

A Probabilistic Approach with Built-in Uncertainty Quantification for the Calibration of a Superelastic Constitutive Model from Full-field Strain Data

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May 20, 2022 | Shape Memory and Superelastic Technologies Conference (2022)

Acknowledgements

- Resources provided by Confluent Medical Technologies, Inc.
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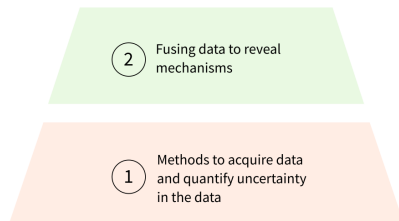
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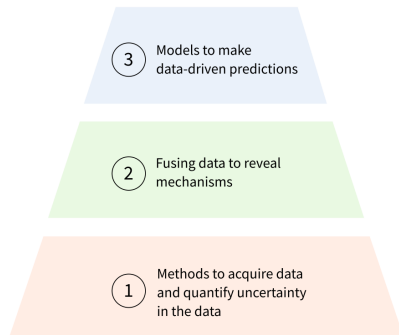
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Methods to acquire data and quantify uncertainty in the data

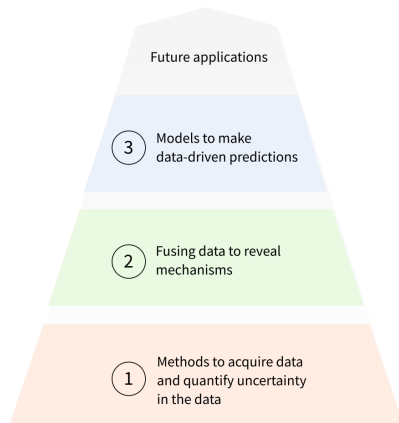
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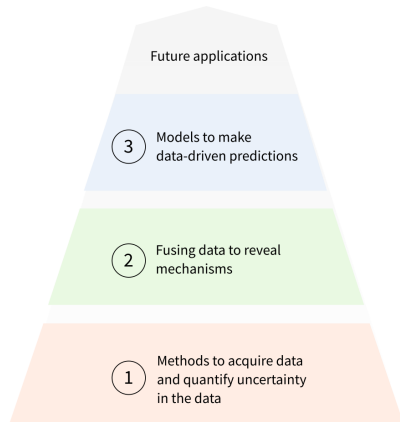
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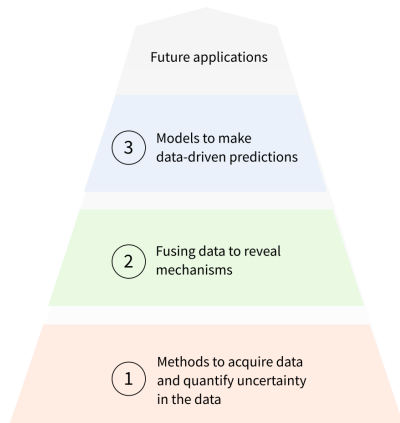
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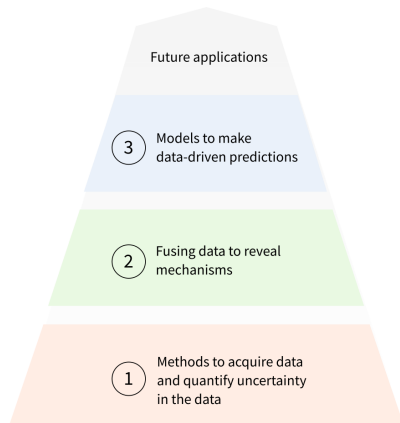
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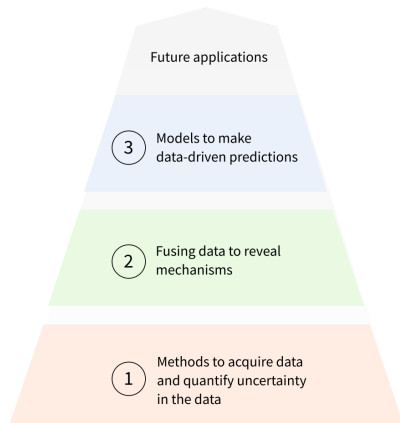
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- End goal: Make data-driven prediction of implant deformation, fatigue susceptibility under in-vivo boundary condition.



