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subject: Completion of L2 Milestone for PPM Task 3 – Laser Weld Modeling

We believe that this memo, along with the slides that document the details of the effort, fulfills the L2 milestone. We appreciate the time and the effort that has been expended in evaluating our effort. It is our hope that we have both adequately considered and implemented the changes the committee has suggested. The work is stronger because of this invaluable review process.

Introduction

Micro-laser welds are prevalent in complex engineering systems and typically result in partial penetration of the base metals leaving sharp, crack-like notches at their root. Inherent to the process is a high degree of uncertainty in the resulting geometry and material properties. Modeling these types of welds in large systems is important for predicting structural reliability, yet challenging because of the disparate length scales and significant variability. In this work, we address the variability in laser welds through the construction of stochastic reduced-order models (SROMS). Here, the uncertainty in weld microstructure and geometry is captured by calibrating plasticity parameters to experimental observations of necking and, due to the ductility of the welds, necking plays the pivotal role in structural failure. The method is exercised for a simple, self-consistent welded coupon and compared to 5,000 finite element calculations of the coupon with rather remarkable results.

In addition to the obvious stress concentration at the root of the partial penetration weld, significant porosity can arise throughout the weld [1, 2]. In very ductile alloys such as 304L austenitic stainless steel (SS), the geometry and porosity of the weld interact to create a very complex necking process that dominates the strength of the weld, eventually leading to fracture well after the load carrying capacity of the weld has diminished. Figure 1 illustrates the complex deformation process observed throughout tensile loading with significant cross-section reduction and fracture occurring only after the load was reduced to 7% of peak load. The figure makes clear that for 304L SS, the load carrying capacity under far-field tension is dominated by the necking process. We emphasize that we are not attempting to predict the unloading regime shown in Figure 1. Many of the configurations under consideration for abnormal environments are overdriven. Our goal is to predict the onset of necking.

Past work at Sandia has illustrated that the performance of laser welds is highly variable. That variability derives from both the geometric and material variability and is usually represented via probabilistic methods.

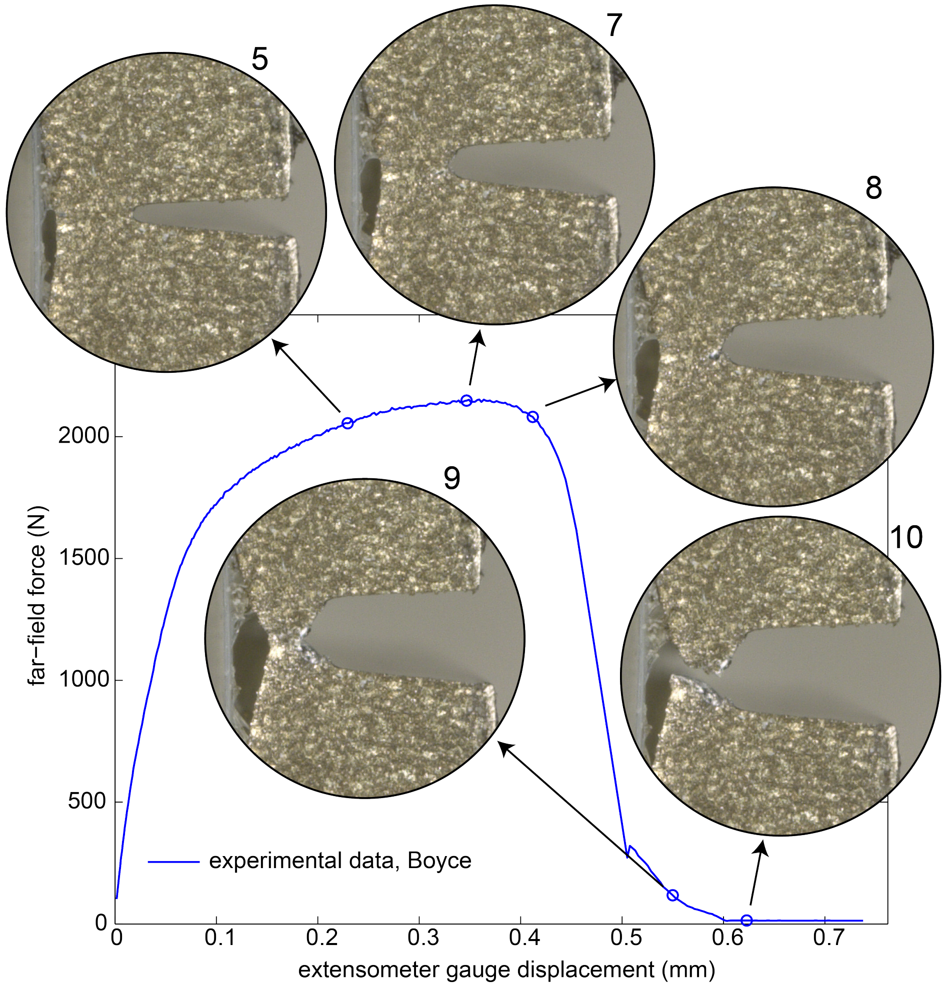

Figure 1: The load-displacement curve illustrating the necking of the laser weld under far-field tension. The appearance of new surface area does not occur until the load has significantly dropped.

