ERSI WORKSHOP: RISK AND UQ SUBCOMMITTEE OVERVIEW

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Southwest Research Institute
September 2017

OUTLINE

- Objectives for the ERSI Risk Subcommittee
- Review types of uncertainty and random variables for risk assessment
- 2017 Workshop goals
- Presentation by Laura Domyancic on residual stress methods in DARWIN
- Presentation by Juan Ocampo on residual stress methods using SMART

RISK SUBCOMMITTEE OBJECTIVES

- **GOAL**: Develop methods and procedures that enhance the overall understanding of how residual stress affects life prediction analyses by using uncertainty quantification
- **Questions we'd like to answer**:
  - By how much, with quantified confidence, does the engineered residual stress process affect life?
  - What are the most significant variables in the ERS process?
    - How can we maximize/minimize the benefits/damages of these variables?

TYPES OF UNCERTAINTY

- **Aleatory**: Uncertainty relating to inherent variation of a property
  - Fracture toughness variation
  - Material yield stress variation
- **Epistemic**: Uncertainty due to incomplete or erroneous data, "lack of knowledge"
  - Model form uncertainty
  - Measurement error
  - Unknown physics
- Example: Taking into account aleatory uncertainty makes the yield stress a random variable. Taking into account epistemic uncertainty makes the mean and standard deviation *themselves* into random variables.

RISK ANALYSIS CONSIDERING ERS

From Min Liao's 2016 ERSI Pres.

RA Inputs	ERS Impact	Significance / Confidence	How to quantify uncertainty and variability
Initial crack size distribution (ICSD/IDS/EIFSD): related to material, geometry, manufacturing, usage/load, plus analytical method for EIFSD	Nucleation mechanism (sub-surface cracking, fretting etc.), EIFSD changed if DaDTA method changed too	High / ?	Discussion -- below
Crack growth a-t curve: material/ geometry/loads fracture mechanics (LEFM) modeling	Short crack growth, near threshold growth, high quality data. New a-t with ERS	High / ?	Discussion -- below
Maximum stress distribution: stress exceedance, loads/usage	Nominally no effect	None / None	Discussion ?
Fracture toughness (Kc) distribution or residual strength: material, geometry/thickness, analytical method	Bulk ERS may affect Kc or σ_{RS} (integral panel with ERS), self-equilibrating RS effect? conservative assumption?	Low-Med / High?	Discussion ?
POD data: over 20 factors including human factor	Lower POD, higher a90/95	High / ?	Discussion
Repaired crack size distribution: repair & modification (drilling/grind-out/cold-work/peening/bonding…)	Different RCSD (CW) from ICSD (non-CW), EIFSD also depending on DaDTA method/curve. New a-t curve, new POD	High / ?	combine EIFSD and POD discussion

2017 WORKSHOP

- The ERS process introduces additional variables and uncertainties. The subcommittee's goals for this workshop is to
  - Review current methods within risk analysis that address residual stresses
  - Identify method development that remains (gaps)
- Although software programs will be discussed, our final product is methodology recommendations

Random Residual Stress Modeling in DARWIN

Probabilistic Integration of Material Process Modeling and Fracture Risk Assessment Using Gaussian Process Models

AIAA SDM Conference
Boston, Massachusetts
April 8-11, 2013

Michael Enright, John McFarland,
Craig McClung
Southwest Research Institute

Scientific
Forming
Technologies
Corporation

Wei-Tsu Wu, Ravi Shankar
Scientific Forming Technologies Corporation

Presented by:
Laura Domyancic
Southwest Research Institute

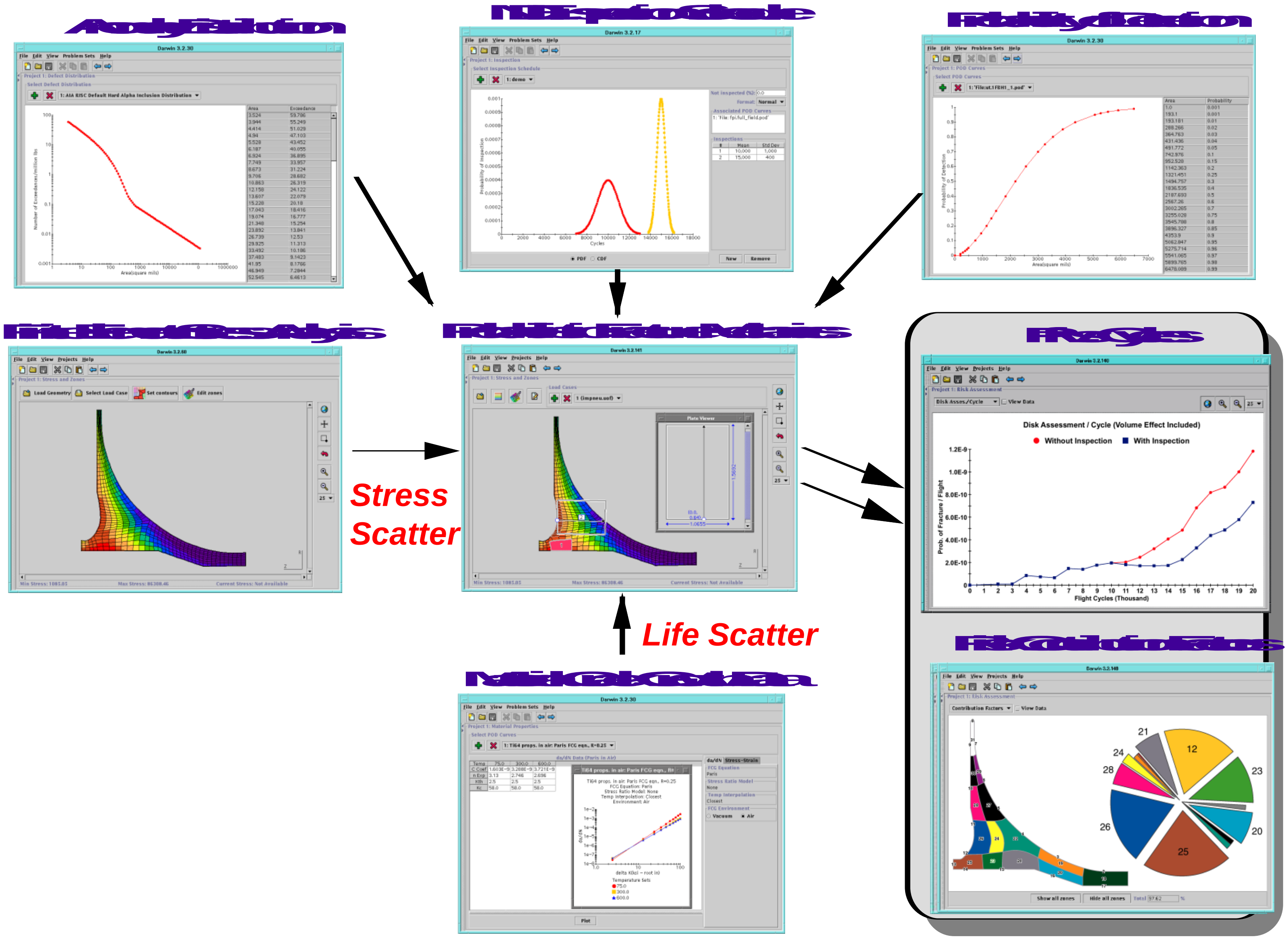
ERSI Workshop 2017

Acknowledgments

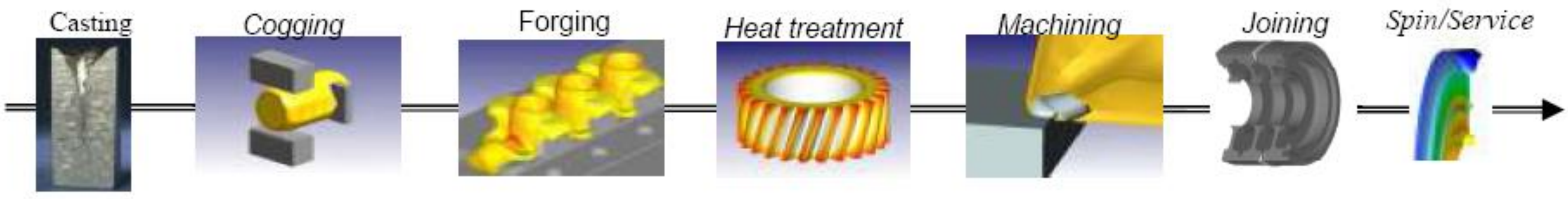
- Funding for this effort was provided by the US Air Force Research Laboratory
  - Rollie Dutton, AFRL Program Monitor
- Primary funding for DARWIN has been provided by the Federal Aviation Administration through a series of grants
  - Tim Mouzakis, FAA Engine and Propeller Directorate
  - Joe Wilson, FAA Technical Center
  - Industry Steering Committee (GE, Honeywell, P&W, Rolls-Royce)
- Technology implemented in DARWIN® software

DARWIN Overview

Design Assessment of Reliability With INspection



Integration with Manufacturing Process Simulation



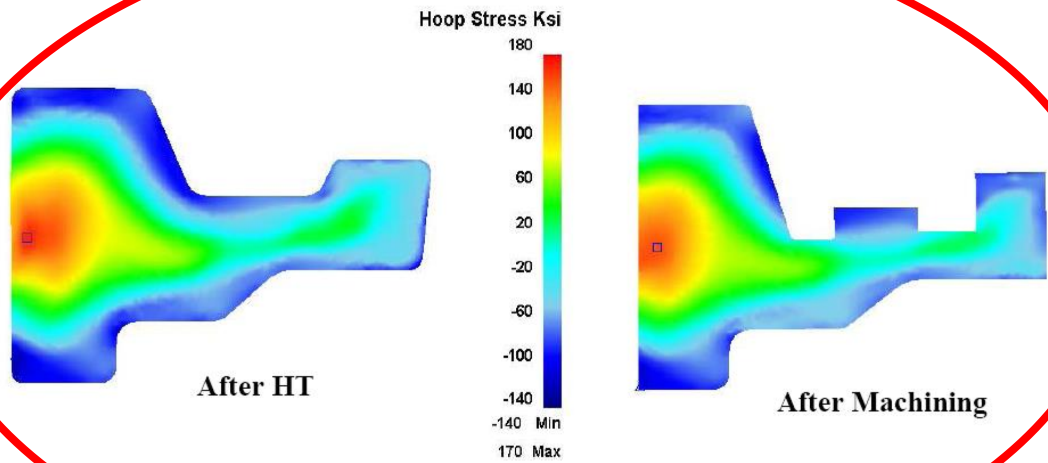
Link DEFORM output with DARWIN input

- Finite element geometry (nodes and elements)
- Finite element stress, temperature, and strain results
- Residual stresses at the end of processing / spin test
- Location specific microstructure / property data
- Tracked location and orientation of material anomalies