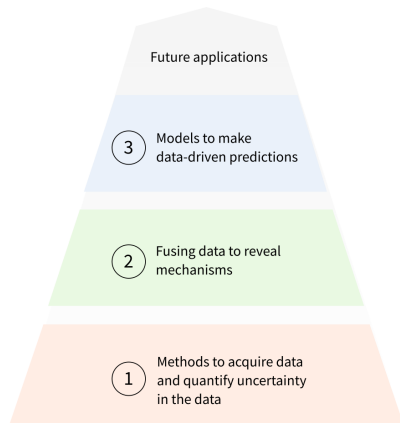
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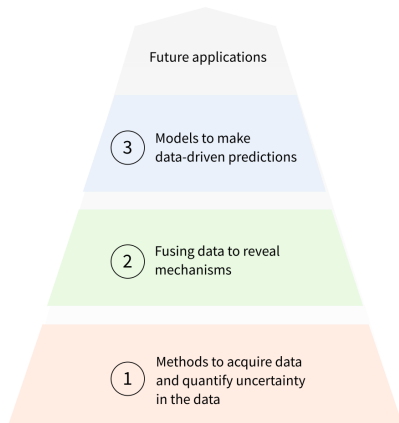
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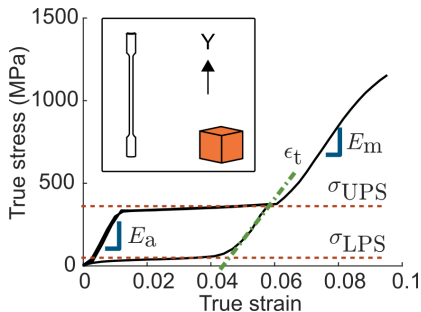


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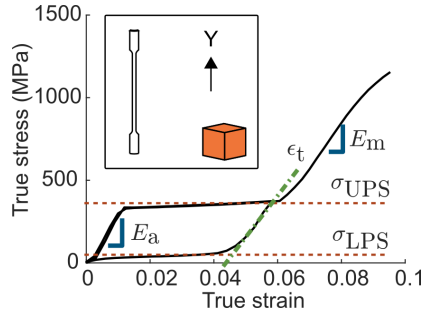
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- Elastic modulus, plateau stresses, transformation strains: Material inputs for the simulation of superelastic deformation.



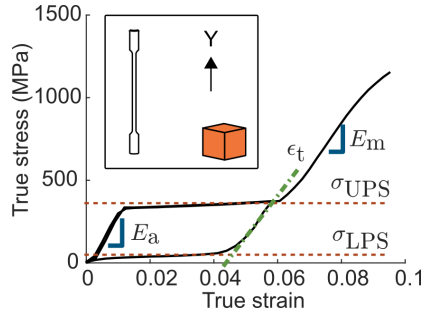
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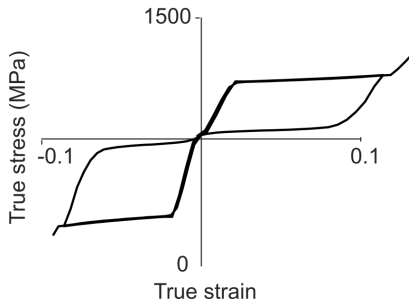
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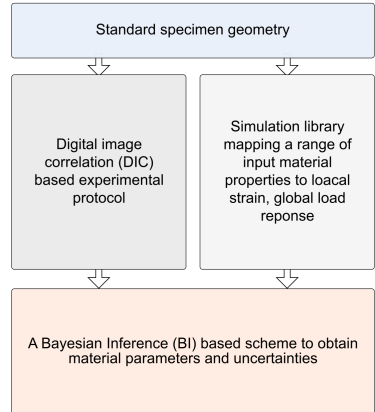
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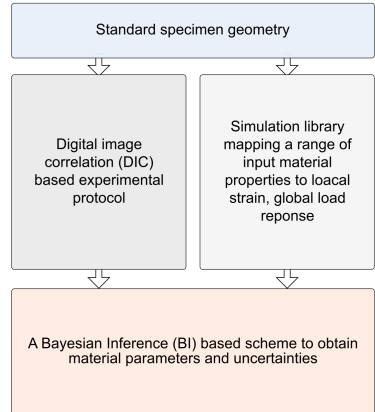


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- Calibration to just tensile test data does not capture **tension-compression asymmetry**.

