An Approach Based on Bayesian Inference and Machine Learning for Calibrating a Superelastic Constitutive Model from Full-field Strain Data

H. M. Paranjape[a †], K. I. Aycock[b], C. Bonsignore[a], J. D.Weaver[b], B. A. Craven[b], T. W. Duerig[a] | [a]Confluent Medical, Fremont, CA, United States. [b]U.S. Food and Drug Administration, Silver Springs, MD, United States.

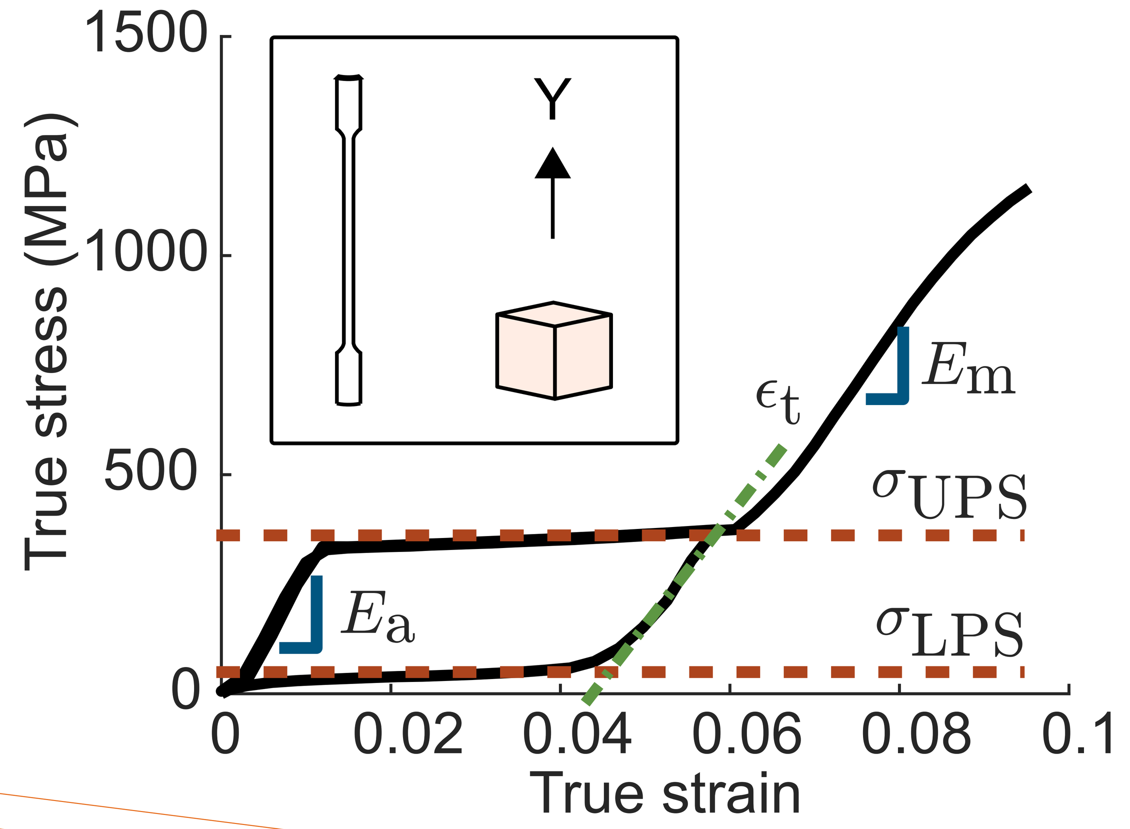
† harshad.paranjape@confluentmedical.com | +1 (510) 683-2184

Objective: Develop an efficient approach to calibrate a model for superelastic deformation and furnish quantification of uncertainties in the calibrated parameters.

Method: Build a simulation library spanning material parameter space. Train a machine learning surrogate to forward model local strains. Measure local strain data using DIC during tensile tests. Use Bayesian Inference to determine material parameters and uncertainties.

Outcomes: Efficient determination of calibrated material parameters and uncertainties. Better local strain predictions.

Calibrating a Superelastic Model



Superelastic models used to simulate the deformation of NiTi (a common material for medical implants) are generally calibrated using an *ad hoc* approach.

Key model parameters (annotated left) are determined by comparing the response of a single element model to the experimental response (e.g., tensile test on dogbone).

⚠ This approach leaves out quantifying uncertainties in the calibrated parameters.

⚠ Generally compressive parameters are not explicitely calibrated

Alternative: Design a specimen geometry suitable for calibrating tensile and compressive properties. Perform calibration using Bayesian Inference to quantify uncertainty.

