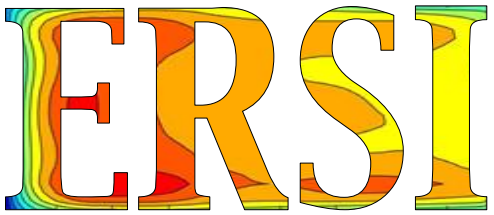


ERSI RISK AND UQ SUBCOMMITTEE ACTIVITIES

Virtual ERSI Workshop

December 2020

Committee Members

- Co-chairs: Juan Ocampo (StMU) and Laura Hunt (SwRI)
- Participating Organizations
  - Analytical Processes/Engineering Solutions (AP/ES)
  - Booz Allen Hamilton
  - Hill Engineering
  - Lockheed Martin
  - NRC Canada
  - SmartUQ
  - Southwest Research Institute
  - St. Mary's University (TX)
  - University of Pittsburgh
  - USAF

Committee Overview

- **GOAL**: Investigate and implement UQ methods that enhance the overall understanding of how residual stress affects life prediction analyses
  - Uncertainty Quantification
    - How do we understand and describe the uncertainty and variability in the relevant parameters?
  - Sensitivity Analysis
    - What are the most significant variables in the ERS process?
    - How can we maximize/minimize the benefits/damages of these variables?

Outline

- Risk and UQ Subcommittee Overview

- Short Presentations of Current Activities
  - **"Residual Stresses Activities at StMU"** Juan Ocampo, StMU
  - **"Residual stress characterization for cold expansion utilizing spatial statistics: The SpARS Methodology"** Dallen Andrew, Hill Engineering
  - **"Stress Gradient Surrogate Model Using PCA"** SwRI
- Future Activities

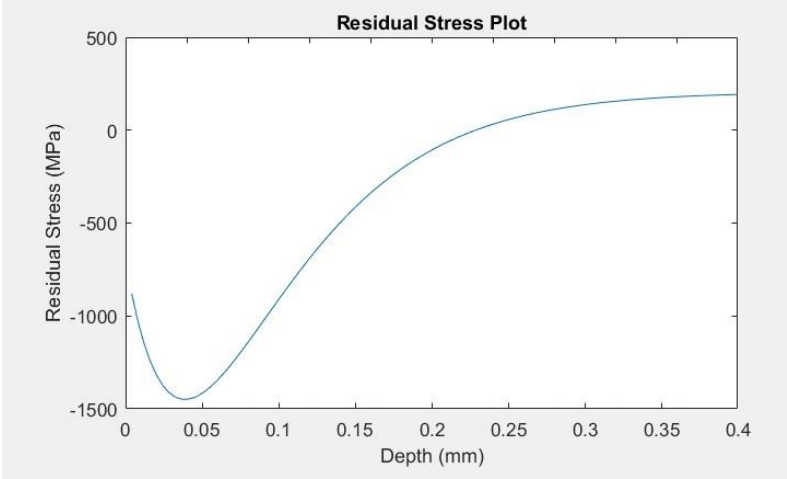
Residual Stresses Activities at St. Mary's University

Juan D. Ocampo
St. Mary's University

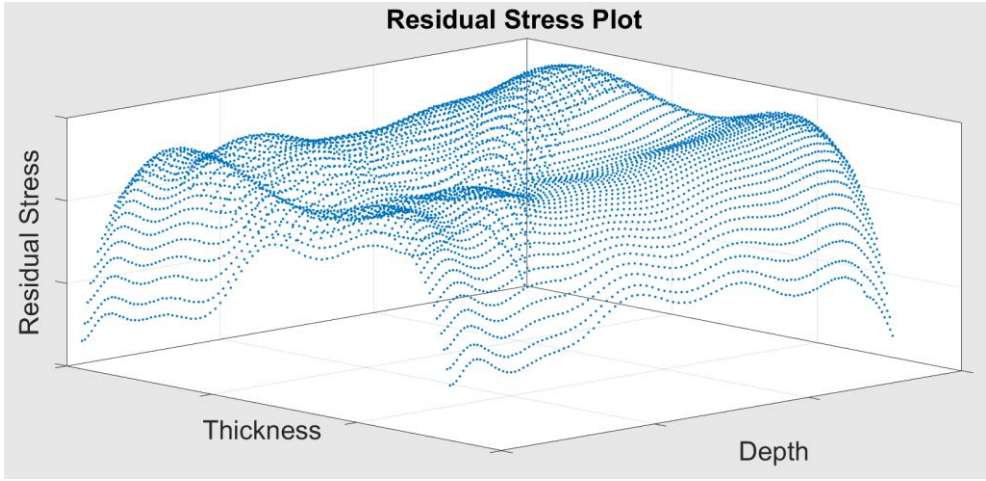
Engineered Residual Stress Implementation

Residual Stress Modeling Software

- Standalone executable to read experimental/ simulated data and find the best deterministic and probabilistic fit parameters.
  - 2 Models Available (Expandable)
  - 2D (Stress vs Depth) and 3D (Stress vs Depth vs Thickness).
  - Read input data in .txt & .csv format



2D



3D

Models

- Model I*

$$\sigma(x) = (ss - si + C_1 x)Exp(-C_2 x) + si$$

$$C_1 = \frac{\{(ss - si)\big(1 - Exp(-C_2 B)\big) + siBC_2\}C_2}{(C_2 B + 1)Exp(-C_2 B) - 1}$$

