The Application of Artificial Intelligence and Machine Learning for Steel Characterization and Modeling

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Auto/Steel Partnership

GREAT DESIGNS IN STEEL™

The Application of Artificial Intelligence and Machine Learning for Steel Characterization and Modeling

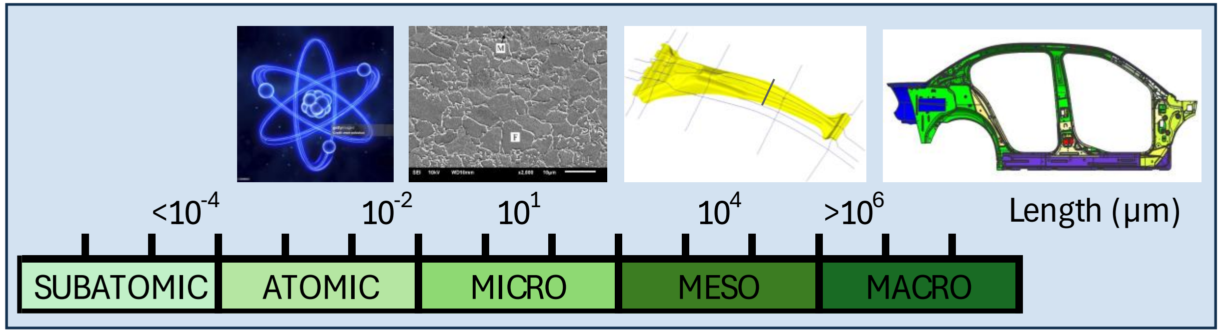
GDIS

A/SP research is **precompetitive**, as such the lower and upper bounds of the vehicle length scale are excluded

- Lower bound: Steel chemistry, steel processing, etc.
- Upper bound: Discrete component/assembly design or manufacturing processes

A/SP's application of ML/AI is focused on systemic issues that inhibit the selection and implementation of steel in automotive components and assemblies

- Material testing and characterization
- Steel formability and fracture
- Process and performance modeling



GM
NUCOR
POSCO
Ternium
MARTINREA
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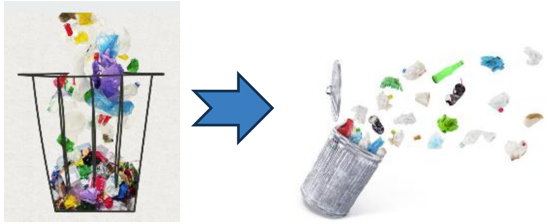
DIC Procedures and Standardization for the Constitutive and Fracture Characterization of AHSS Sheet for CAE Application

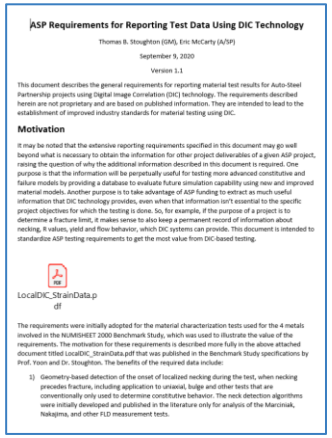
Team: A/SP Constitutive and Fracture Modeling Team



<u>Garbage in – Garbage Out</u>
Computer models are only as good as the data that feeds them

Problem Statement

- Application of DIC is undisciplined and results are sensitive to lab expertise and equipment
- A/SP generates vast amounts of DIC data across its projects with multiple vendors
  - Digital Image Correlation Material characterization data sets can be large (>1TB)
- DIC testing, analysis and reporting need standardization to support ML/AI initiatives



ASP Requirements for Reporting Test Data Using DIC Technology

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Version 1.1

This document describes the general requirements for reporting material test results for Auto-Steel Partnership projects using Digital Image Correlation (DIC) technology. The requirements described herein are not proprietary and are based on published information. They are intended to lead to the establishment of improved industry standards for material testing using DIC.

Motivation

It may be noted that the extensive reporting requirements specified in this document may go well beyond what is necessary to obtain the information for other project deliverables of a given ASP project, raising the question of why the additional information described in this document is required. One purpose is that the information will be perpetually useful for testing more advanced constitutive and failure models by providing a database to evaluate future simulation capability using new and improved material models. Another purpose is to take advantage of ASP funding to extract as much useful information that DIC technology provides, even when that information isn't essential to the specific project objectives for which the testing is done. So, for example, if the purpose of a project is to determine a fracture limit, it makes sense to also keep a permanent record of information about necking, R values, yield and flow behavior, which DIC systems can provide. This document is intended to standardize ASP testing requirements to get the most value from DIC-based testing.