Methodology

Propose a standard specimen geometry

Manufacture test specimens | Create virtual specimen

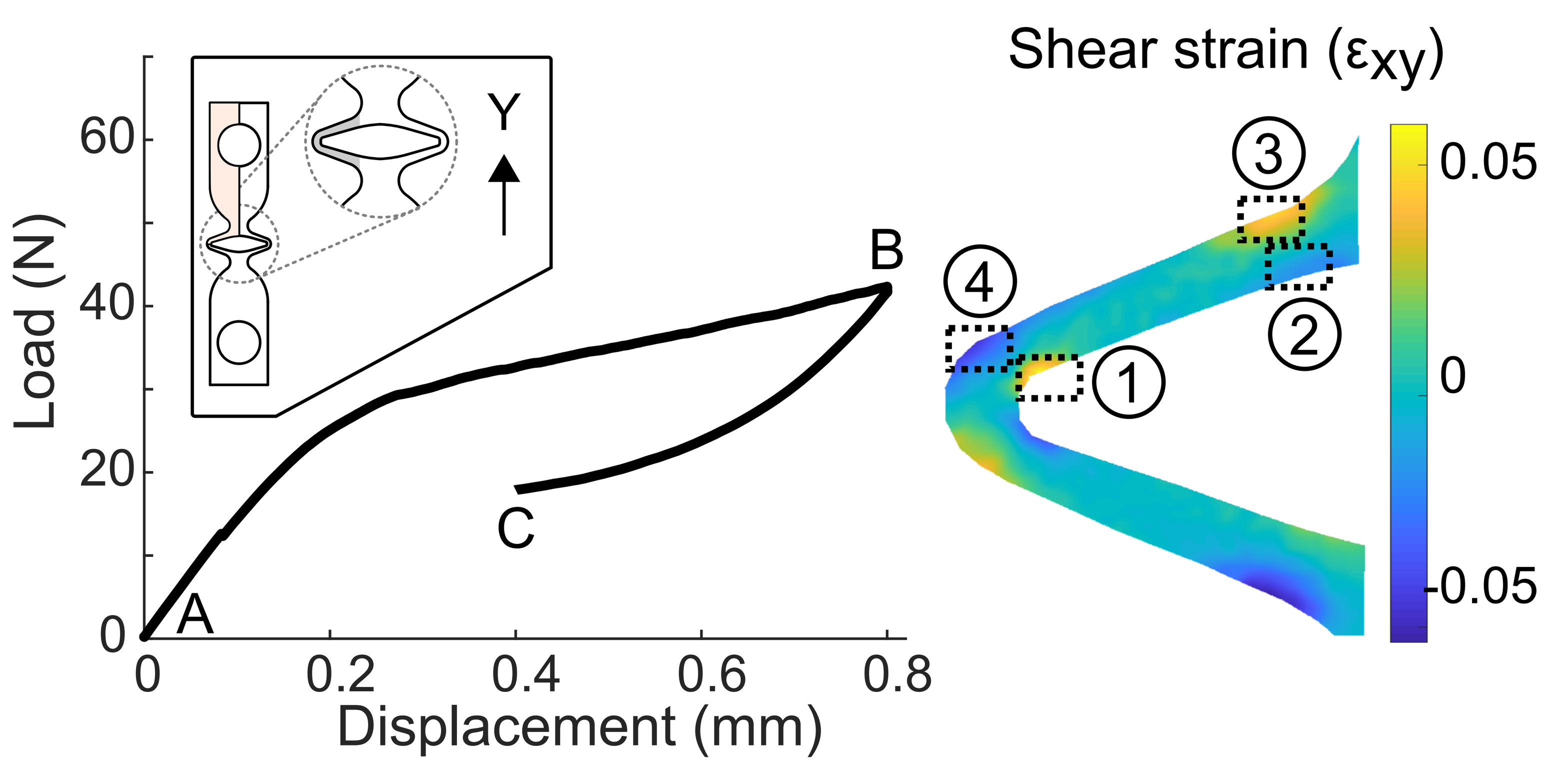
Measure quantities of interest (strain, load) to act as comparators | Generate simulation library

Expand lib. using machine learning

Bayesian Inference: Sample calibrated mat. props. using Markov Chain Monte Carlo

Report point estimate (median, MAP) and credibility interval for calibrated params.

Measurement of Experimental Quantities of Interest



We propose to use a diamond-shaped specimen geometry that exhibits both tensile and compressive strains.

Perform tensile test through load path A → B → C.

Measure full-field surface strain using digital image correlation (DIC) and calculate mean strains over regions ①,②,③,④.

Experimental quantities of interest (Q^{expt}) = Load and mean strains at ① - ④ at ten equispaced points between A and B and ten points between B and C.

Generation of Simulation Library

Create a simulation of tensile loading based on the diamond specimen geometry.

Use superelastic model implemented in Abaqus finite element framework (Auricchio, Taylor, Lubliner. 1997. CMAME).

Six parameters sampled using latin hypercube sampling:

E_a E_m Austenite and martensite modulus	σ_{UPS} σ_{LPS} Upper and lower plateau stress
ϵ_t Transformation strain	σ_{CPS} Lower plateau stress

Determine simulation counterpart of the five quantities of interest (Q^{sim}).

Representative results shown in this poster used a library of 544 simulation instances.