- Model II**

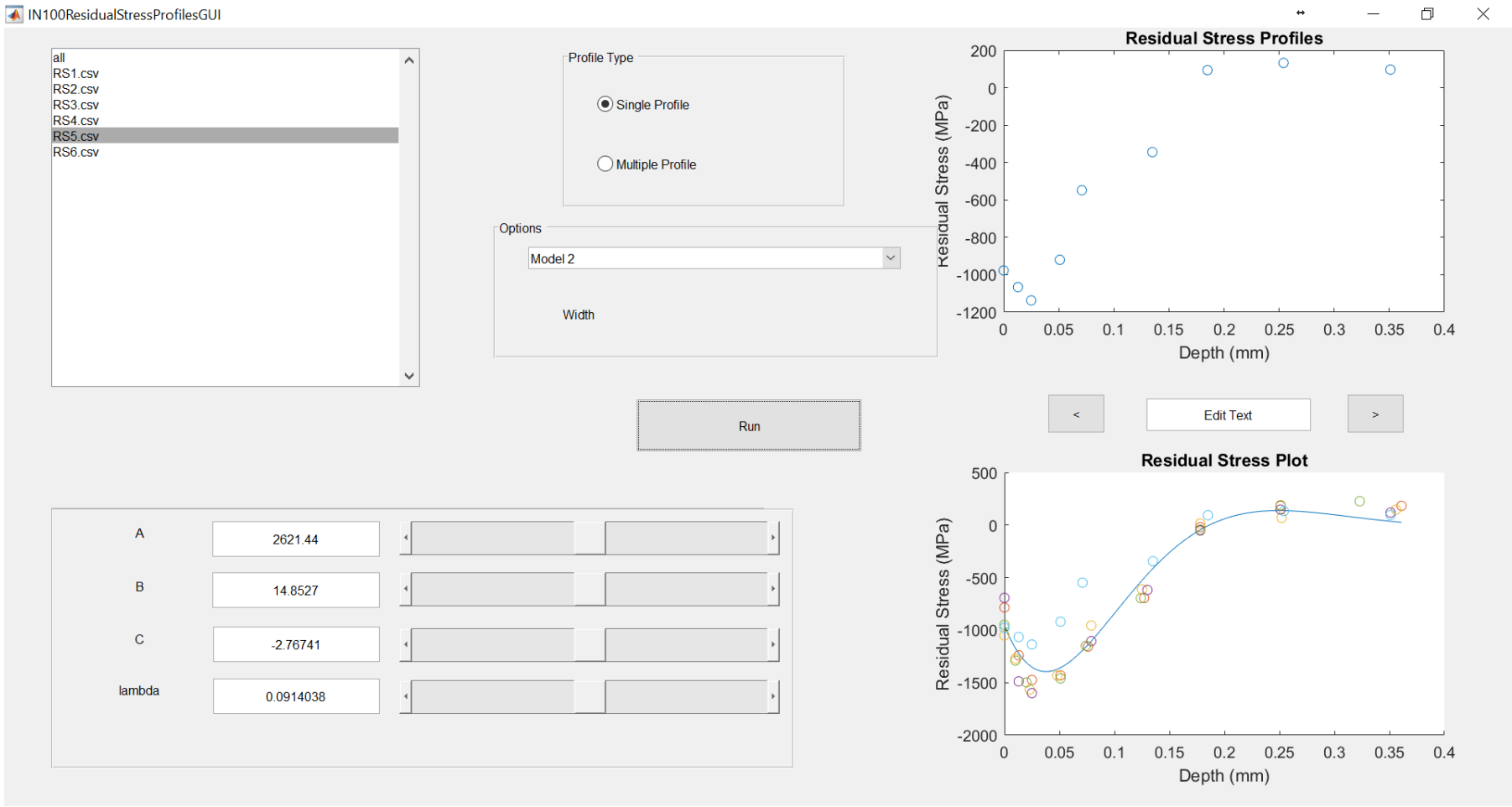
$$\sigma(x) = Asin(Bx + C)Exp\left(-\frac{x}{\lambda}\right)$$