LocalDIC_StrainData.pdf

The requirements were initially adopted for the material characterization tests used for the 4 metals involved in the NUMISHEET 2000 Benchmark Study, which was used to illustrate the value of the requirements. The motivation for these requirements is described more fully in the above attached document titled LocalDIC_StrainData.pdf that was published in the Benchmark Study specifications by Prof. Yoon and Dr. Stoughton. The benefits of the required data include:

1) Geometry-based detection of the onset of localized necking during the test, when necking precedes fracture, including application to uniaxial, bulge and other tests that are conventionally only used to determine constitutive behavior. The neck detection algorithms were initially developed and published in the literature only for analysis of the Marciniak, Nakajima, and other FLD measurement tests.

Goal: Standardize material characterization using DIC with emphasis upon supporting CAE simulation and correlation

Primary Deliverable: **<u>Industry Consensus Material Cards.</u>**

Applications:

Edge Cracking Prediction
Laser Welded Blank Formability
Nonlinear Strain Path - Crash Prediction

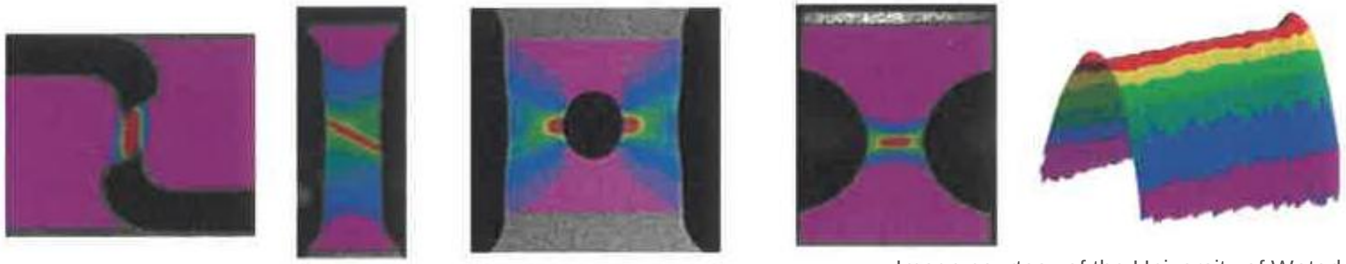


Image courtesy of the University of Waterloo

Laser Welded Blank Formability

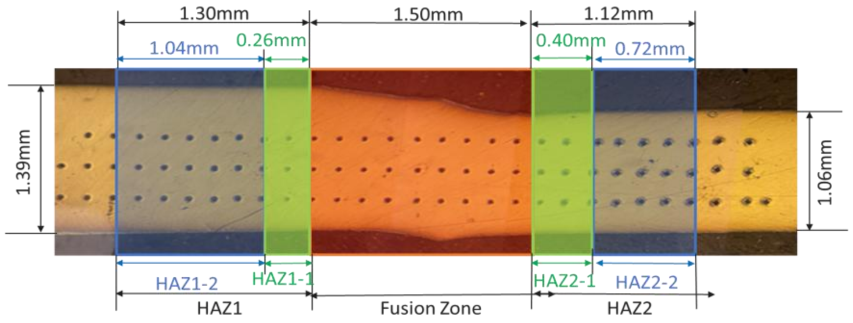
Teams: A/SP Joining and Stamping Teams

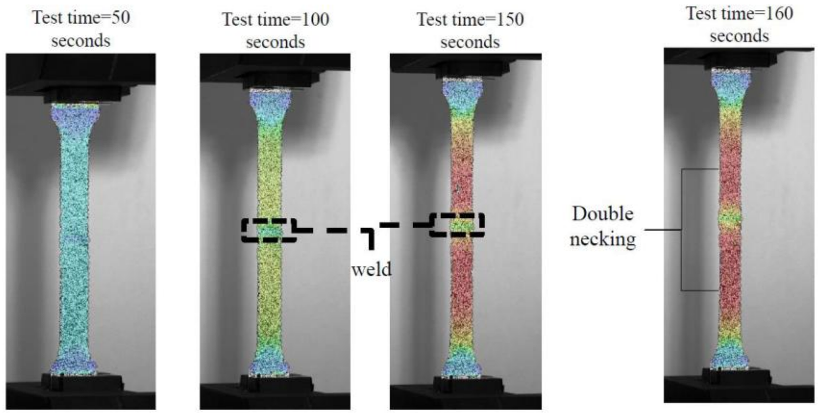
Goals:

- Develop laser welding process models for optimizing laser weld performance
- Develop laser welded blank formability models for weld placement and performance optimization

Objectives:

- **<u>Develop a ML approach to predicting LWB performance from limited but expandable datasets</u>**
  - Base material cards
  - HAZ material cards
  - Load paths (Coupon performance data (tensile, bending, biaxial, plane strain, etc.)
- **<u>Reduce the amount of constitutive and coupon testing</u>**
  - Infinite number of variables
  - Material grade, orientation and thickness
  - Laser weld process parameters
  - Laser weld properties (base material, fusion zone, heat affected zone)
  - Weld topography (same thickness, different thickness, wire assisted, etc.)
  - Joint alignment
  - Load paths





Use of ML/AI is constrained by length-scale application and size of the datasets.

