s(r)|}_{\text{moments}} + \max_x \max_{1 \leq s \leq d} \underbrace{\beta_s |\tilde{F}_s(x) - \hat{F}_s(x)|}_{\text{cumulative distribution}} + \zeta_{s,t} \max_{s,t} |\tilde{c}(s,t) - \hat{c}(s,t)|$$

SROM-based surrogate

2D Example: probability density

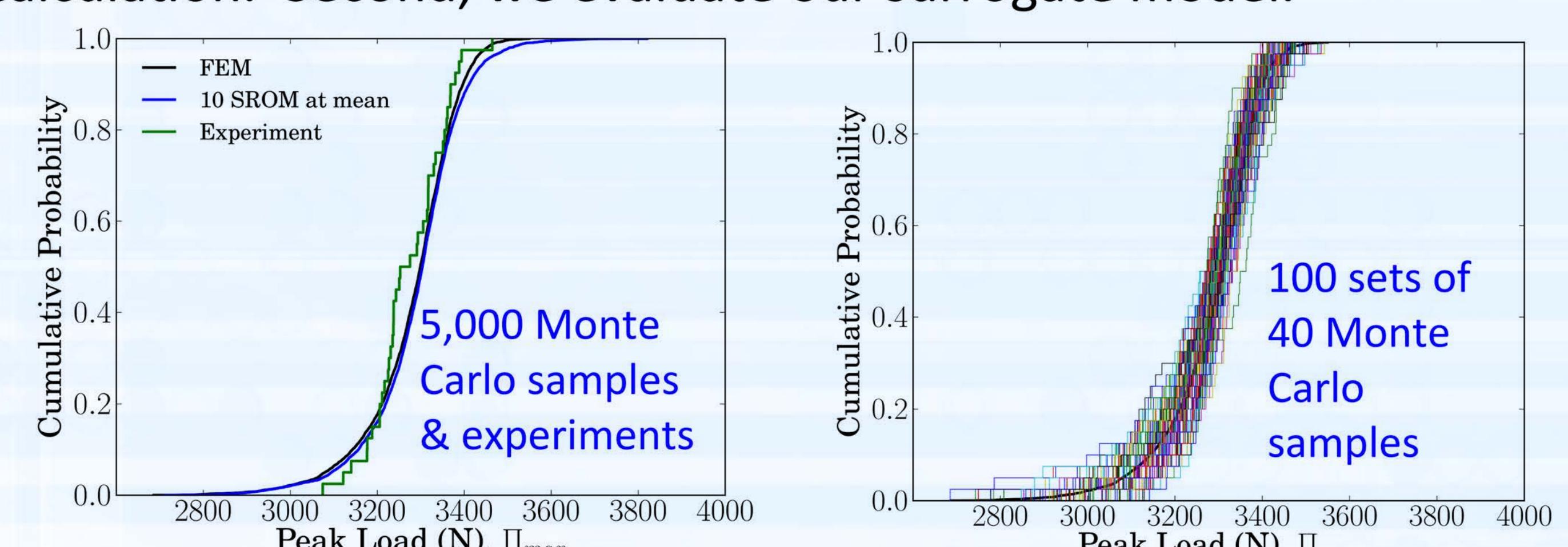


A response surface is constructed for the structural response of the component using a series of hyper-planes described with a first-order Taylor approximate:

$$\tilde{\Pi}_L(u; \Theta) = \sum_{k=1}^m 1(\Theta \in \Gamma_k) [\tilde{\pi}_k(u) + \nabla \tilde{\pi}_k(u) \cdot (\Theta - \theta_k^*)]$$

Output

We perform MCS two ways. First, we use brute force FE calculation. Second, we evaluate our surrogate model.



For 5,000 samples, brute force MCS is 65x more expensive for comparable accuracy. For equal computational work (40 samples), brute force MCS is much less accurate.

Publications/Conferences

Emery, Field, Foulk, Karlson, Grigoriu *JNME* (in review)

Emery, Field, Grigoriu, Foulk 2014 *TMS Annual Meeting*, San Diego, CA.

Emery, Grigoriu, Field, Foulk 2013 *SIAM CSE*, Boston, MA.