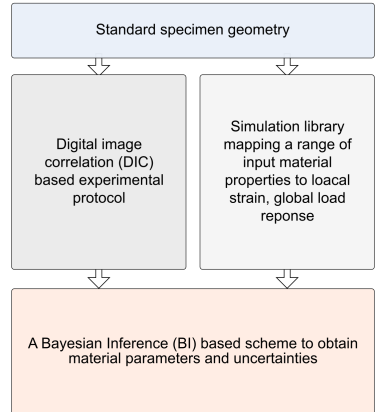
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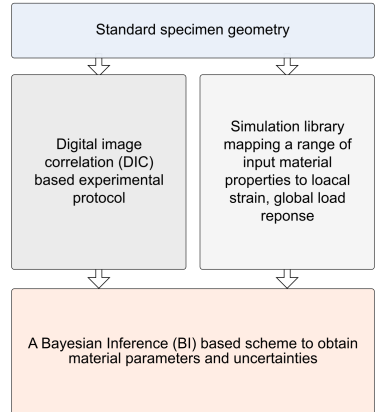
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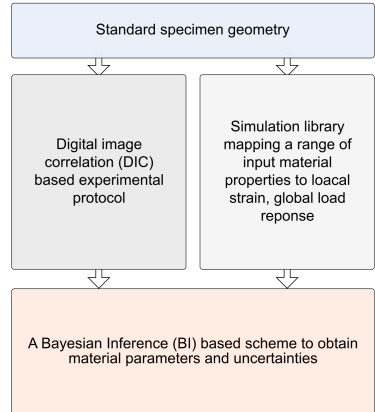
- Four **components** of the calibration scheme:
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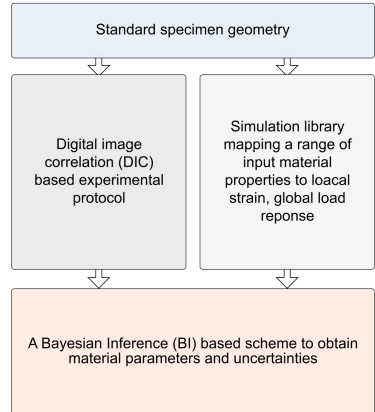


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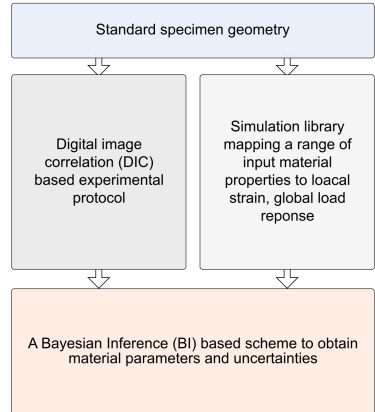


Probabilistic Calibration Methodology

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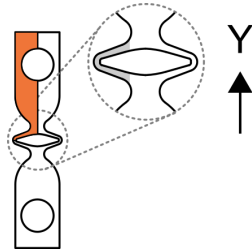


Details:

Paranjape et al. (2021). Computational Materials Science. <https://doi.org/10.1016/j.commatsci.2021.110357>.

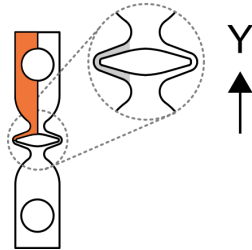
Standardized Specimen Geometry

- A **diamond** specimen geometry that produces both tensile and compressive strain fields when loaded in Y.