Working to include Kriging to the GUI

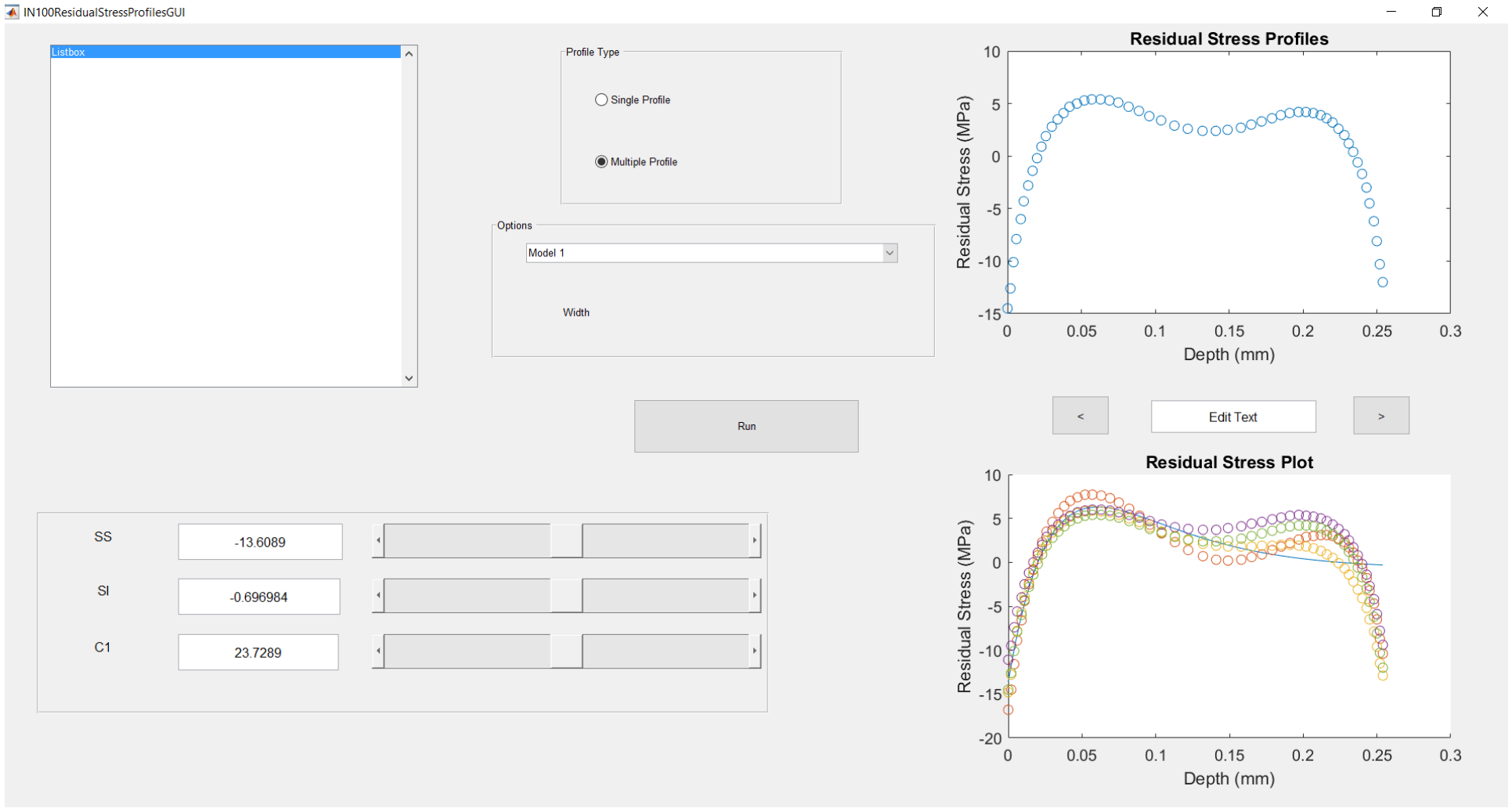
* *User Manual for ZENCRACK™ 7.1*, Zentech International Ltd., Camberley, Surrey, UK, September, 2003.

** R. VanStone, "F101-GE-102 B-1B Update to Engine Structural Durability and Damage Tolerance Analysis Final Report (ENSIP), Vol. 2," General Electric, p. 5-2-2.

Single Profile Model I & II



Mult. Profile Model I



Variogram Selection

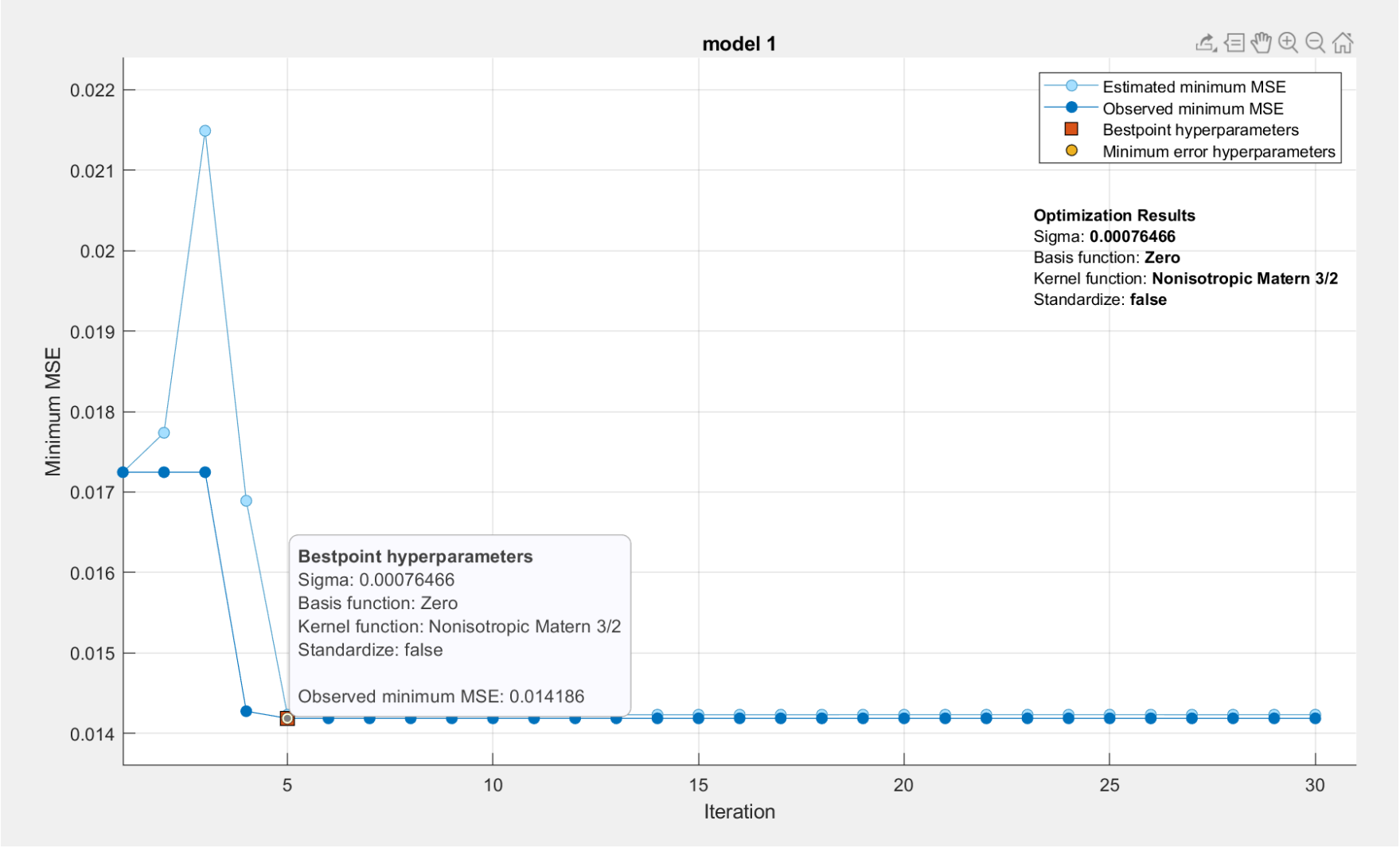
Study to find best Kriging Variogram for our data
Initial study performed with data provided by Carlson. I Need more data to have better conclusions