Because we must be able to make quantitative statements regarding system reliability, we need to employ approaches that capture the tails of the probability distributions of system quantities. While there are numerous methods for uncertainty propagation, some of which are included in Dakota [3], the only general approach to determine the tails of the output distribution is through repeated random sampling, Monte Carlo Simulation (MCS). We do not, however, have the computational resources to repeatedly sample component or system level finite element models. The objective of this work is to present a method that captures the relevant physics and uncertainty within a tractable computational effort. This requires methods to reduce both the stochastic and physical dimensions of the problem. For the former, we employ stochastic reduced-order models (SROMs) [4, 5]. For the latter, we make prudent selections with regard to both the input finite element (FE) discretization and output metrics that capture the necking process. We avoid remeshing through tailored meshes in the reference configuration that can accommodate the necking process. Given an output metric for failure, we can construct a surrogate model of the response surface via a piecewise first-order (linear) Taylor series expansion derived from FE calculations at finite SROM samples [6]. Rather than repeatedly sample the FE model to obtain the needed response, we choose to sample the surrogate. In the language of the accompanying documentation, we do not apply “brute force” MCS. We are “smarter” and randomly sample the surrogate at minimal computational cost.

In this study, we have restricted our work to quasi-static loadings and room temperature. This restriction ignores the rate and temperature dependence of 304L SS. Our current focus is to illustrate the methodology. Future work will include these additional physics that are needed for abnormal mechanical environments.

Milestone

Description: Thousands of feet of 304L stainless steel laser welds reside in numerous weapon components, including first-order nuclear safety systems, that serve a wide variety of functions. These welds must remain structurally sound in both normal and abnormal environments. Variability in weld geometry and material properties can have a critical impact on performance margins and uncertainties in both current and future designs. Historically, component analysis models have incorporated variability through a statistically limited set of experimental data. This milestone will deliver a capability for constructing component-scale models from a statistically significant population of the weld response obtained from both experiments and higher fidelity simulations.

Completion Criteria. Demonstration of a framework that accounts for 304L weld variability through the construction of component level models for quasi-static mechanical environments.

Milestone Certification Method. A program review is conducted and its results are documented. Professional documentation, such as a report or set of viewgraphs with a written summary, is prepared as a record of milestone completion.

We must emphasize that we are demonstrating a framework for constructing stochastic component level models. Although 304L laser welds represent our model system, we are not burdened with a predictive model for laser weld failure. Rather, our goal is to illustrate how one can incorporate stochasticity into a predictive model for laser weld failure. Indeed, we believe that the component-level discretizations employed in this work are a necessary first step in applying stochastic reduced order models to both component-level and system-level models.

Framework

Although the supporting documentation in Section adequately document the flow, we include Figure 2 in this summary memo for completeness. It highlights the need be clear about relevance of input data and assumed modes of failure. Robust methods for calibration via optimization are critical. We wrap Dakota [3] to perform the calibration through optimization. We often need to enrich calibrated data and choosing models for enrichment is yet another physical assumption on par with material model selection and parameter identification. The enrichment uses translational random vectors to generate the desired number of samples [7]. After stipulating the statical measures of importance, one can then construct the SROM in an optimal manner through a statistical objective function. The number of SROM samples is chosen based on available computational resources and is convergent with refinement [6]. We can then employ the SROM samples to create a response surface through finite element analysis. We construct a surrogate model of that response surface through a series expansion (Taylor) at the SROM samples. We assume the response surface to be differentiable and employ first derivatives (linear) to obtain promising results. In the current work, the surrogate model is constructed on the model employed for calibration. This is a necessary first step to illustrate the consistency of the method. Given the SROM-based surrogate, we can efficiently sample the surrogate with MCS. Thousands of samples are calculated effortlessly. The additional samples afforded by the surrogate model enable the methodology to capture the tails of the probability distribution of the response of interest.