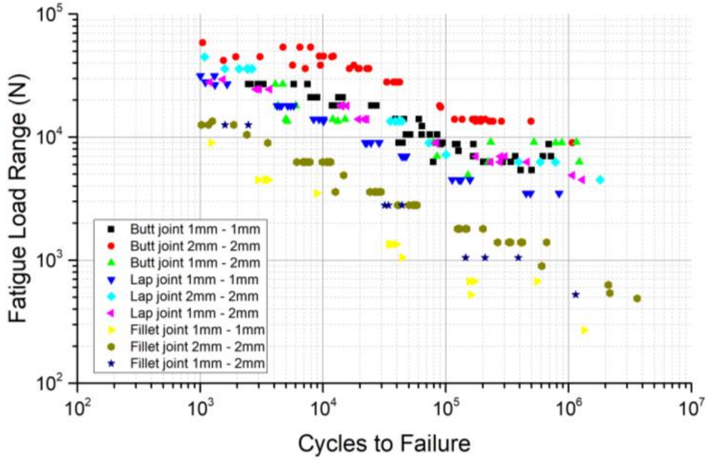
Fatigue Life Prediction of Gas Metal Arc Welded Assemblies

- **Team: Gas Metal Arc Welding – Fatigue Characterization and Modeling**
- Problem Statement:

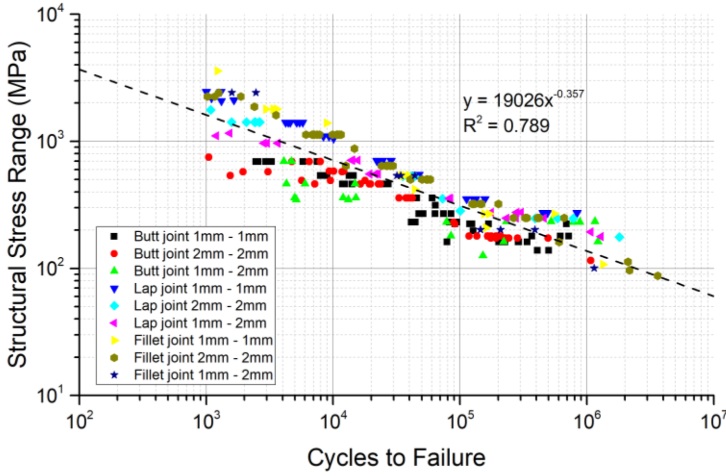
  Structural Stress is the only factor for the fatigue life prediction and do not include the influence of welding conditions, material composition, and other parameters that can affect weld fatigue life. Therefore, prediction results may have more variability.
- Goal:

  To develop a Machine Learning (ML) model for fatigue life prediction of GMAW joints using machine learning platforms such as Tensorflow and Pytorch.
- Objectives:
  - Overcome the shortcoming of stress-based fatigue life prediction methods by including industrial factors that affect fatigue life of welds.
  - Improve the accuracy of fatigue life prediction of GMAW joints
- Approach:
  - Record fatigue test results of welded joints including test, weld, and material information
  - Develop a ML Model
  - Train and validate ML Model with the collected data
  - Validate the ML Model with structural component test results.