Variogram Selection

Kernel function – The software searches among:

- Nonisotropic Rational Quadratic
- Isotropic Rational Quadratic
- Nonisotropic Squared Exponential
- Isotropic Squared Exponential
- Nonisotropic Matern 5/2
- Isotropic Matern 5/2
- Nonisotropic Matern 3/2
- Isotropic Matern 3/2
- Nonisotropic Exponential
- Isotropic Exponential

Optimization Tool



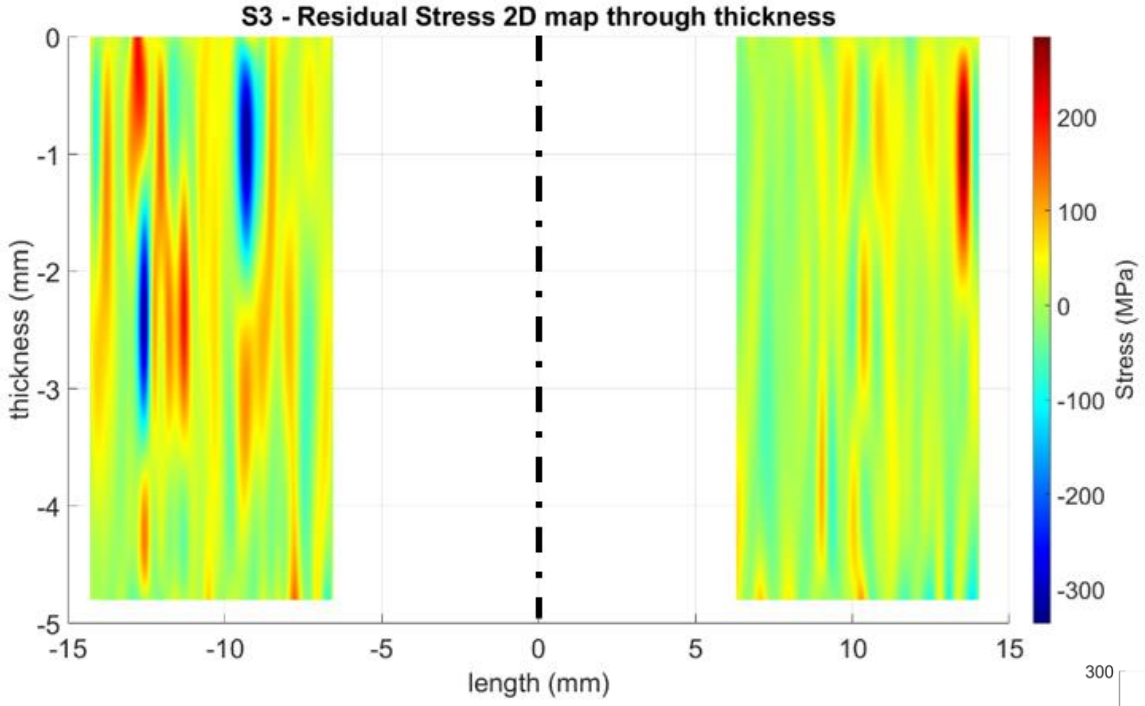
RS – Force Equilibrium

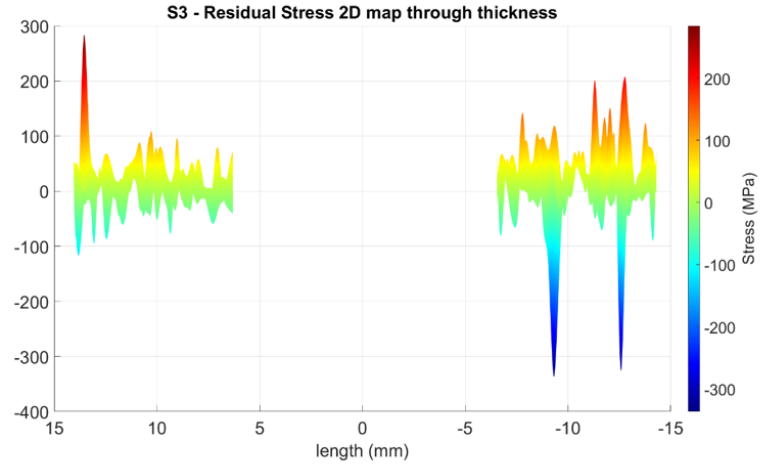
$$\int_{o}^{Thickness} \sigma(x)dx = 0$$

Our residual stresses models (Deterministic or Probabilistic) need to Account for force equilibrium.
How this group is planning to incorporate equilibrium.