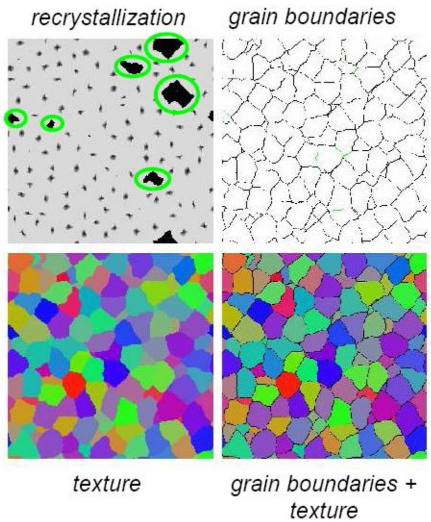
DEFORM™

Design Environment for FORMing

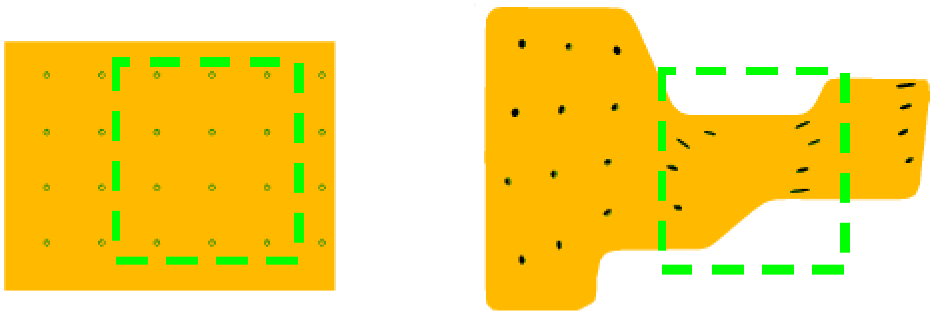
DARWIN-DEFORM Links



Residual Stresses



Microstructure

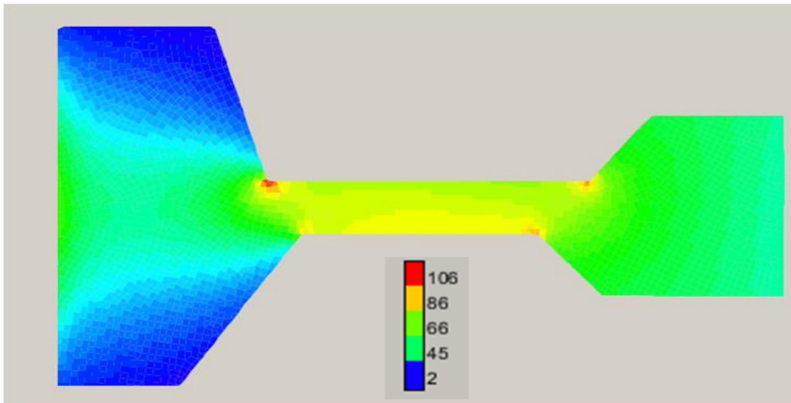


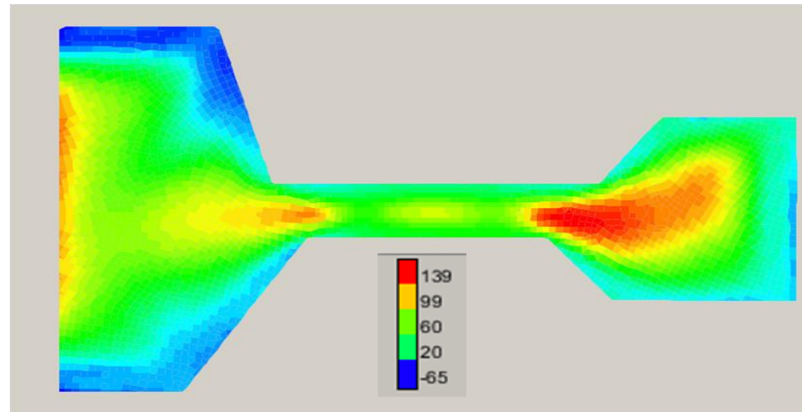
Anomaly Tracking and Deformation

Effect of Material Processing Residual Stress on FCG Life

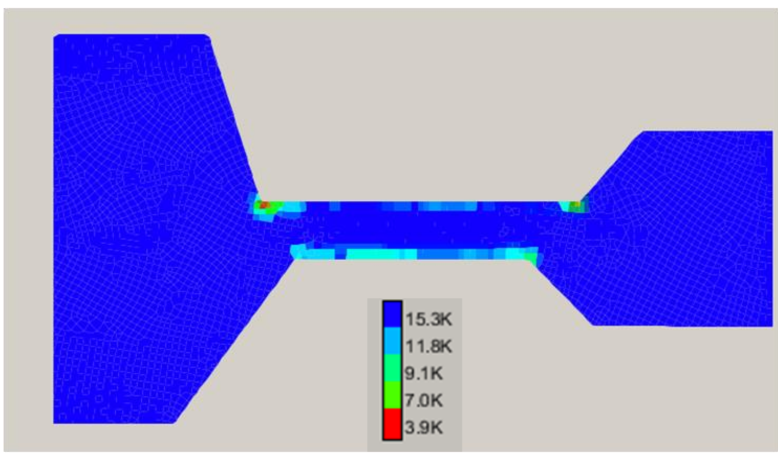
Without Residual Stress | With Residual Stress

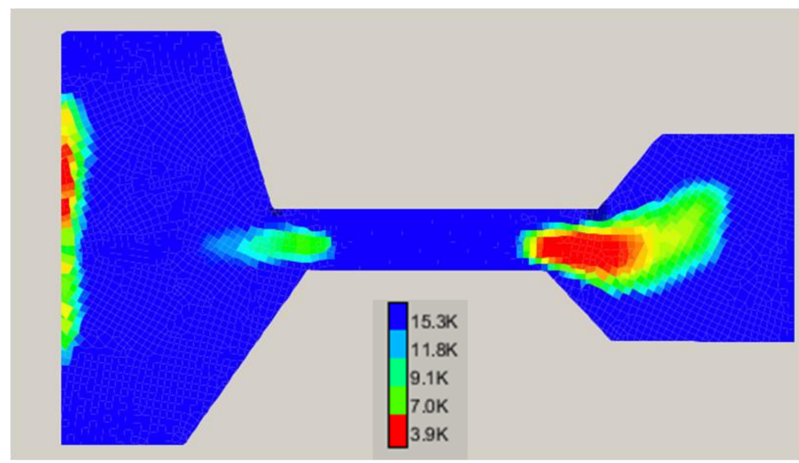
Stress





Life

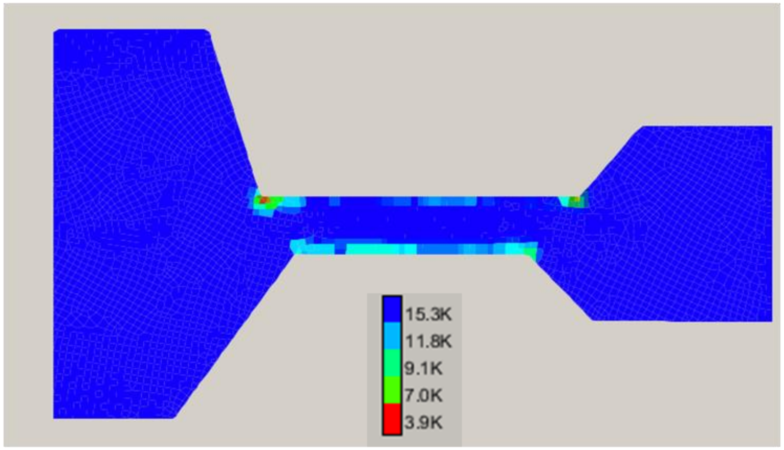


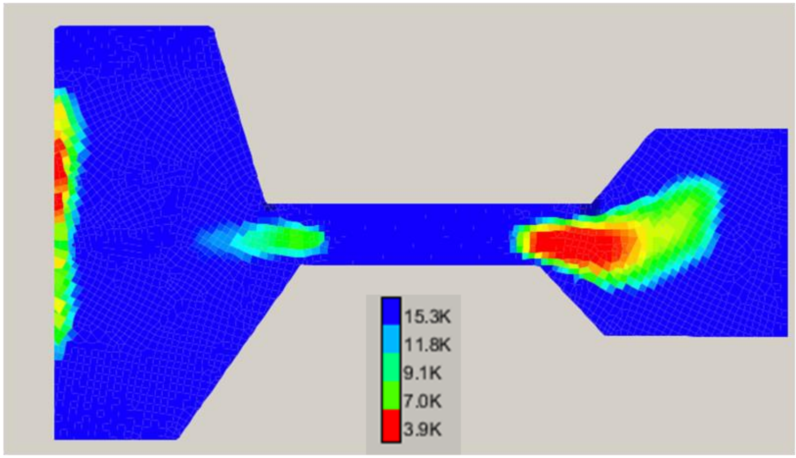


Effect of Material Processing Residual Stress on Risk

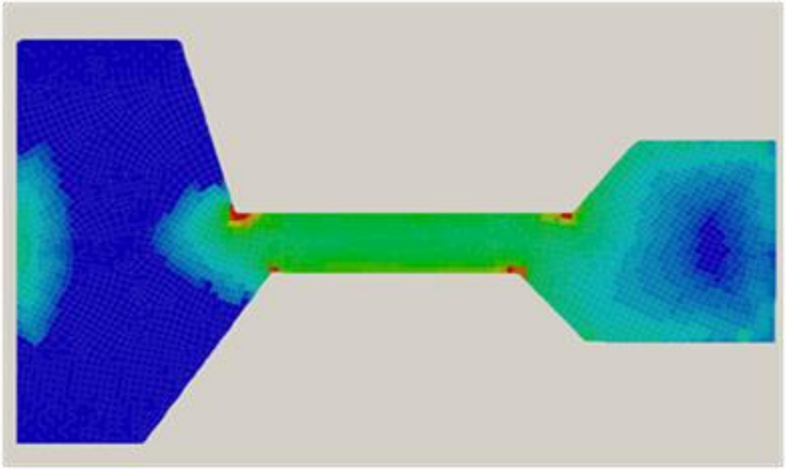
Without Residual Stress | With Residual Stress

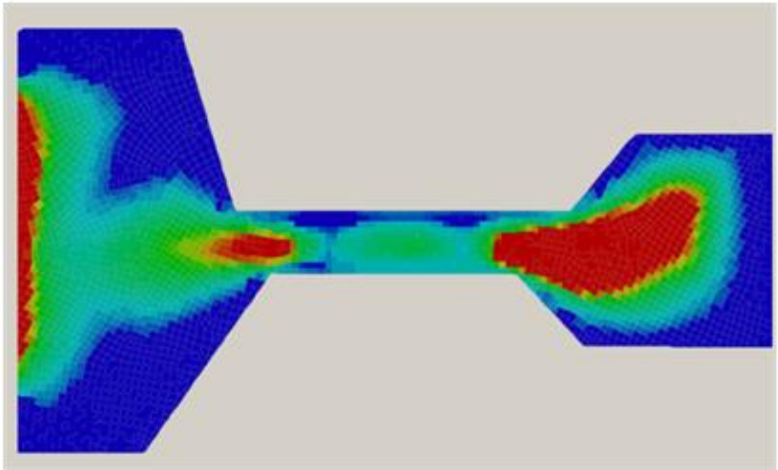
Life





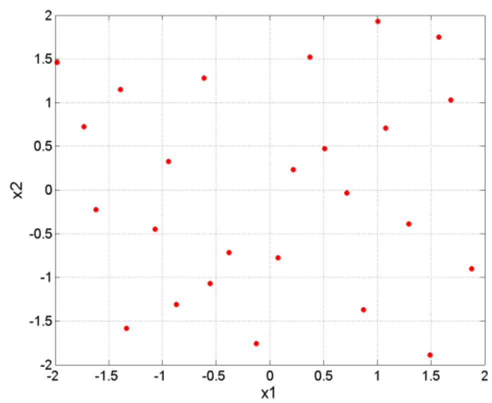
Risk





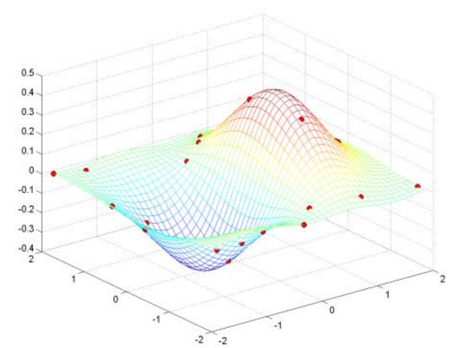
Phase II: Random Residual Stress Modeling

- Objective
  - Determine random residual stresses associated with material process modeling random input variables at any location within a component



Design of Experiments

- Approach
  - Design of Experiments
    - Perform deterministic DEFORM runs to obtain residual stress values at all FE nodes
  - Response Surface Fitting
    - Determine the residual stress response using Gaussian Process (GP) model
  - Monte Carlo Simulation
    - Propagate random variables through response surface



Response Surface

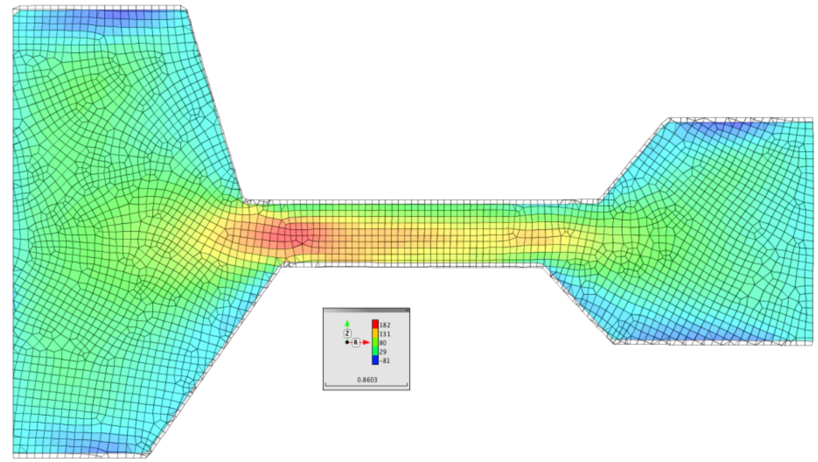
Demonstration Example: Modeling Random Residual Stresses