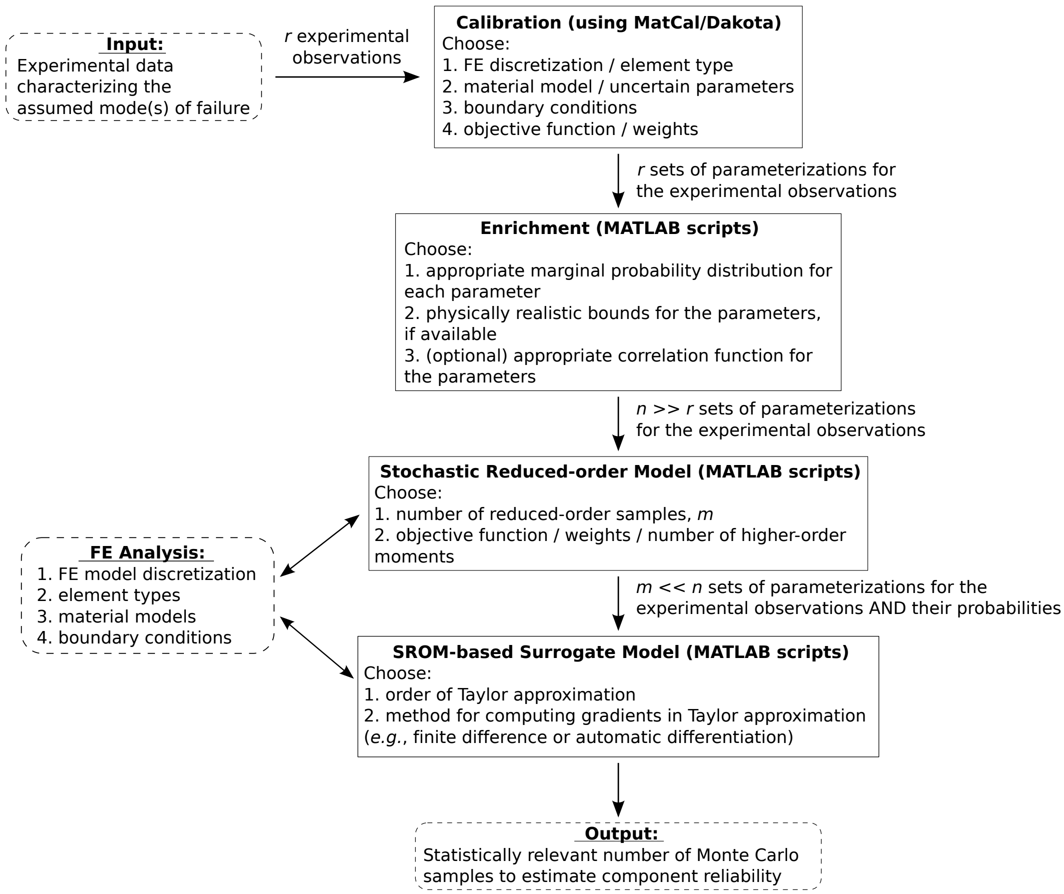

Figure 2: Flowchart demonstrating the procedure for estimating component reliability due to laser weld failure.

Supporting documentation

The team has submitted a set of slides to fulfill the requirements for documentation. The slides submitted with the L2 Milestone can also be found on the Sandia Wiki under

`https://snl-wiki.sandia.gov/display/PPM/L2+Milestone`

and we intend to update the documentation based on future feedback. We will also be posting a journal publication (based on our L2 findings) in the coming months. To add structure to our findings, we have partitioned our results into eight broad sections:

1. Milestone, Motivation, & Expectations
2. L2 Framework
3. Calibration
4. Enrichment
5. Stochastic Reduced Order Model

6. Consistency
7. SROM surrogate vs. Monte Carlo
8. Summary, Conclusions, & Extension

Based on committee suggestions, we begin the document with high-level motivations and an executive summary. The first five sections provide a basis for the acceptance of the milestone. In those sections, we detail our processes and provide examples that aid the reader. Highlights include an analyst checklist, method workflow, details of the calibration, guidelines for enrichment, and the stochastic reduced order model (SROM) employed for this work. In addition to providing the essential components for acceptance, we also attempted to help the reader through additional examples in the sections devoted to enrichment and the SROM. The following two sections were added to illustrate the promise of the methodology. The team thought it prudent to not only check for consistency but to also contrast Monte Carlo on finite element models with Monte Carlo on an SROM-based surrogate model. We illustrate that for equivalent computational cost, Monte Carlo Simulation on an SROM-based surrogate, "smart" MCS, is superior to Monte Carlo on finite element models, "brute force" MCS.

Summary

Thought this work, we have demonstrated a framework that accounts for 304L weld variability through the construction of component level models for quasti-static mechanical environments. The physical motivations are shown in Figure 1 and the developed framework is illustrated in Figure 2. Throughout the slides submitted to document this work, we have:

1. Illustrated that laser welds are pervasive and dictate issues of nuclear safety.
2. Developed a stochastic framework that addresses variability.
3. Employed a calibration process through optimization which employs Dakota to increase usability.
4. Established a physical basis for enrichment of available data.
5. Constructed an optimal Stochastic Reduced Order Model.
6. Developed an SROM-based surrogate to contrast "smart" MCS with "brute force" MCS.
7. Illustrated that MCS on the SROM-based surrogate is superior at equivalent computational cost.

In future work, we will continue to improve the approach through increased physics and validation exercises. We also seek to improve our SROM approach through the inclusion of spatial variability of ligament length and the construction of an adaptive approach to increase accuracy at minimal computational cost. As always, the team understands that success is not measured in implementation but in analyst adoption. We will continue to improve these tools for analyst adoption and pursue leveraged funding to apply and iterate with our colleagues.

Again, we thank the chair and the committee for their efforts. We look forward to continued interactions and candid feedback.

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