- Constrained Kriging?

Reduce Variation





Residual stress characterization for cold expansion utilizing spatial statistics: The SpARS methodology

Dallen L. Andrew, Ph.D.
Hill Engineering LLC
916.701.5045 | dlandrew@hill-engineering.com

ERSI 2020 Virtual Workshop

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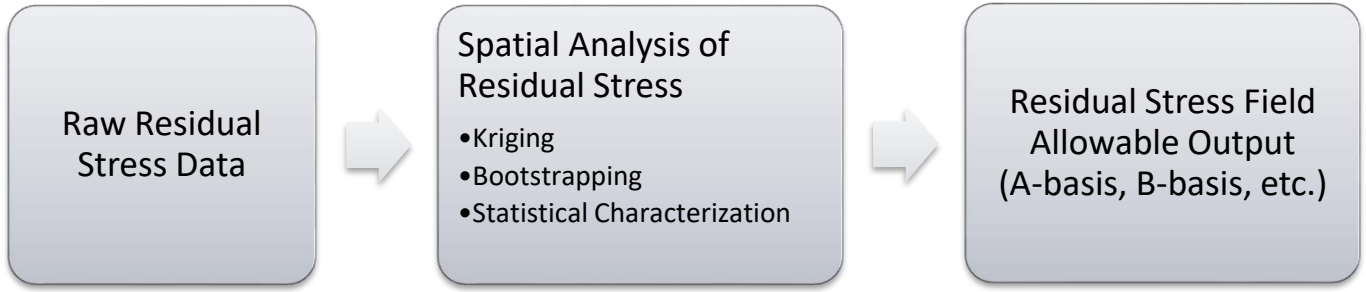
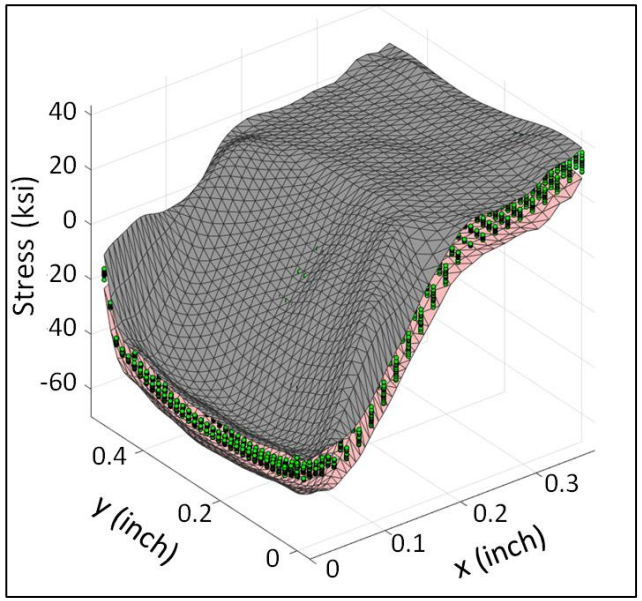
ENGINEERED RESIDUAL STRESS IMPLEMENTATION

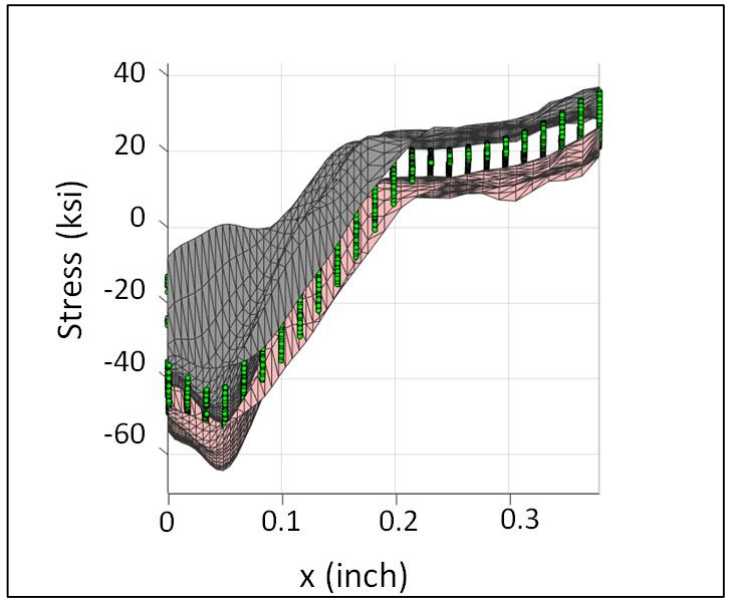
Spatial Analysis of Residual Stress (SpARS)