DEFORM
DOE

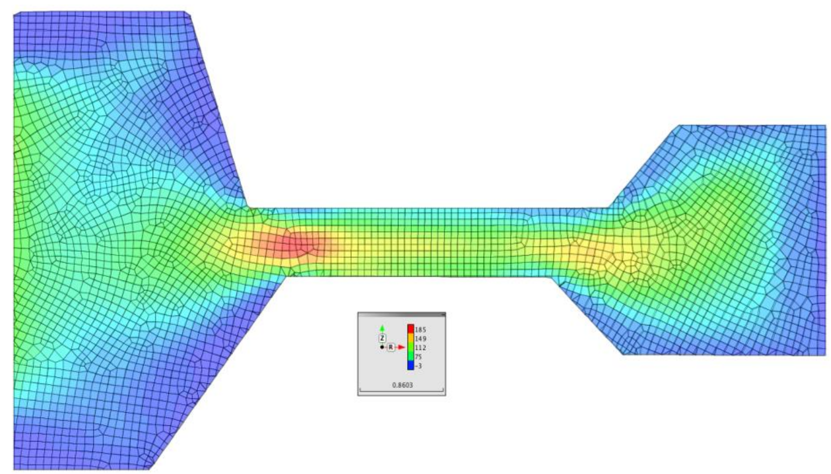
Stress Results Files

DARWIN

NESSUS
GP Model



residual stress DOE 1 contour

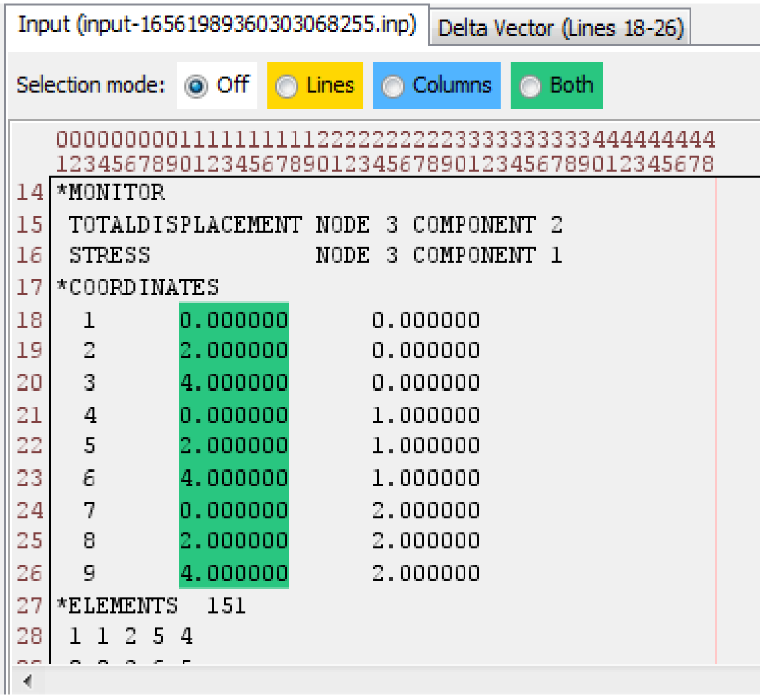


residual stress DOE 12 contour

Response Surface Generation

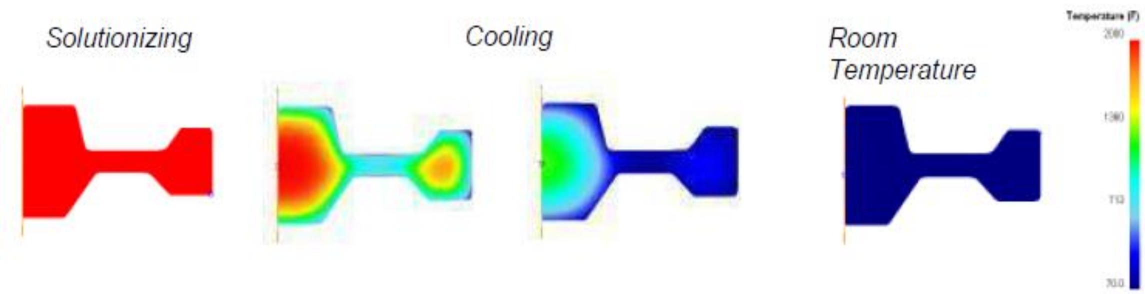
NESSUS software facilitates response surface generation:

- Defines input ranges or distributions
- Generates a design of input values to run
  - Supports multiple DOEs
- Interfaces with external numerical model
  - Variables are graphically mapped to input file
  - NESSUS generates input deck for each run
  - NESSUS can execute model and extract outputs
- NESSUS can fit the response surface
  - 1^{st} or 2^{nd} order polynomial
  - Gaussian Process model

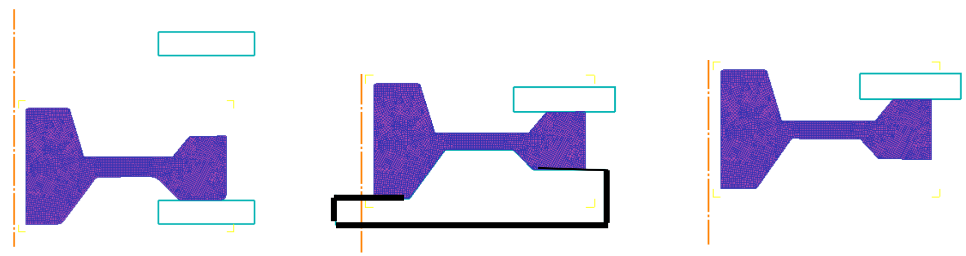


Residual Stress Model

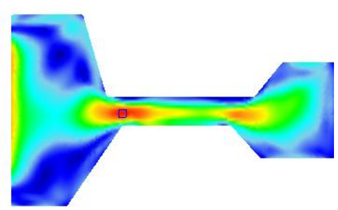
- Three DEFORM input random variables were considered:
  - ➢ Solution temperature



  - ➢ Material removal



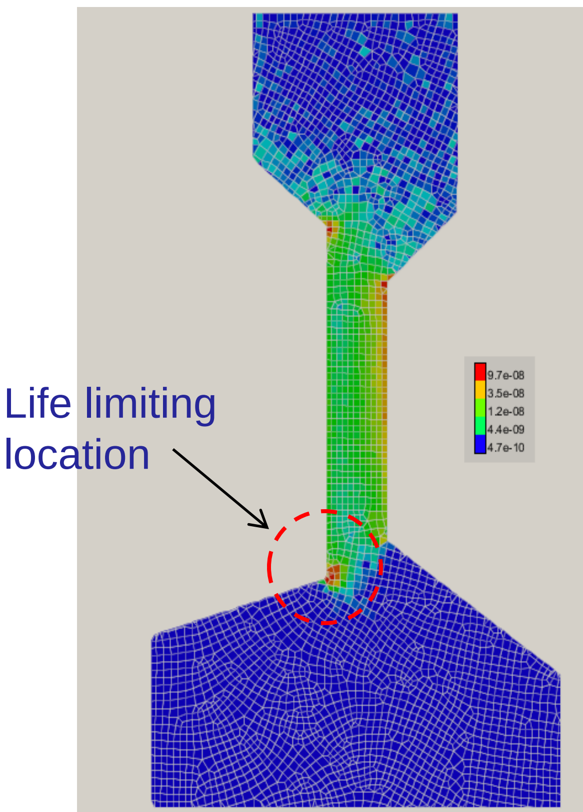
  - ➢ Spin test speed

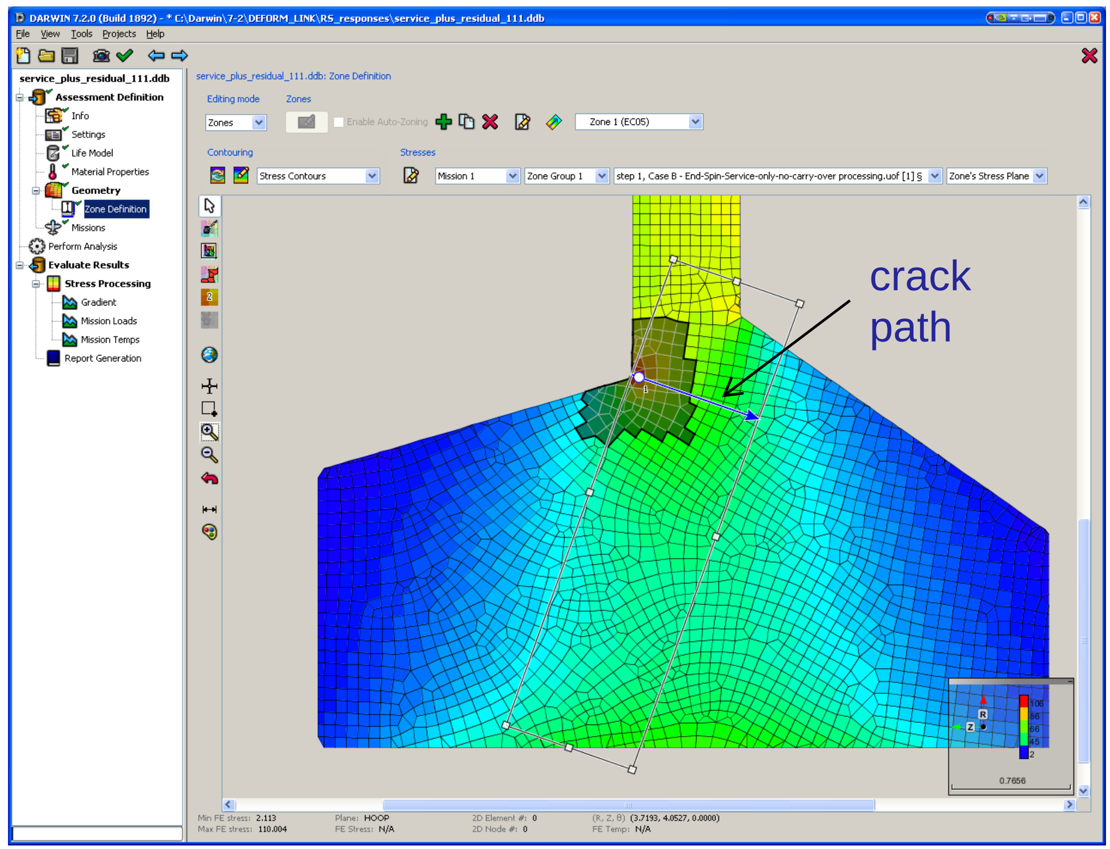


- DOE
  - ➢ Initial case: three-level full factorial design (Phase I results)
  - ➢ 27 training points – combined residual and service stress results

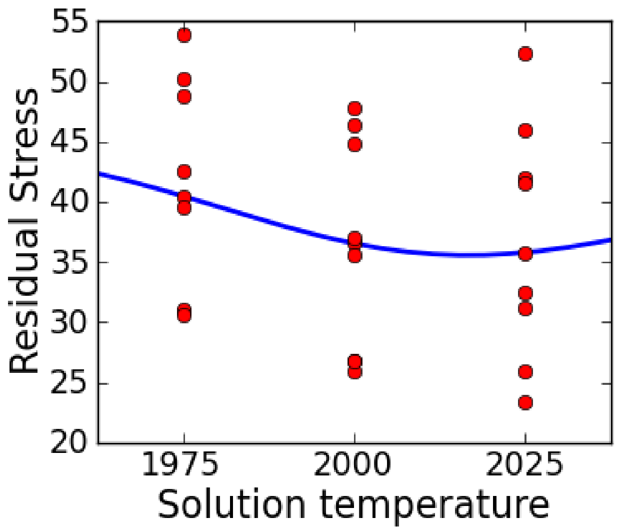
Demonstration Example

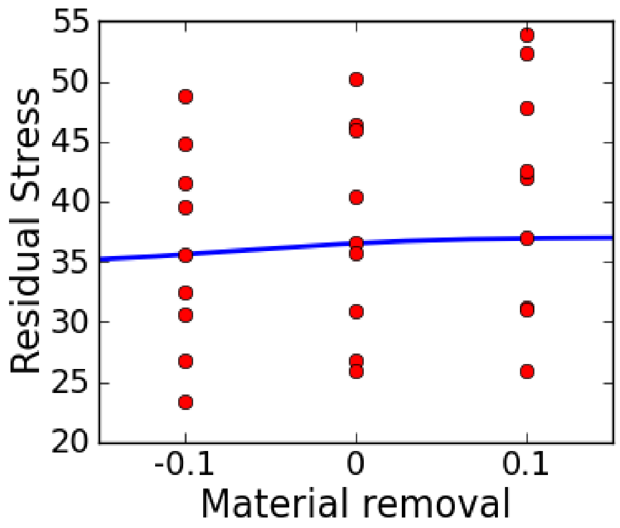
- Anomaly at life limiting location (service stress)
- Computed response surfaces for the following:
  - Individual locations – single response surfaces based on 27 training points each
  - Entire crack path - 100 locations along crack path