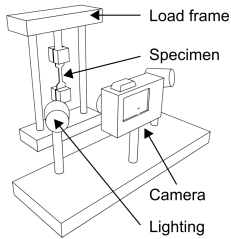
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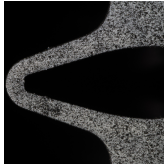
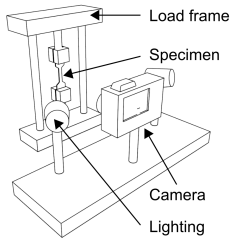
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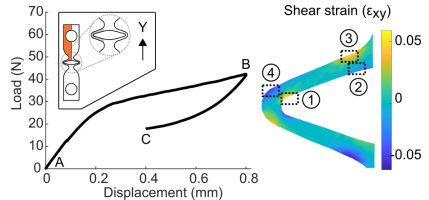
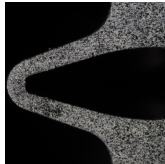
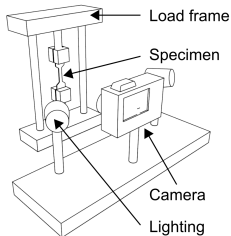
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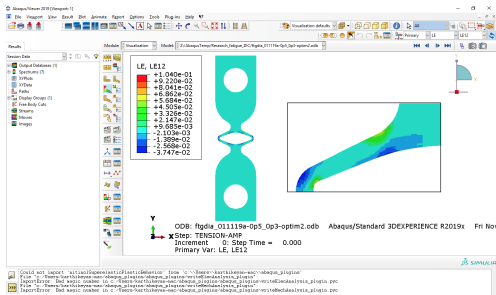


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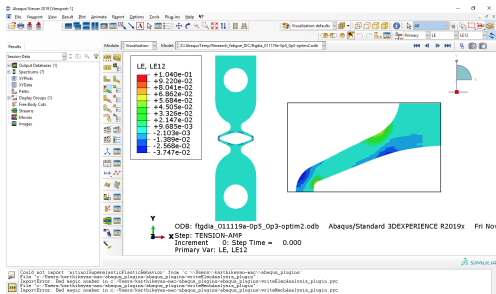
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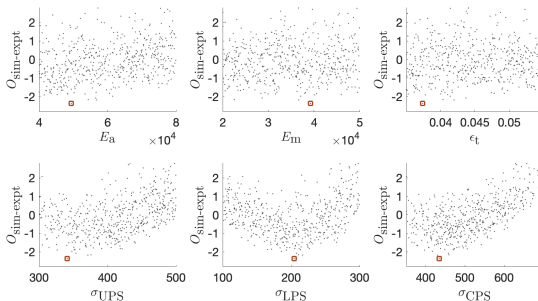


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- Identical boundary conditions (BCs) as in the experimental protocol.



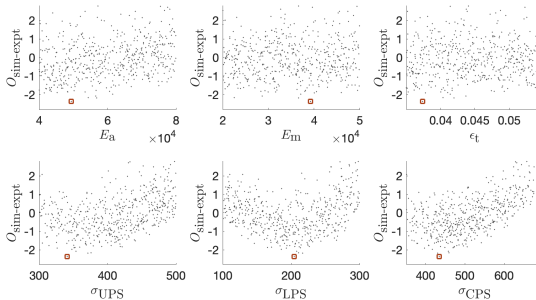
Material Property Calibration: The Easy Way (a.k.a. least-squares)

- Define a quantity Q based on the local strains and global load. It can be either experimentally measured (Q^{expt}) or obtained from simulations (Q^{sim}).



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- The calibrated material parameters $m_{\text{LSQ}}^{\text{cal}}$ can be determined by performing the minimization: $m_{\text{LSQ}}^{\text{cal}} := \arg \min_m \sum_i^N w_i (Q_i^{\text{sim}} - Q_i^{\text{expt}})^2$.



- Calculate the probability distribution (posterior) of the calibrated material parameters using Bayes' theorem and Markov Chain Monte Carlo (MCMC) sampling.

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Material Property Calibration: Bayesian Inference

- Calculate the probability distribution (posterior) of the calibrated material parameters using Bayes' theorem and Markov Chain Monte Carlo (MCMC) sampling.
- The **median** material properties and their **uncertainty** (standard deviation) can be calculated from the posterior distribution.

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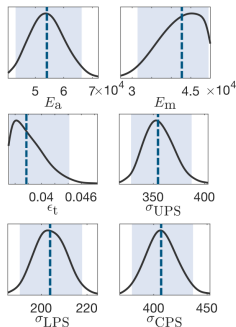
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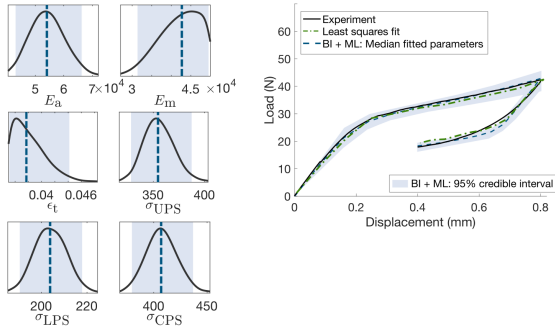
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- It is computationally expensive to build a very large library using the full-field FEA simulations.
- Thus, we fitted a support vector machine (SVM) regression model to predict Q^{sim} for an arbitrary value of m .