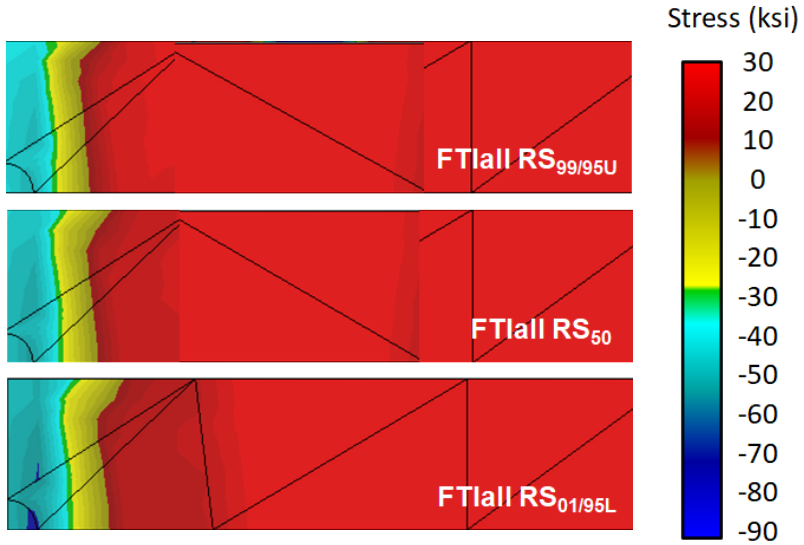
- Purpose
  - Develop process to statistically quantify RS fields from Cx by utilizing spatial statistical methods, then quantify impact on analytical fatigue crack growth life



- Results: Residual Stress
  - Upper and lower tolerance bound surfaces created from RS data





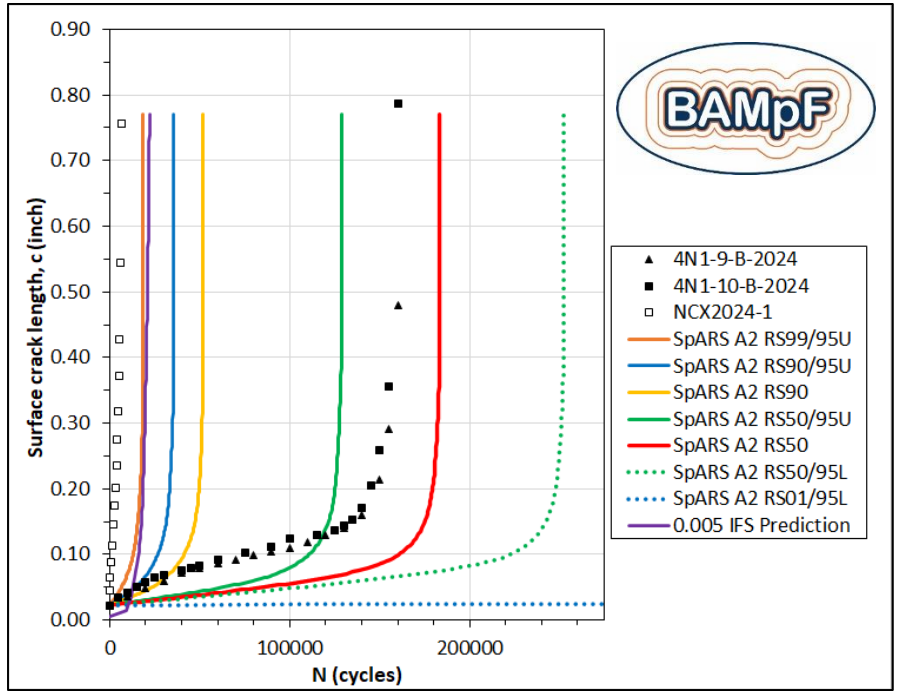


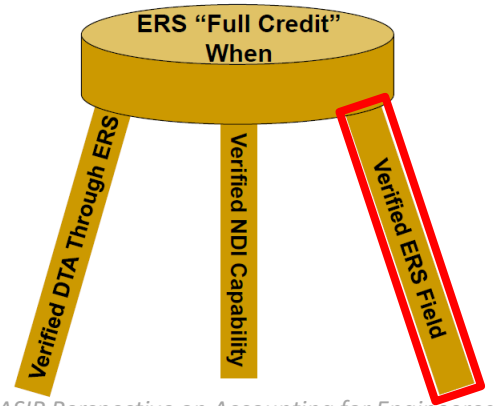
Andrew et al. Characterization of residual stresses from cold expansion using spatial statistics. Fatigue Fract Eng Mater Struct. 2020; 1– 14.

ERSI
ENGINEERED RESIDUAL STRESS IMPLEMENTATION

Spatial Analysis of Residual Stress (SpARS)

- Results: Crack Growth
  - 2024-T351, D=0.5", t=0.25", min %Cx
  - Analyses performed using BAMpF
  - Benefit from SpARS allowable RS fields compared to 0.005" approach
  - Selected upper tolerance bound was $RS_{50/95U}$
- Conclusion:
  - SpARS addresses one leg of stool and is an acceptable means of compliance for the draft structures bulletin:
    - "Multiple residual stress field characterizations must be used to generate a statistical representation that quantifies the cold expansion…variability, with the less compressive 95% upper bound statistical representation…to be utilized in all crack growth analyses utilized for fleet management."





Babish C. ASIP Perspective on Accounting for Engineered Residual Stress in Damage Tolerance Analysis. Paper presented at: Aircraft Structural Integrity Program Conference. 2017; Jacksonville, FL.