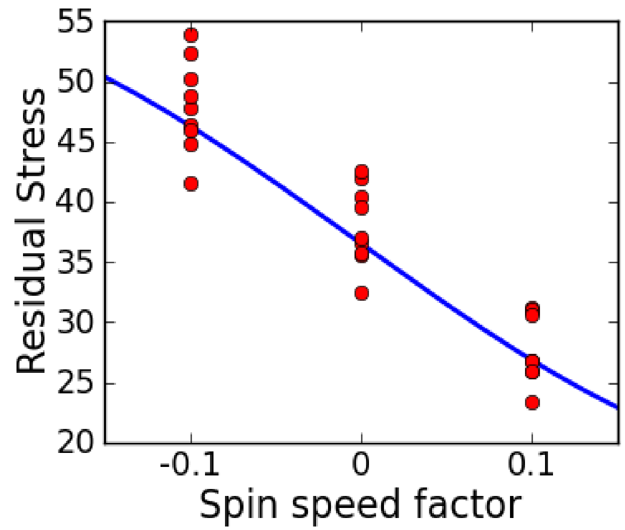


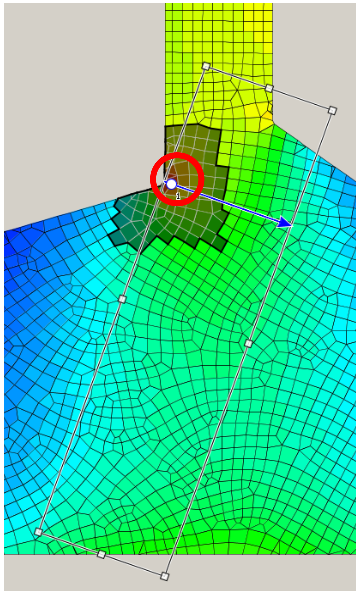


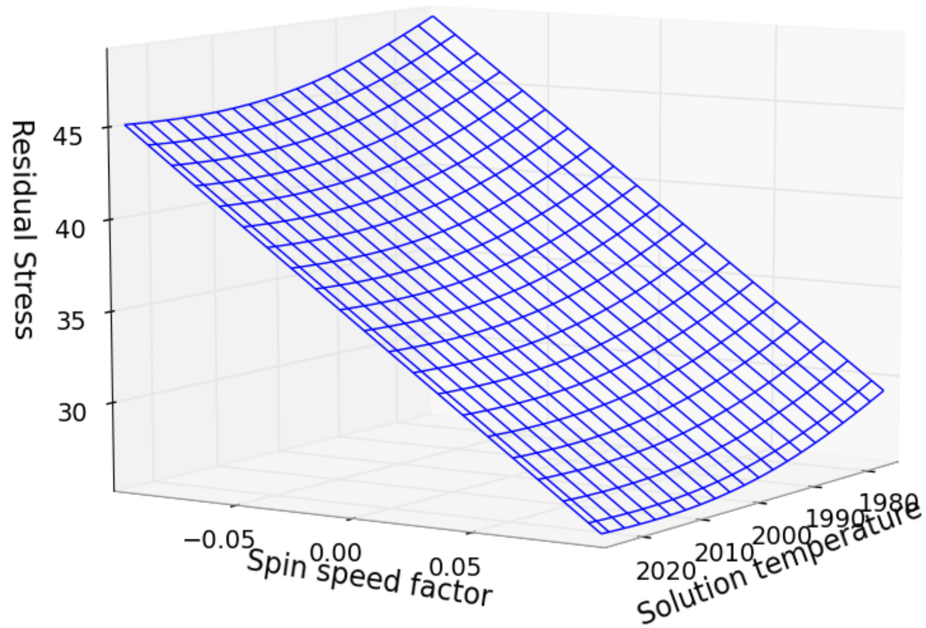
GP Response Surface at Location 1



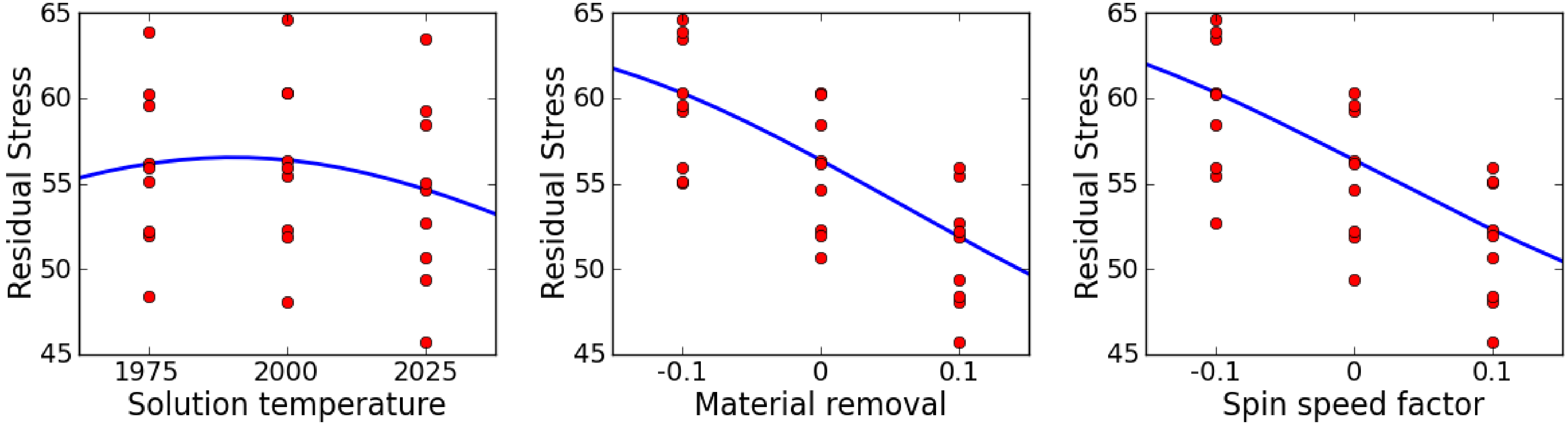


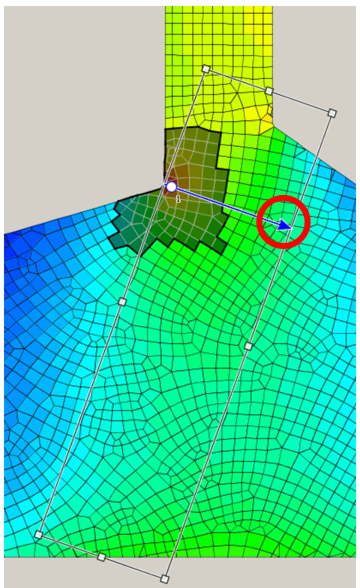


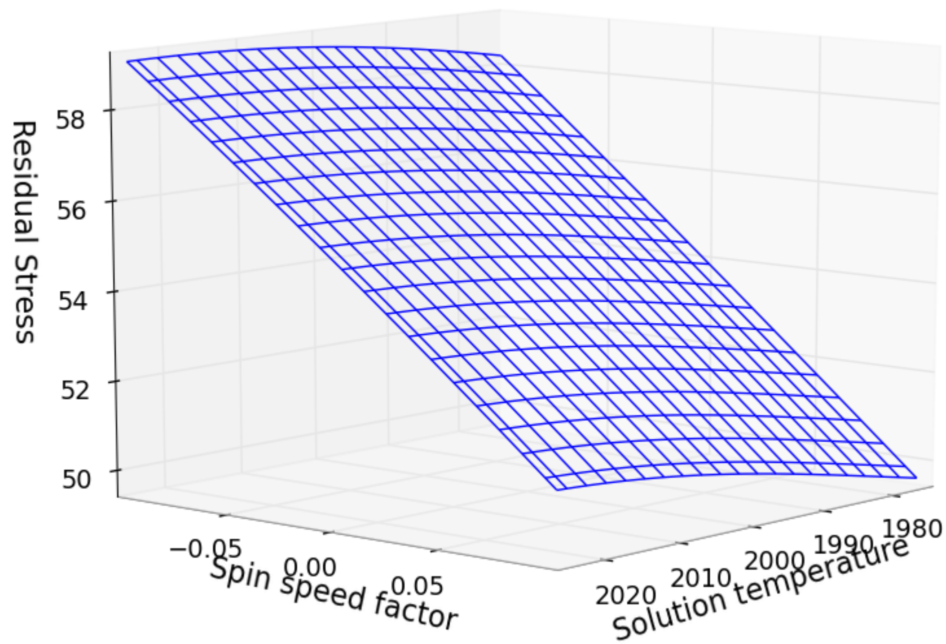




GP Response Surface at Location 100







Modeling the Stress Field Along the Entire Crack Path

- Principal Components Analysis (PCA) enables modeling of the variations in the high-dimensional stress field (100 locations) using a smaller number of coordinates (the principal components)
- The response surface models are used to relate the input variables to the principal components

One response surface for each principal component

$$\mathrm{RS}_1 : \mathbf{X} \to \alpha_1$$

$$\vdots$$

$$\mathrm{RS}_k : \mathbf{X} \to \alpha_k$$

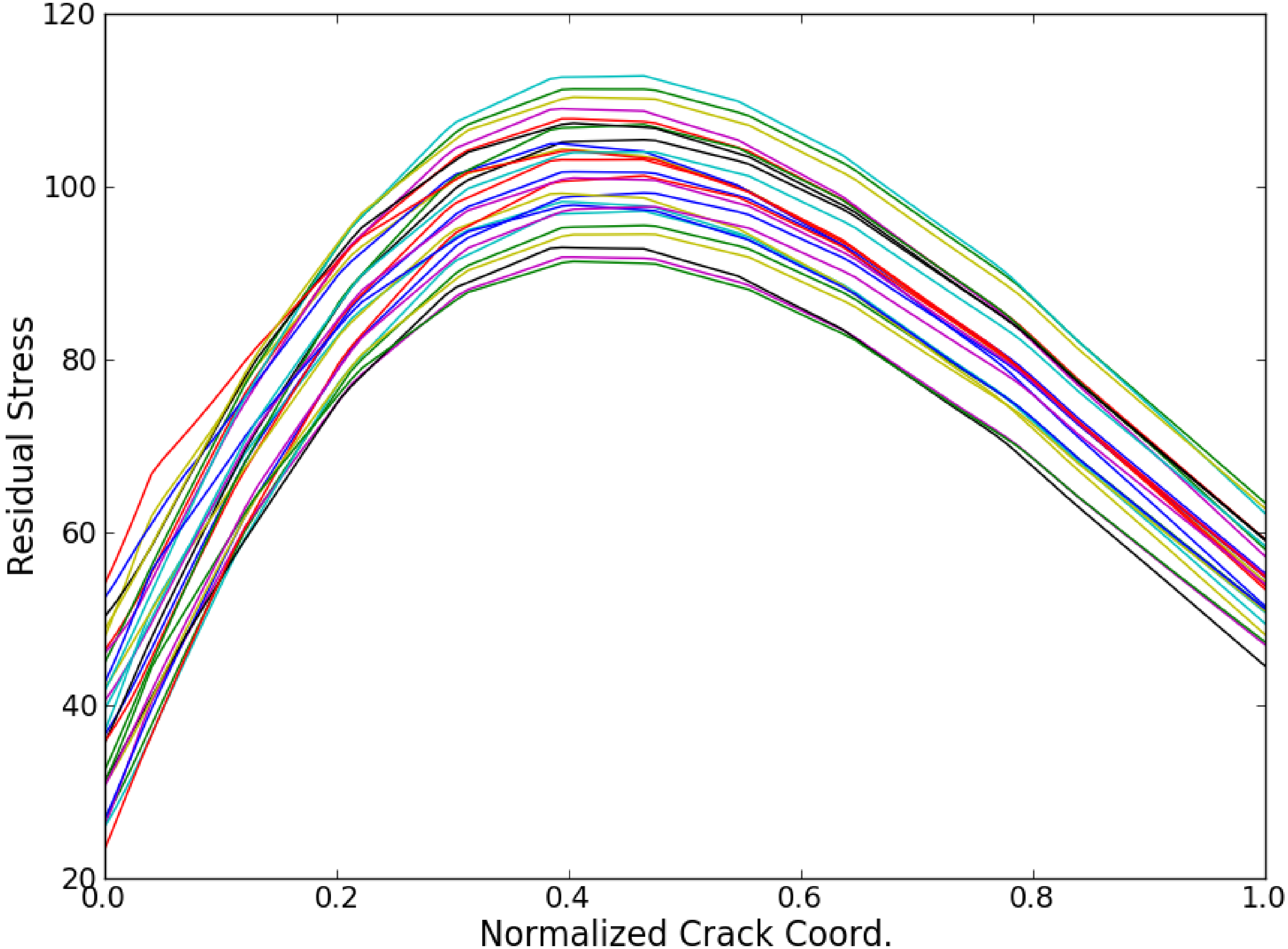
Project components back onto original space

$$\text{Stress Field} = \mathbf{U}^{(k)} \boldsymbol{\alpha}^{(k)} + \boldsymbol{\mu}$$