Results: Calibrated Parameters using BI + ML Approach



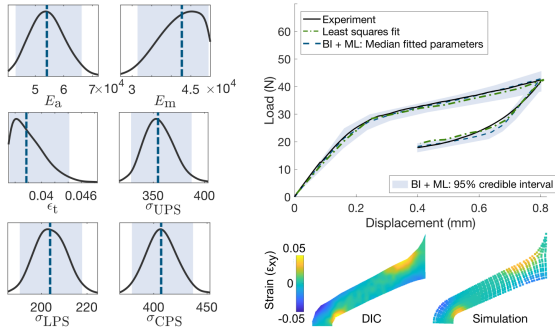
- Left: A probability distribution of the calibrated parameters obtained using tensile and DIC test data for a diamond specimen.

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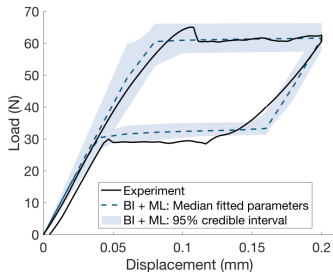
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- Top right: A comparison of the experimental data, the simulation result using the median calibrated parameters, and the 95% interval.

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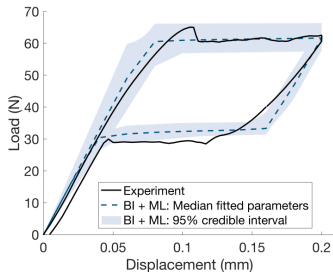
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Results: Simple Validation of Results



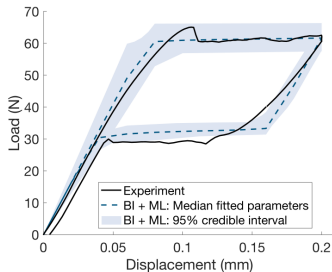
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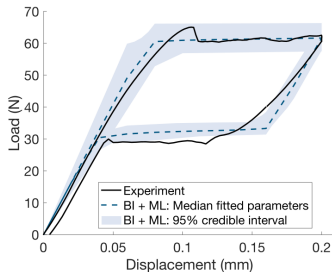
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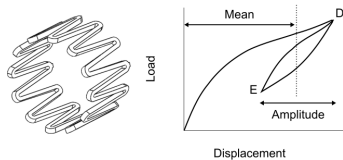


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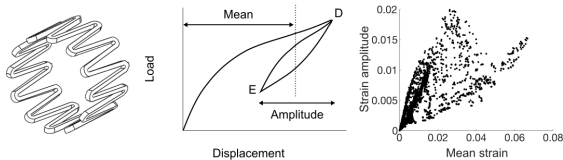
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Results: Propagation of Uncertainty to Subsequent Simulations



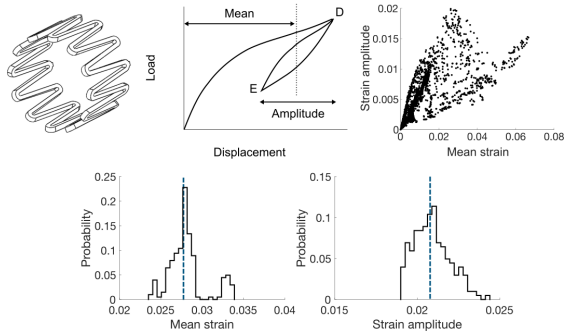
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- Probability distribution of the calibrated material properties → probability distribution of the simulated fatigue indicators.

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- The quantified uncertainties in the material parameters can be propagated to the results of subsequent simulations.

- The Bayesian material property determination approach is extensible to other testing methods.