Stress gradient surrogate model using Principal Components Analysis (PCA)

SOUTHWEST RESEARCH INSTITUTE®

John McFarland, David Riha, Laura Hunt

This presentation was from the NASA Layered Pressure Vessel Project dealing with weld residual stresses – the method is currently being demonstrated on ERS-type profiles

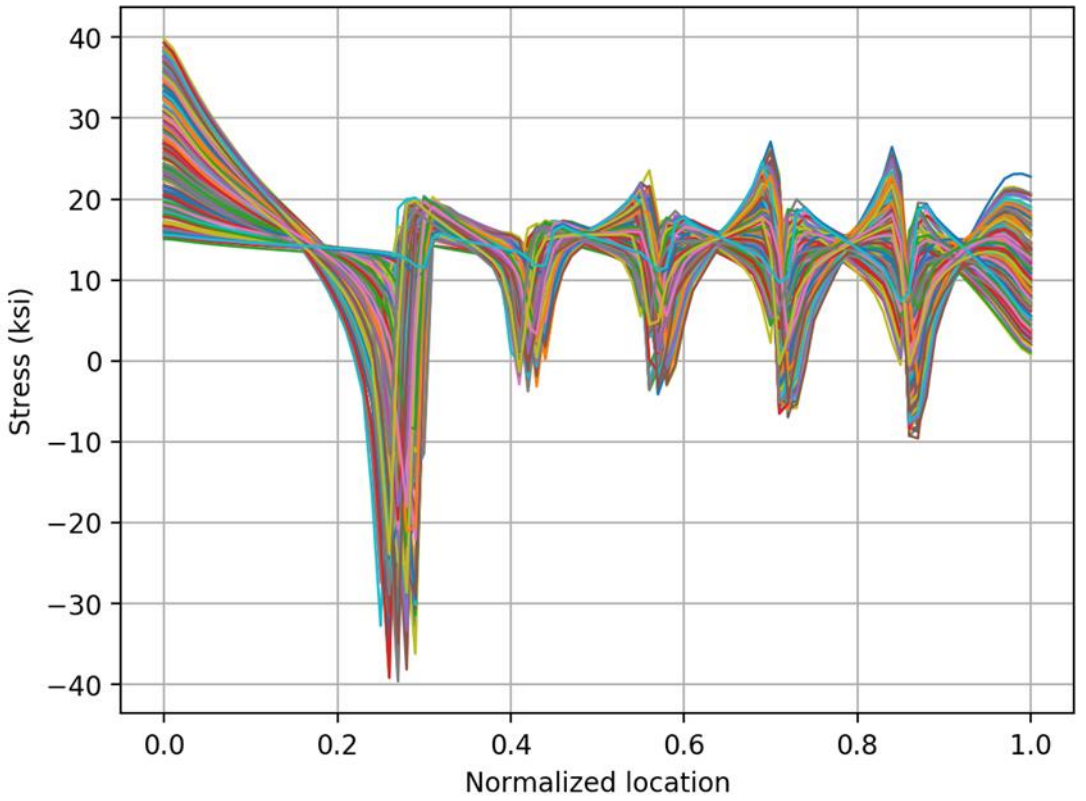
Overview

Objective

- Create a fast-running surrogate model that is capable of predicting stress gradient (in given direction and at particular location) as a function of a set of selected variables

Approach

- Use Latin Hypercube DOE to generate surrogate model training data over range of values for input variables
- Use Principal Components Analysis (PCA) to express stress gradient using a reduced set of coordinates
- Fit Gaussian Process (GP) regression models to predict PC scores, which can be used to reconstruct full stress gradients



- 250 axial stress gradients in a pressure vessel weld based on 7-variable DOE
- 101 points along each gradient