Load range vs. Fatigue life



Structural stress method

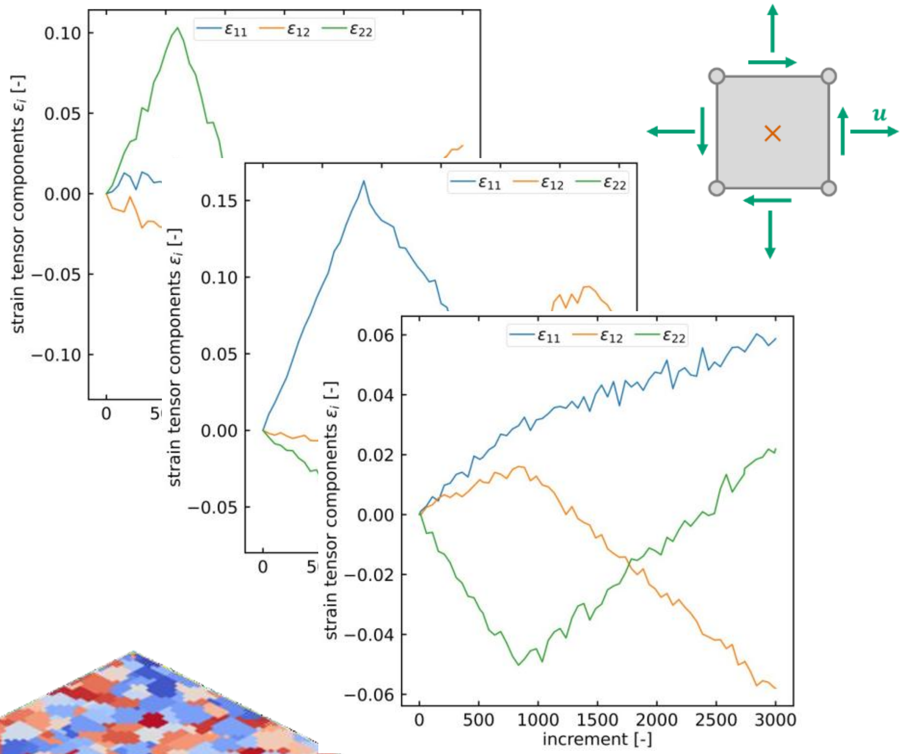


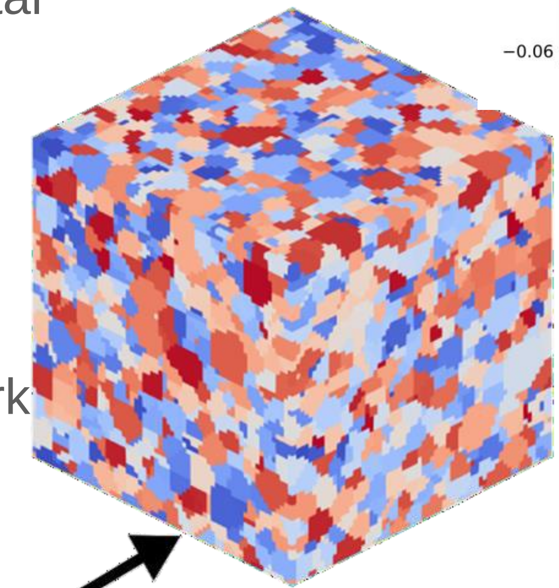
Industrial Fracture Consortium (ETH/MIT)

A/SP is a member of the IFC

Examples of important developments in the application of ML/AI in constitutive, forming and fracture modeling:

- Crystal Plasticity Constitutive Model
  - Crystal plasticity can be used to generate a high-fidelity database of material response. This database is used to train a Minimal State Cell model
- Replacing FE analysis through ML predictions
  - Convolutional Neural Networks (CNNs) can accurately predict the thickness distribution of an elastoplastic metal sheet during forming
- Training Neural Network-based constitutive models from biaxial random walk experiments
  - Train a MSC model based on $\boldsymbol{\sigma}$, $\boldsymbol{\varepsilon}$ –sequences on a single element (reduced required data and simulation time)
  - Uses random walk method – can enable simulating work history (nonlinear strain paths)





Summary

Successful application of ML/AI solutions is highly dependent upon the amount and quality of data used to train the models

AI/ML has been successfully applied in the development of steel constitutive, forming and fracture models.

A/SP's goals

- Standardized DIC material test procedures
- Development of DIC best practices for data recording and analysis
- Improved steel material cards and data sets for constitutive, forming and fracture modeling
- Development of comprehensive ML/AI computer models for modeling LWB formability
- Development of comprehensive ML/AI computer models for modeling RSW, LWB, and GMAW component performance.

Questions

Q: How will AI/ML be integrated into materials and manufacturing?

A: There are obvious cost drivers to incentivize the application of AI/ML in manufacturing, such as developing steel alloy design, reducing scrap, reducing manufacturing defects, etc. Applications in material science will likely focus on modeling material behavior, which will be highly dependent on available data to ensure the models are comprehensive. Unlike in manufacturing, where data is continuously generated, upstream applications of AI/ML in material science initiatives, will depend on the availability of existing data, where data quality is a concern, and the feasibility and cost of generating needed data. These challenges increase the further up the length-scale you go. However, as discussed earlier, the minimal state variable approach used by IFC may be able to significantly reduce the amount of constitutive data needed for ML/AI based material modeling.

Q: What are the barriers inhibiting the application of AI/ML in steel research.

A: The availability of quality and comprehensive material data sets is the most significant impediment to applying AI/ML in the steel modeling. For example, comprehensive material cards tend to be proprietary limiting availability, whereas the quality of generic material cards can be questioned. Complicating things is the lack of consensus on the constitutive data needed for a comprehensive material card, let alone the test methodologies for collecting constitutive data. Unfortunately, the cost of generating data is prohibitive, especially when considering the impact of industrial factors. anisotropy, strain rate, etc. Cooperative work within consortiums, like A/SP and the IFC, offer opportunities that balance the proprietary concerns of material producers with customer interests for effective modeling of material and joint behavior.