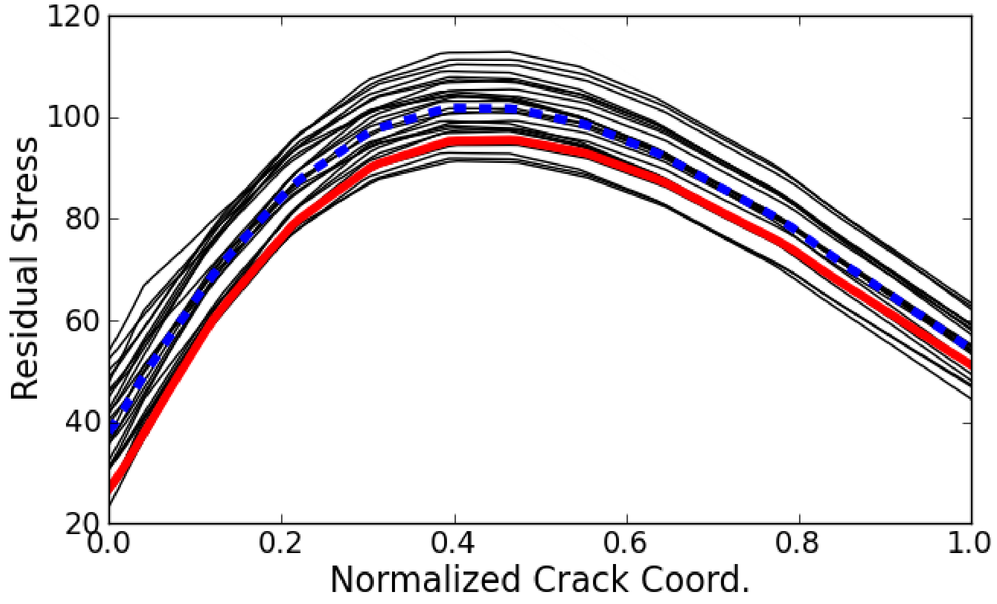
$\mathbf{U}^{(k)}$ contains first k eigenvectors of the covariance matrix

$\boldsymbol{\mu}$ is the stress field mean

Residual Stress Training Data (27 values) Along Crack Path



Principal Components Results

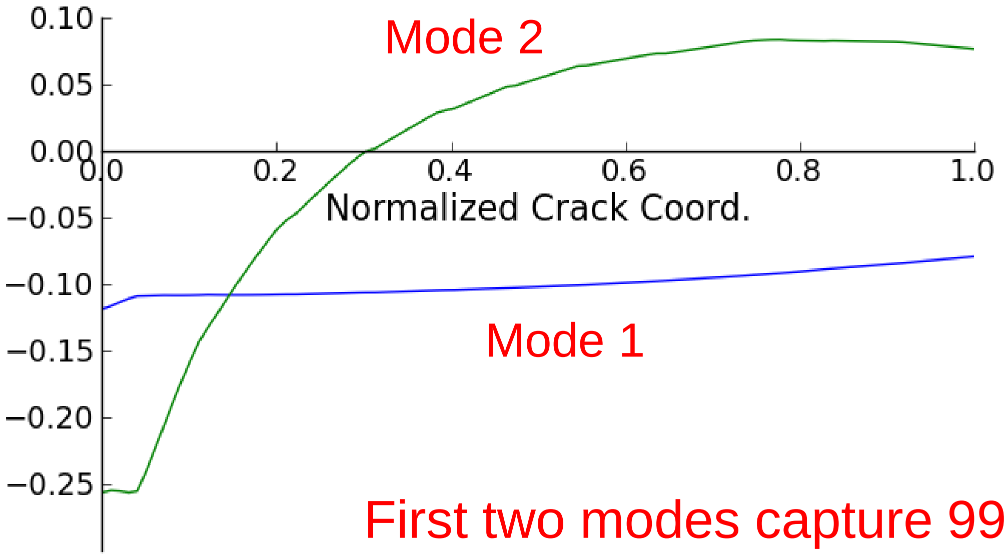


$$\text{Stress Field} = \mathbf{U}^{(k)}\boldsymbol{\alpha}^{(k)} + \boldsymbol{\mu}$$

Example: Case 2

$\alpha_2 = 16.6$

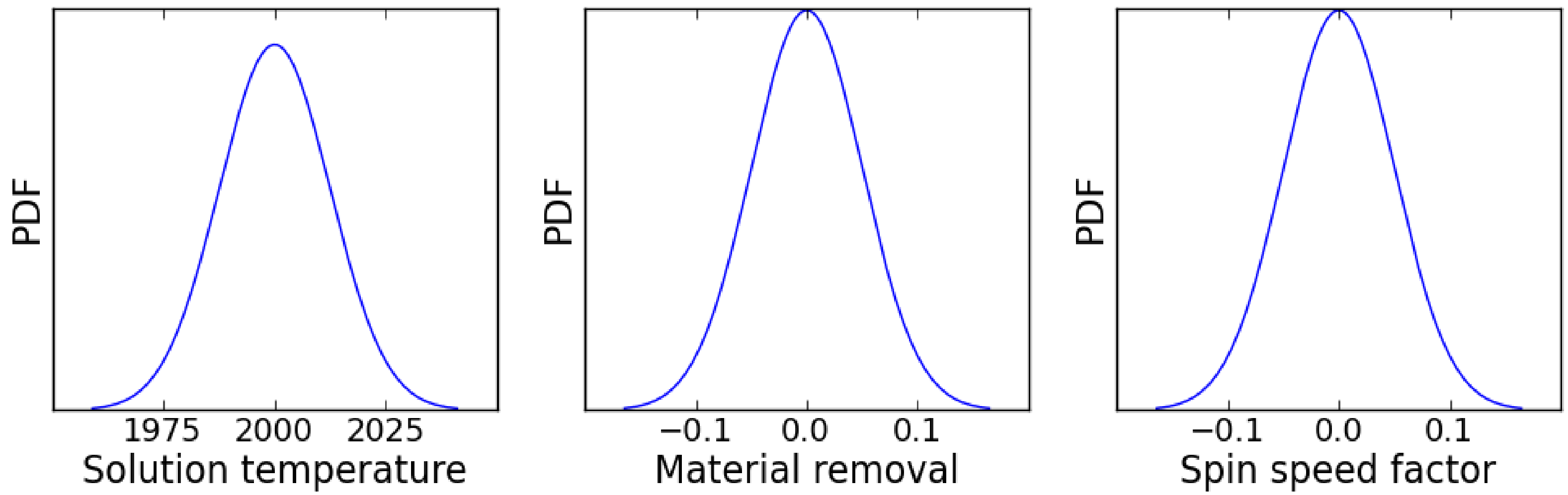
$\alpha_1 = 64.1$



First two modes capture 99.0% of total variation

Probabilistic Analysis

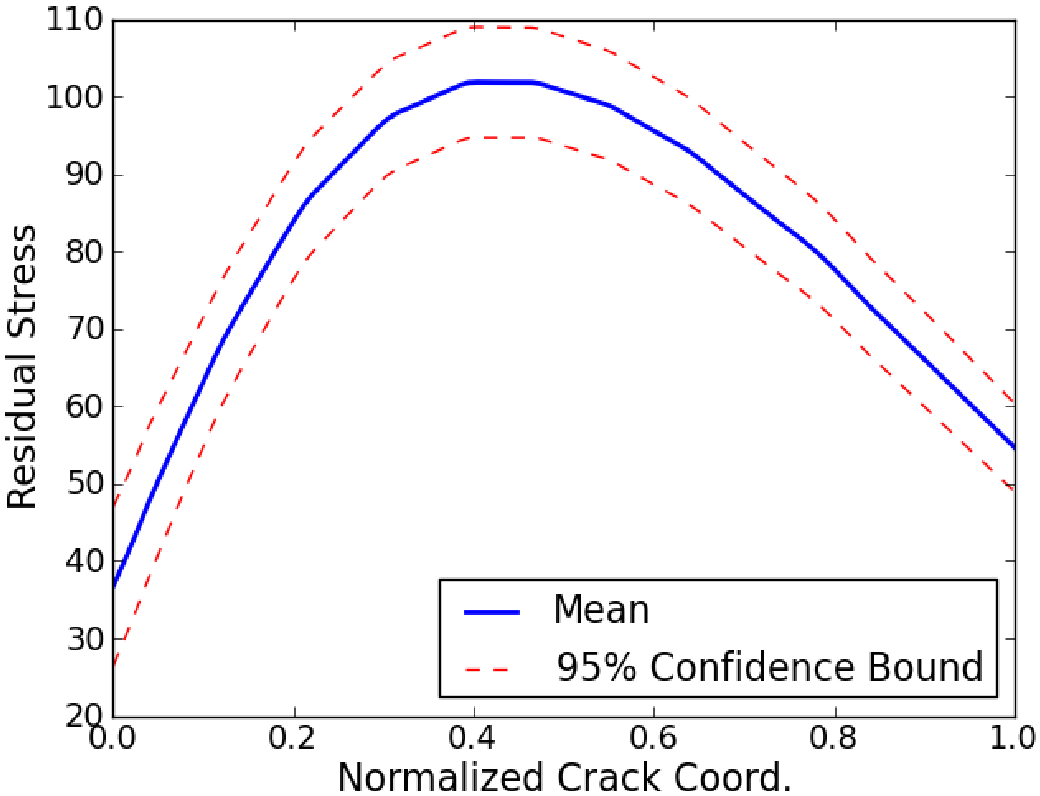
- The three input variables were modeled as normally distributed random variables:



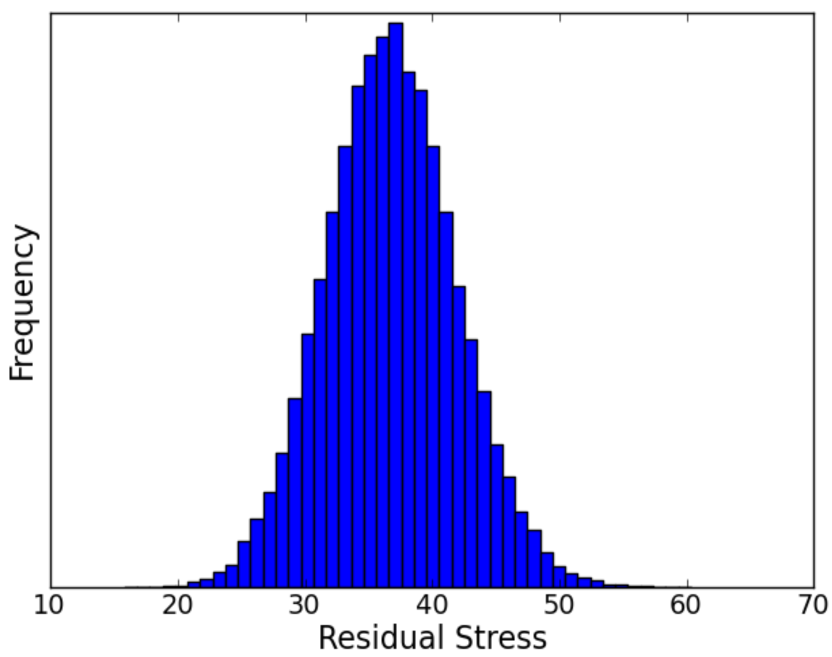
- Using Monte Carlo simulation, the random variables were propagated through the response surface
- The joint distribution of residual stress was identified at all 100 locations along the crack path