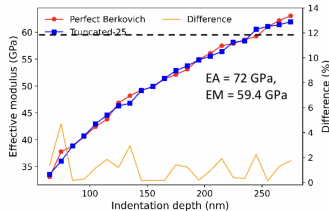
Oliver-Pharr method applied in SMA

Oliver-Pharr equation,

$$\sqrt{A} = \frac{S}{\beta E_r}$$

$\beta = 1.1667$ for Berkovich indenter;
 E_r is reduced modulus,

$$\frac{1}{E_r} = \frac{(1 - \nu^2)}{E} + \frac{(1 - \nu_i^2)}{E_i}$$



- SMA used has a moduli as, EA = 72 GPa, EM = 59.4 GPa.
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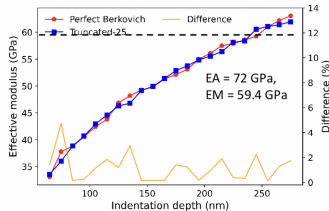
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2

Fatigue: Shift from Deterministic to Probabilistic Approach

- Heart Valve Collaboratory (HVC): A community of practitioners to develop a consensus on heart valve (NiTi and other metals) durability assessment.

The screenshot shows the homepage of the journal 'Cardiovascular Engineering and Technology' (CVET), published by Springer and BMES. The page features a dark blue header with the Springer logo and navigation links for Search, Authors & Editors, and Log in. Below the header, the journal title is prominently displayed next to a cover image. A section titled 'Editorial board' and 'Aims & scope' provides a detailed description of the journal's focus on cardiovascular research and technology. It lists various topics covered, from subcellular to systems level, including medical devices, hemodynamics, tissue biomechanics, functional imaging, surgical devices, electrophysiology, tissue engineering, regenerative medicine, diagnostic instruments, and transport and delivery of biologics and sensors. A 'show all' link is provided for more details. The 'Editor-in-Chief' section identifies Igor Efimov. The 'Publishing model' section states it is a Hybrid (Transformative Journal) and provides a link to 'How to publish with us, including Open Access'. At the bottom, a table displays key metrics: 2,495 (2020) Impact factor, 48 days Submission to first decision, and 83,744 (2021) Downloads. On the right side, there is a 'For authors' section with links to Submission guidelines, Ethics & disclosures, Open Access fees and funding, and Contact the journal, along with a Submit manuscript button. Below that is an 'Explore' section with links to Online first articles and Volumes and issues, and a Sign up for alerts button.

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- Heart Valve Collaboratory (HVC): A community of practitioners to develop a consensus on heart valve (NiTi and other metals) durability assessment.
- Stay tuned for HVC special issue in Cardiovascular Engineering and Technology journal in 2023.

The screenshot shows the journal's homepage with a dark blue header. The journal title 'Cardiovascular Engineering and Technology' is prominently displayed. Navigation links for 'Editorial board' and 'Aims & scope' are present. A detailed description of the journal's scope is provided, covering various aspects of cardiovascular research. Key statistics for 2020 and 2021 are listed at the bottom, including impact factor, submission time, and downloads. A 'For authors' section offers links to submission guidelines and a 'Submit manuscript' button. An 'Explore' section includes links to first articles and a 'Sign up for alerts' button.

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Cardiovascular Engineering and Technology (CVET) presents a wide spectrum of research, from basic to translational, in all aspects of cardiovascular physiology and medical treatment. It offers academic and industrial investigators a forum for the dissemination of research that utilizes engineering principles and methods to advance fundamental knowledge and technological solutions related to the cardiovascular system. Coverage ranges from subcellular to systems level topics, including, among others, implantable medical devices; hemodynamics and tissue biomechanics; functional imaging; surgical devices; electrophysiology; tissue engineering and regenerative medicine; diagnostic instruments; transport and delivery of biologics; and sensors. — [show all](#)

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Call for Papers for Special Issue on Nitinol Medical Devices

The journal *Shape Memory and Superelasticity* is organizing a special issue dedicated to Nitinol medical devices. This issue will address scientific and engineering topics that relate to the durability and the function of cardiovascular implants manufactured from Nitinol. Certain examples of such topics include fatigue properties, influence of processing on device performance, and interaction between cardiovascular physiology and the Nitinol material.

The journal is soliciting original research articles that broadly fall in the scope of this special issue. Typical research articles will be approximately 8 journal pages in length. Longer papers can be accommodated with permission from the guest editors.

Srinidhi Nagaraja and Harshad Paranjape will be guest editors in this special issue. Please inform both guest editors if interested in submitting an article to this special issue by January 14, 2022 .

Thank you

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Calibration of SE Model

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