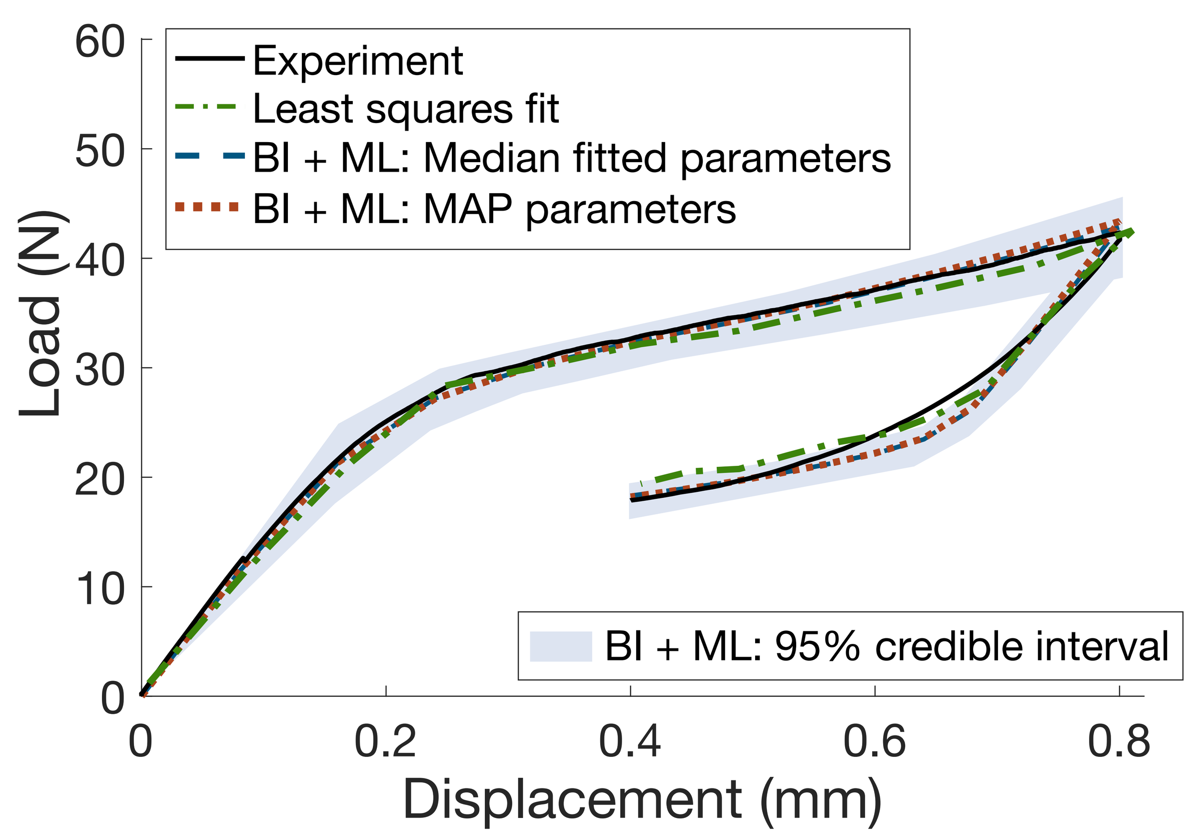
Expansion of Library using Machine Learning (ML)

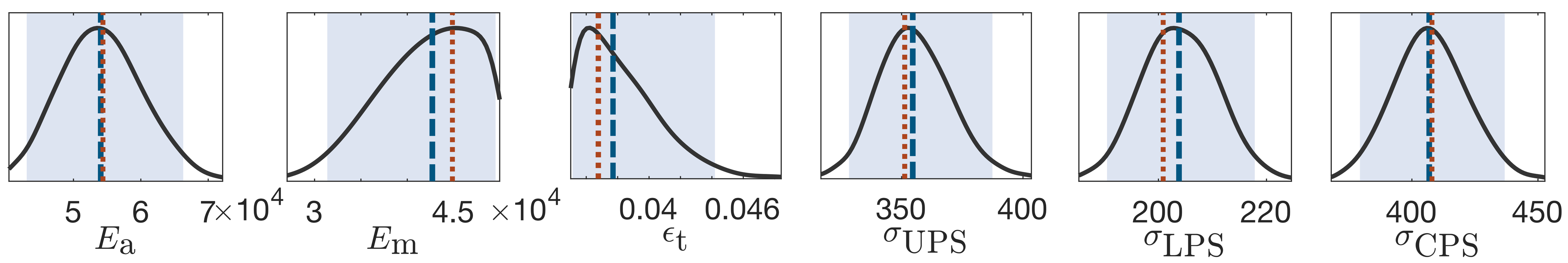
Forward modeling of Q^{sim} using finite element model is expensive.

Use an ML regression method -- kernel support vector machine (SVM) -- to determine Q^{sim} for parameters not in the library.

From Q^{sim} and Q^{expt}, .determine calibrated parameters using Monte Carlo sampling.

Representative Results





■ Probability distribution of calibrated parameters is shown. Calculate median and credibility interval.

■ Results from calibrated parameters with experimental data are shown.

For details, see preprint: https://engrxiv.org/k2dt5/
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