Random Residual Stress Results

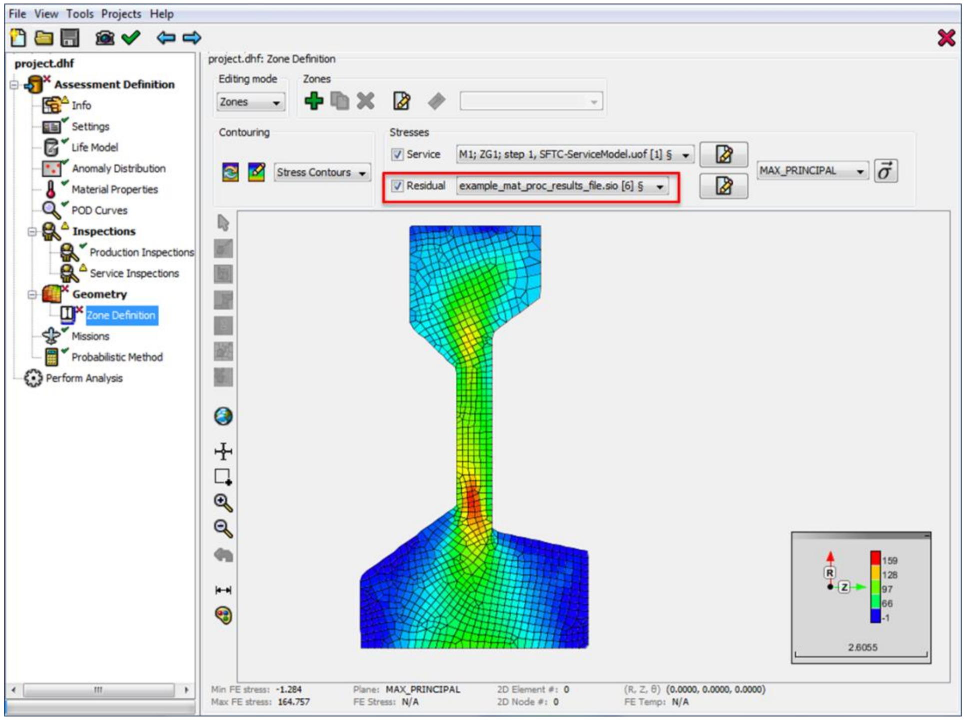
Mean and variation at all locations



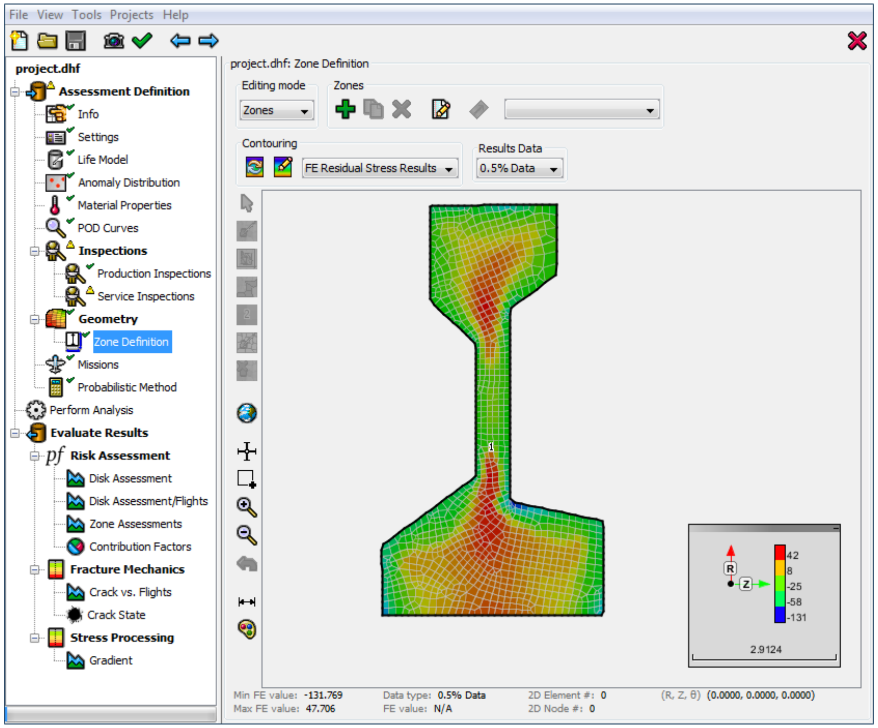
Distribution at Coordinate 0



Visualizing Random Residual Stresses in DARWIN

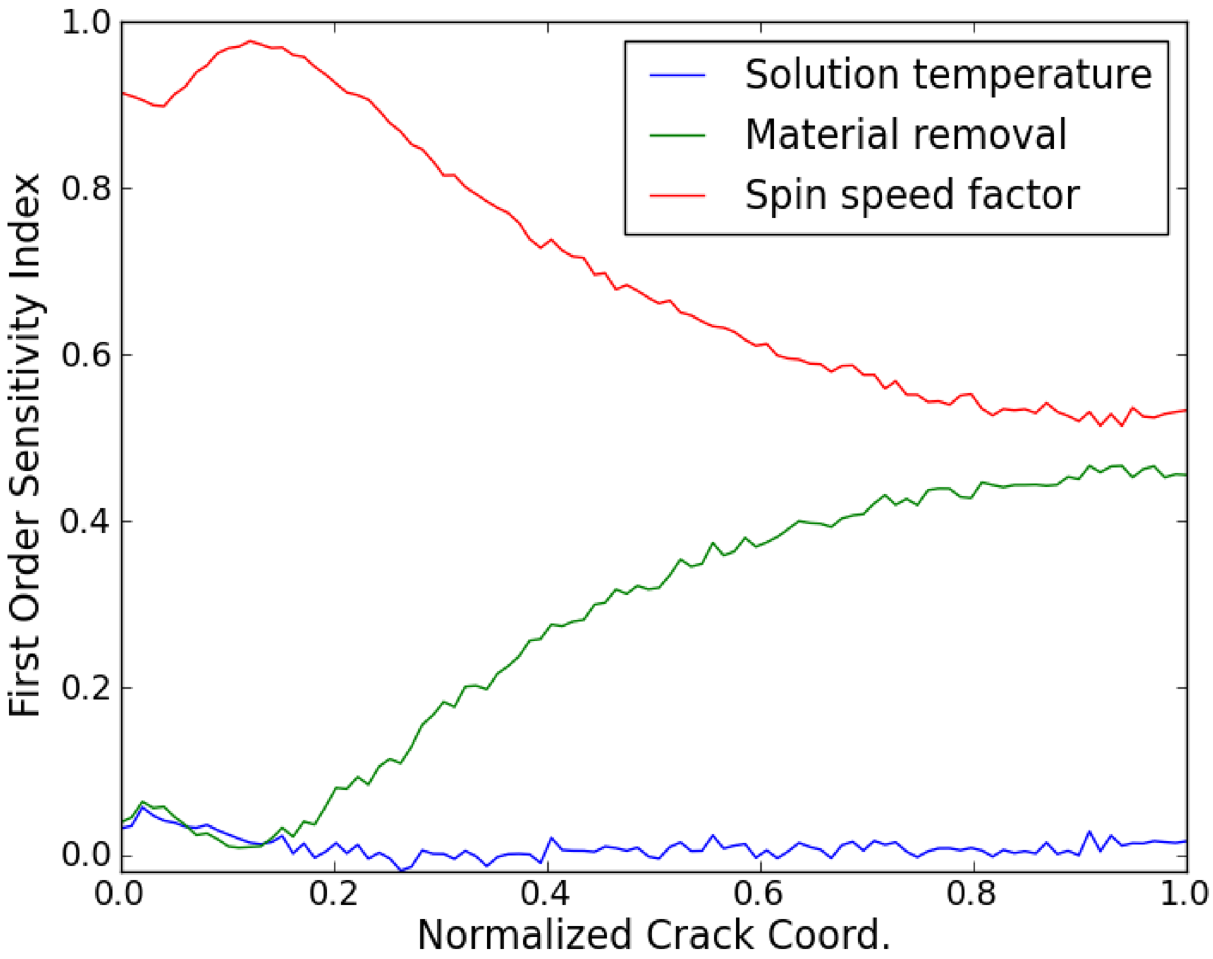


DEFORM Training Data



95th Percentile Response

Sensitivity Analysis



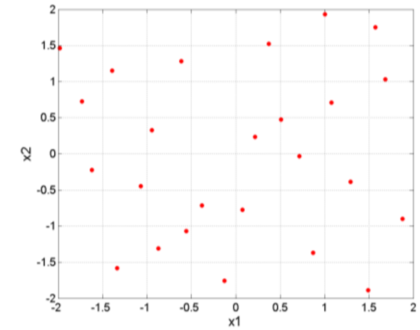
- First order sensitivity index describes fraction of variance in output attributed to each input

$$V\left(E\left(Y \mid X_i\right)\right)/V$$

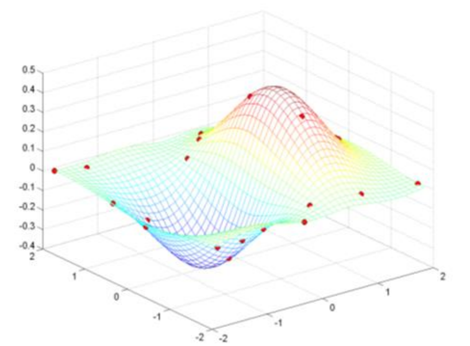
- Sensitivities are computed at each crack location

Summary: Random Residual Stress Modeling

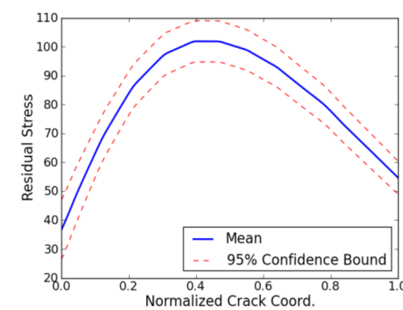
- Design of Experiments
  - ➢ Identify values of input variables for response surface construction in DEFORM using Latin Hypercube sampling
  - ➢ Perform deterministic DEFORM runs to determine residual stress values at all nodes within FE model
- Response Surface Fitting
  - ➢ Determine the residual stress response at selected locations within the FE model in DARWIN using Gaussian Process (GP) model
  - ➢ Determine response along the crack path in DARWIN using GP model combined with Principal Components Analysis
- Monte Carlo Simulation
  - ➢ Propagate random variables through response surface in DARWIN to determine the random residual stresses along the crack path and influence on life and risk values



Design of Experiments



Response Surface



Monte Carlo

Incorporating Residual Stresses into Probabilistic Damage Tolerance Analysis

Juan D. Ocampo and Alexander Horwath
St. Mary's University

Scott Carlson
University of Utah, Salt Lake City

Luciano Smith
Southwest Research Institute

Harry Millwater and Nathan Crosby
University of Texas at San Antonio

Engineered Residual Stress Implementation Workshop 2017
Salt Lake City, UT, September 21–22, 2017.