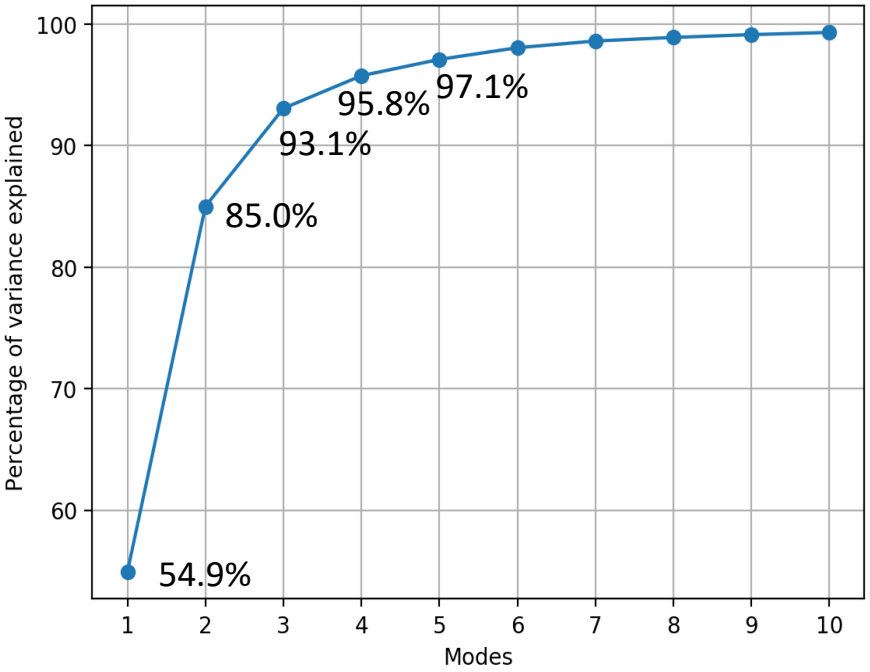
PCA variance explained

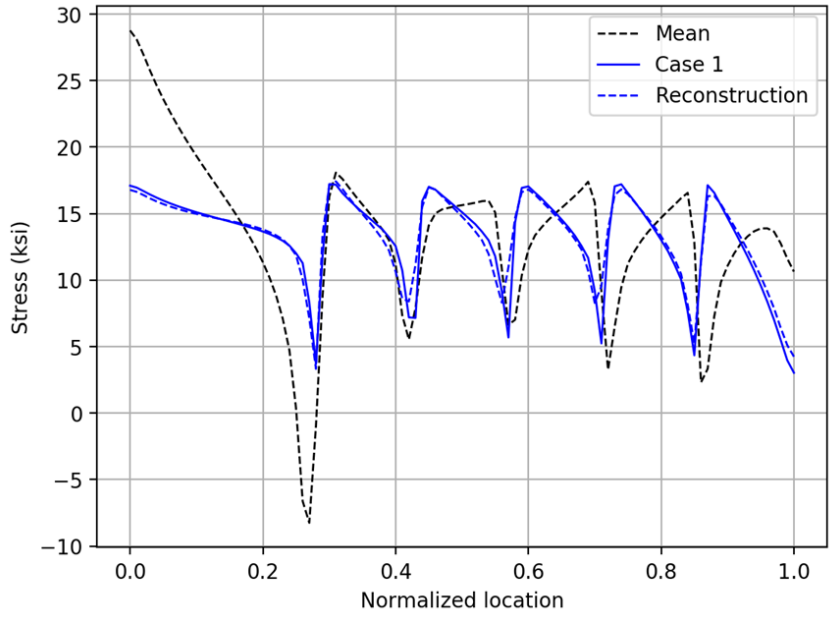
- Singular values from PCA decomposition are related to amount of variance explained by each mode
- For these data, between 4 and 10 modes can capture majority of variation in the stress gradients
- The bottom figure shows the reconstructed stress gradient for Case 1 using only the first four modes

$$\boldsymbol{Y} = \boldsymbol{U\Sigma V}^T$$

RS fields | Shape Vectors | Singular Values

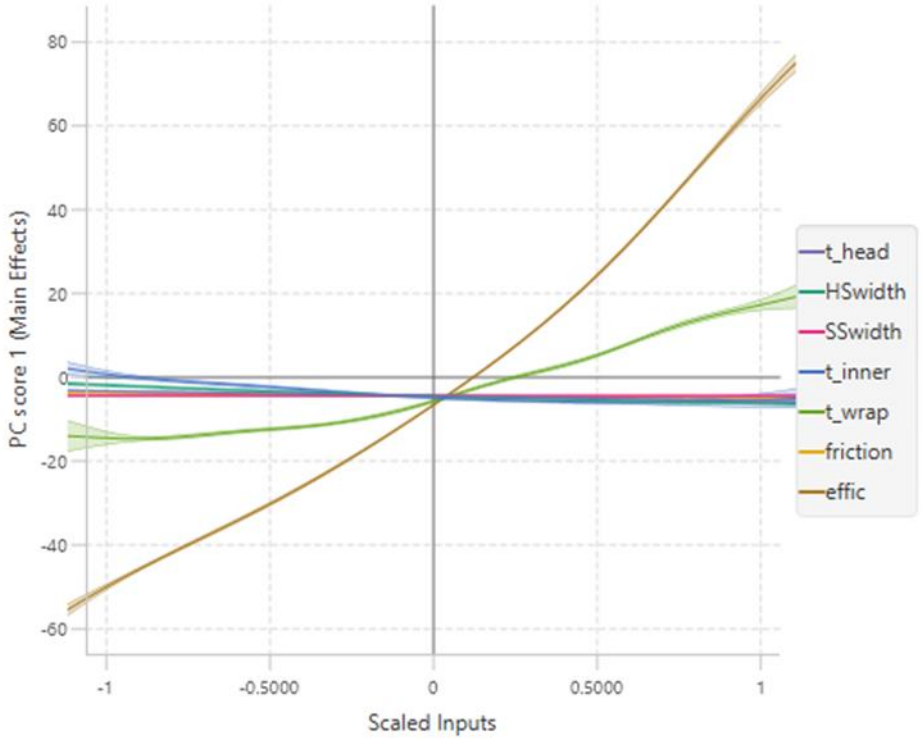
$$\begin{bmatrix} Y_{1,1} & \cdots & Y_{1,n} \\ \vdots & \ddots & \vdots \\ Y_{m,1} & \cdots & Y_{m,n} \end{bmatrix} = \begin{bmatrix} U_{1,1} & \cdots & U_{1,n} \\ \vdots & \ddots & \vdots \\ U_{m,1} & \cdots & U_{m,n} \end{bmatrix} \begin{bmatrix} \Sigma_{1,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Sigma_{n,n} \end{bmatrix} \boldsymbol{V}^T$$





Surrogate model for stress gradient prediction

- PCA represents the variations in the high-dimensional stress field (101 locations) using a smaller number of coordinates (the principal components)
- Then use response surface models to relate the input variables to the principal components (sensitivity analysis)
- Equilibrium is naturally enforced to a degree. Incorporating an optimization formulation can improve it further



Efficiency and wrap thickness have the strongest influence on mode 1 variation in the stress gradient

Activities for Upcoming Year

- Compile literature review on existing UQ studies
- Discuss and exercise USAF-funded Residual Stress Database (currently being organized by AP/ES)
  - 200 total RS profiles of varying completeness
- Provide support to other subcommittees as needed

Questions?