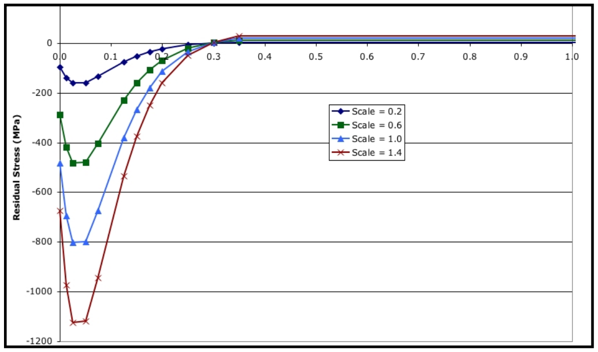
ERSI

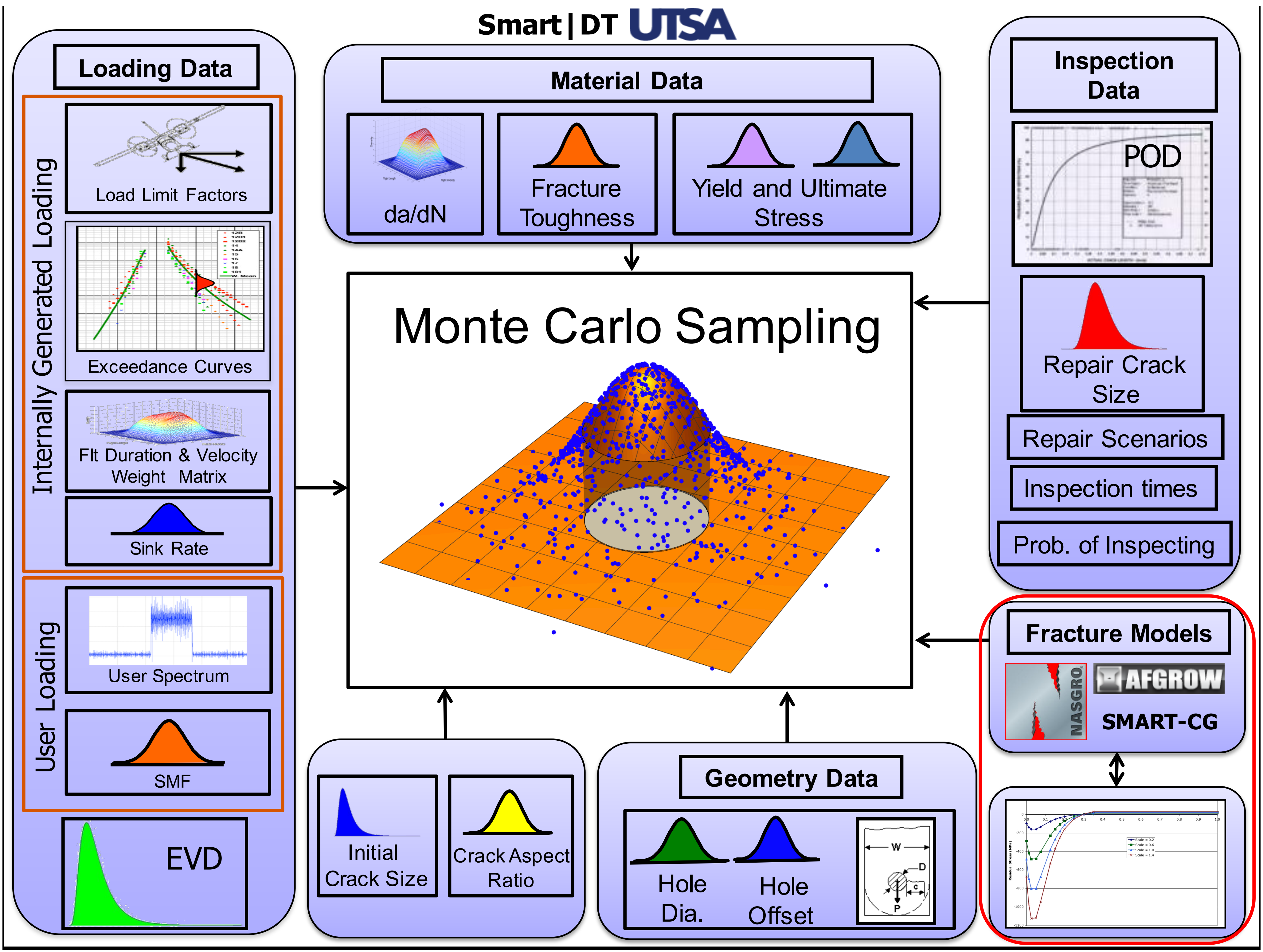
Outline

- ✓ SMART|DT Overview
- ✓ Residual Stresses Modeling Software
- ✓ Are RS needed in PDTA?
  - ✓ Sensitivity Study wrt. Remaining Useful Life
- ✓ Residual Stresses incorporated into PDTA
  - ✓ Deterministic Residual Stresses
- ✓ Future Plans

Probabilistic RS Profile

Deterministic RS Profile

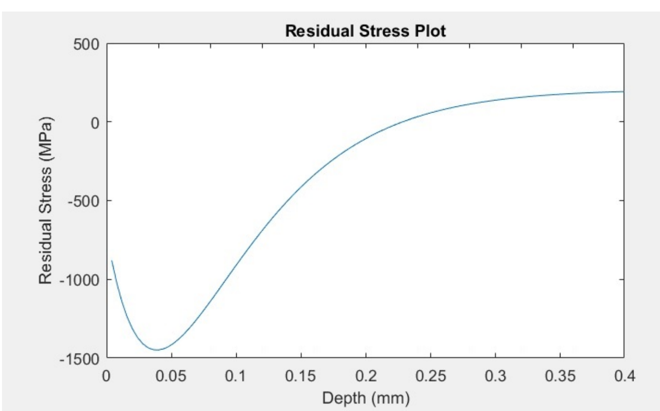




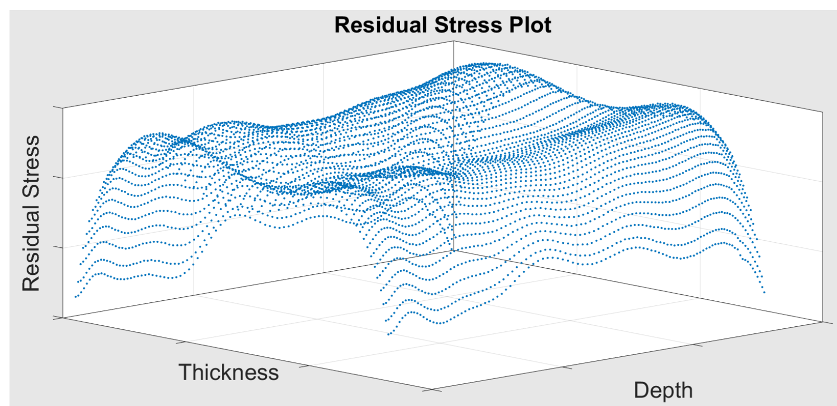
Smart | DT UTSA
Loading Data
Internally Generated Loading
Load Limit Factors
Exceedance Curves
Flt Duration & Velocity Weight Matrix
Sink Rate
User Loading
User Spectrum
SMF
EVD
Material Data
da/dN
Fracture Toughness
Yield and Ultimate Stress
Monte Carlo Sampling
Initial Crack Size
Crack Aspect Ratio
Geometry Data
Hole Dia.
Hole Offset
W
D
c
P
Inspection Data
POD
Repair Crack Size
Repair Scenarios
Inspection times
Prob. of Inspecting
Fracture Models
NASGRO
AFGROW
SMART-CG

Residual Stress Modeling Software

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



2D



3D

ERSI

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**

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

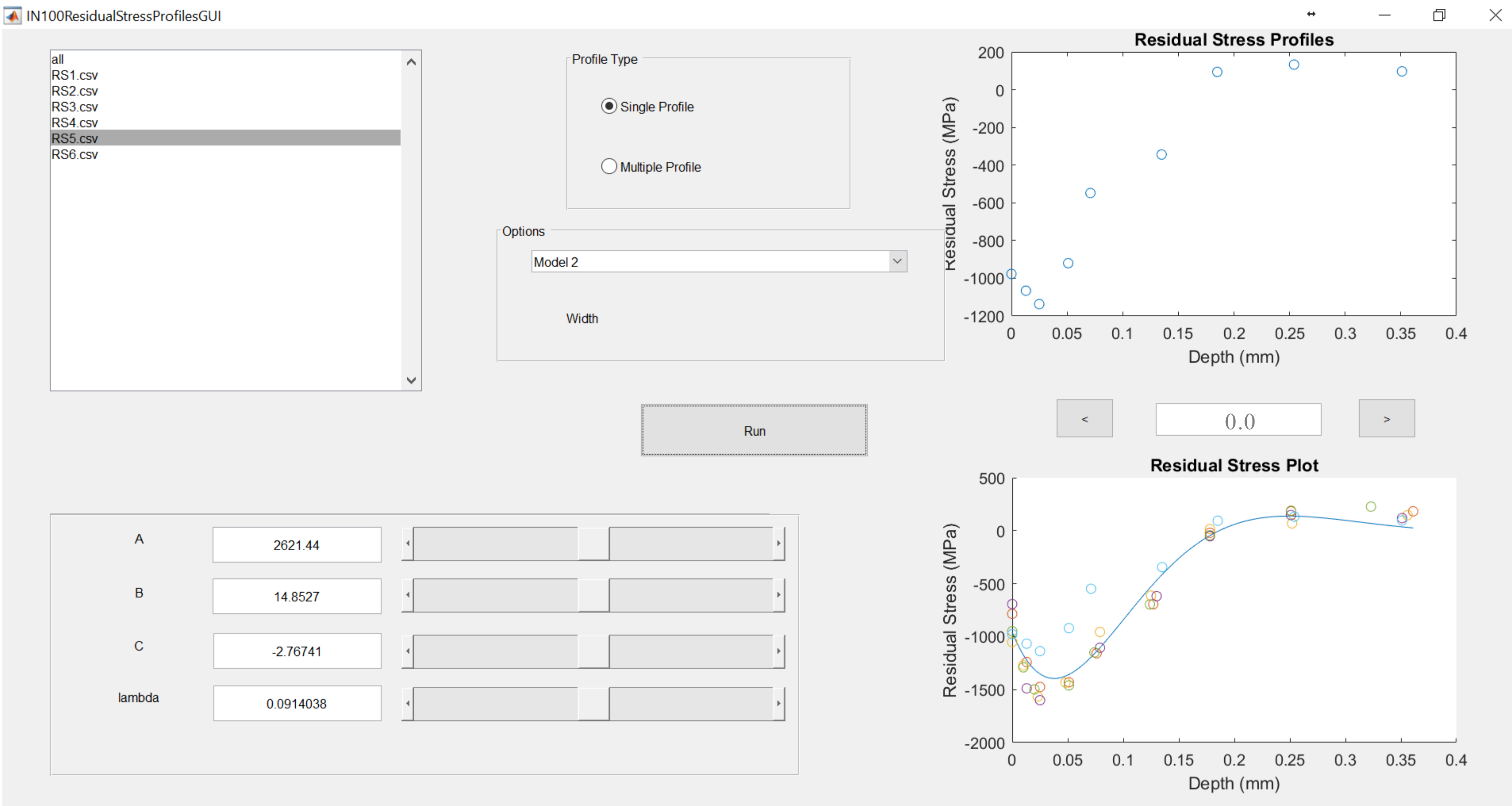
- Model III (Polynomial Fit – Under Development)

$$\sigma(x) = Ax^5 + Bx^4 - Cx^3 + Dx^2 - Ex - F$$

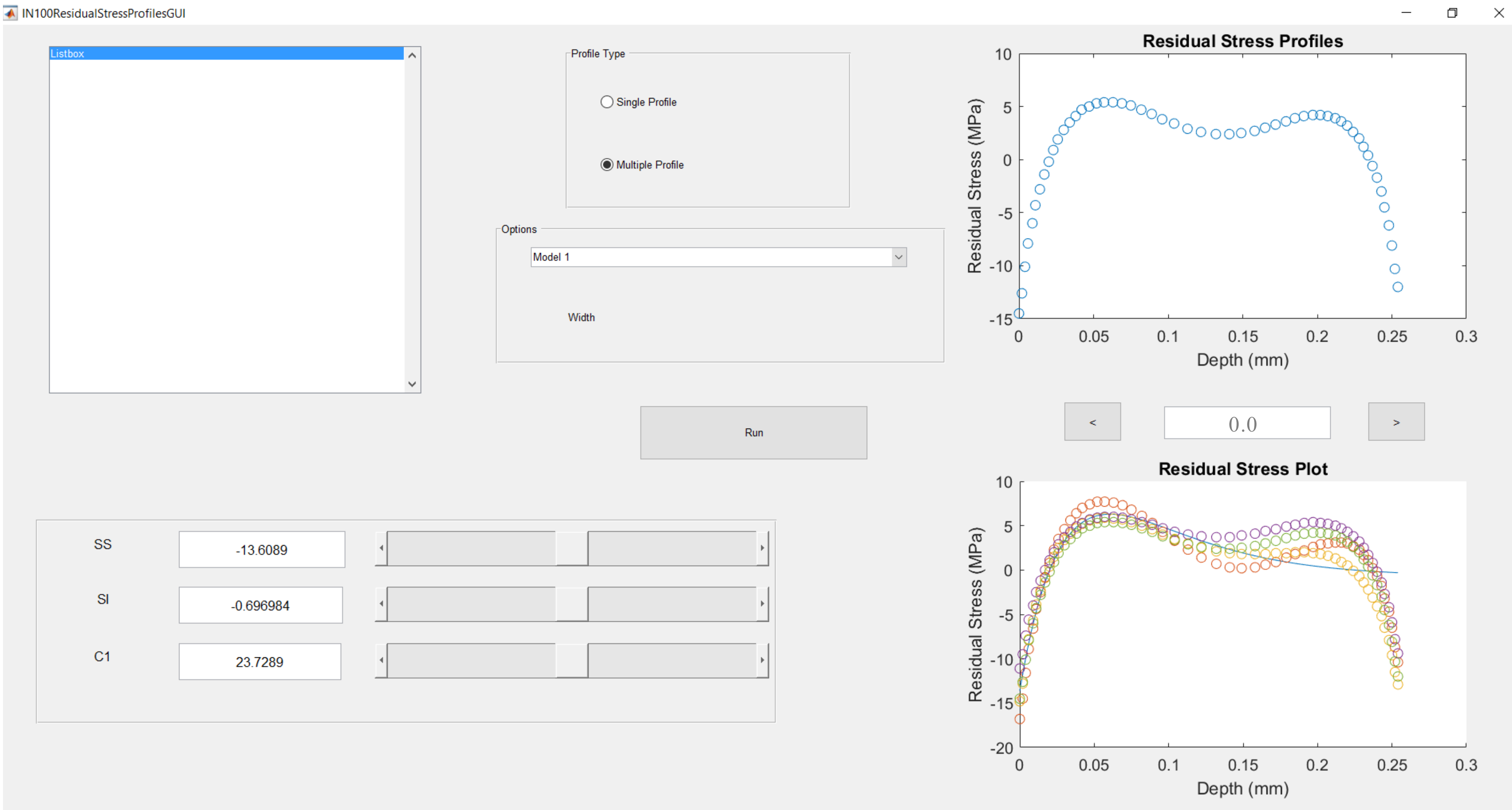
* *User Manual for ZENCRACK™ 7.1*, Zentech International Ltd., Camberley, Surrey, UK, September, 2003.

** 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



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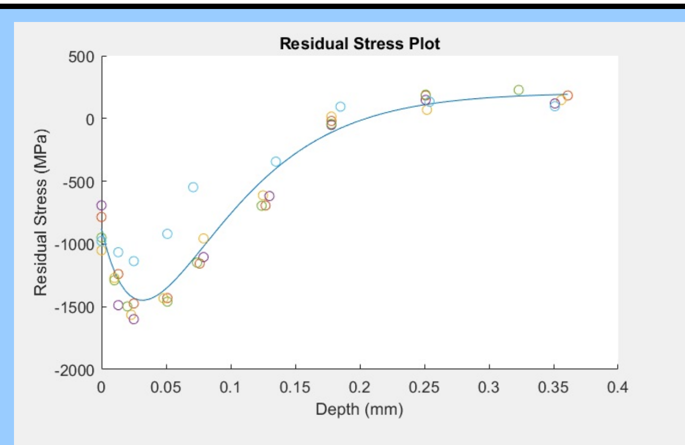
Input/Output

A2-1_stress.txt - Notepad

File Edit Format View Help

-1.928	0.254	0.000	-10.4
-1.928	0.000	0.000	-16.8
-1.928	0.252	0.000	-8.7
-1.928	0.250	0.000	-6.5
-1.928	0.248	0.000	-4.7
-1.928	0.245	0.000	-3.2
-1.928	0.243	0.000	-1.8
-1.928	0.240	0.000	-0.7
-1.928	0.237	0.000	0.2
-1.928	0.234	0.000	1.1
-1.928	0.231	0.000	1.7
-1.928	0.228	0.000	2.3
-1.928	0.224	0.000	2.7
-1.928	0.220	0.000	3.0
-1.928	0.216	0.000	3.1
-1.928	0.212	0.000	3.1
-1.928	0.207	0.000	3.0
-1.928	0.202	0.000	2.9

RS Mod



Mean and Standard Deviation Parameters

	Mean	St dev
ss	-879.16	58.58
si	205.68	9.448
c2	20.872	1.050

Correlation Parameters

	ss	si	c2
ss	1	-0.214	0.402
si	-0.214	1	-0.796
c2	0.402	-0.796	1

Are probabilistic RS needed in PDTA?

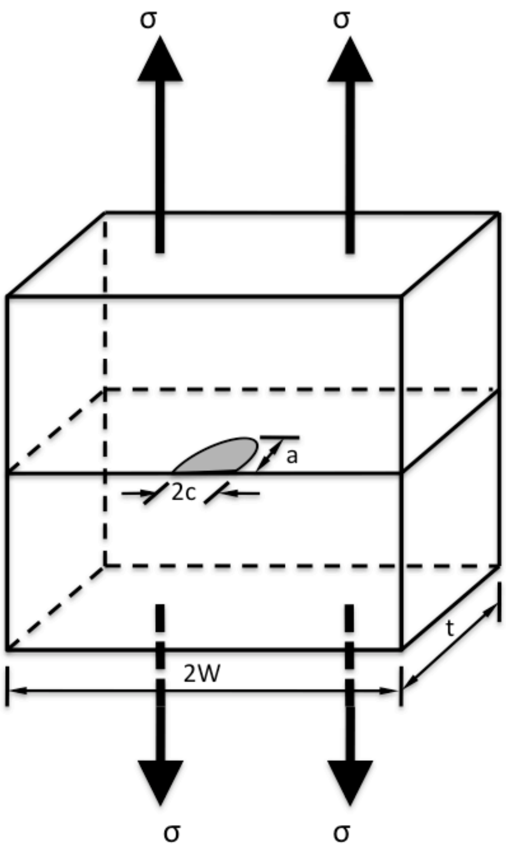
Sensitivity Study wrt Remaining Useful Life

Residual Stress Sensitivity Study

- Random variable sensitivity wrt remaining useful life

Variable Name	Type
Geometry (W)	Random
Geometry (t)	Random
Initial Crack Size (a)	Random
Initial Crack Size (c)	Random
Fracture Toughness (Kc)	Random
Residual Stress	Random
Paris Coefficients (C, m)	Random
Loading	Random
Walker m parameter	Deterministic
Stress Gradient (die out)	Deterministic
Threshold Kth	Deterministic

Residual Stress Sensitivity Study



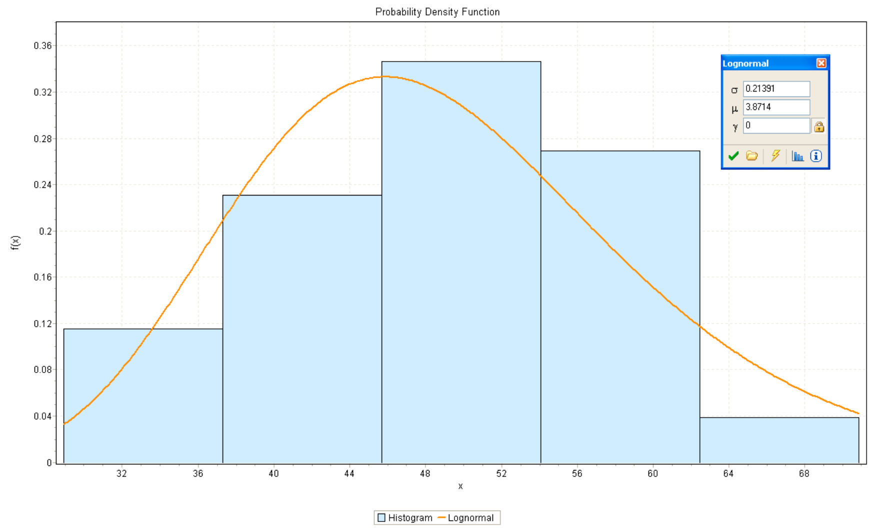
Parameter	Mean (m)	COV
W = 2t	0.5	10%
t	0.25	10%

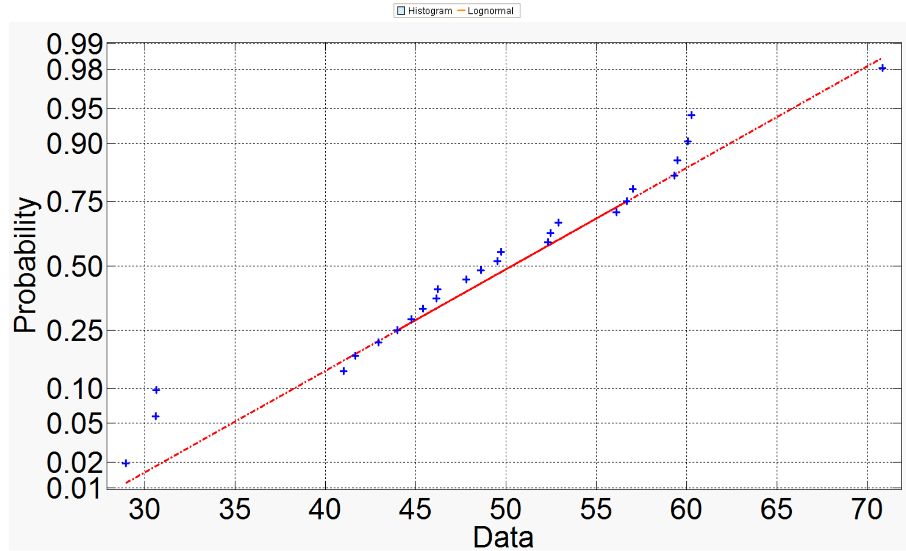
Residual Stress Sensitivity Study

Raw Data

Equivalent Semi-elliptical Crack Depth (a/c=1) (um)
42.94
43.98
28.93
48.63
52.48
60.26
52.32
47.82
44.75
59.34
70.83
59.49
41.65
56.68
49.72
41.01
30.65
45.40
57.04
52.90
46.20
49.53
56.11
60.08
46.14
30.60

Lognormal distribution with histogram and lognormal probability plot
LN~(3.871, 0.23)





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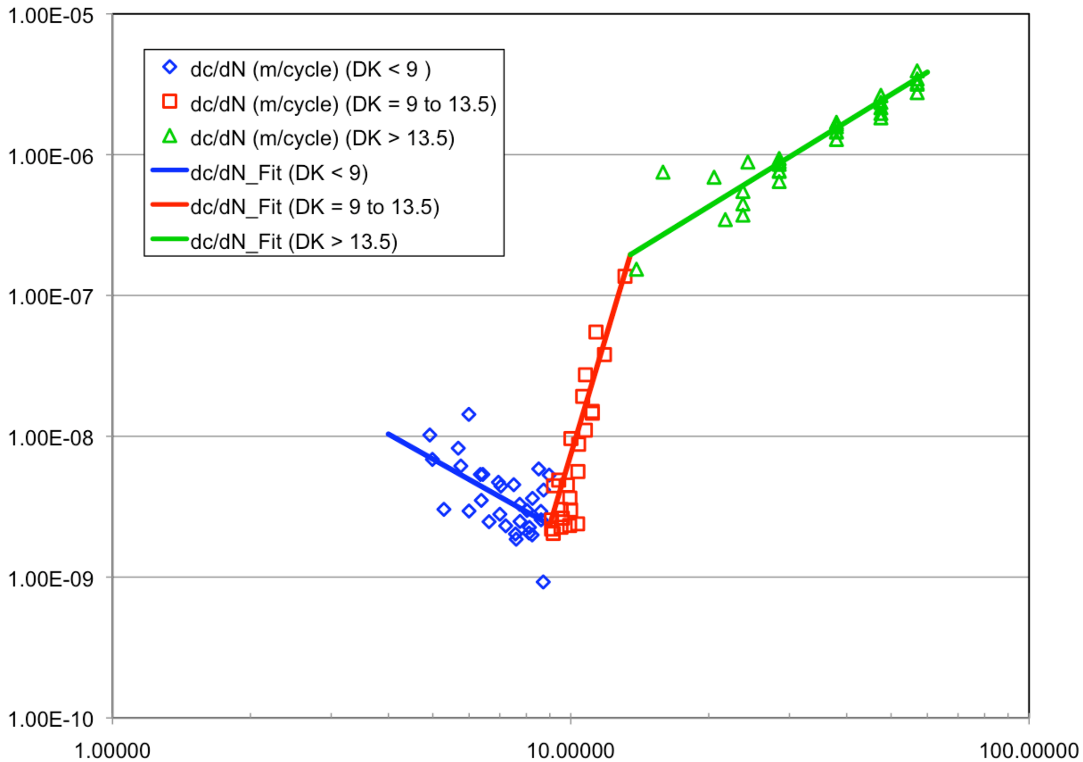
Residual Stress Sensitivity Study



Curve Section	C	m
ΔK > 13	1.602E-09	1.8753
9 < ΔK < 13	2.425E-20	11.3580
ΔK < 9	1.306E-07	-1.8293

SAS Code to find the regression parameters and the variation on the parameters (Using simple linear regression)

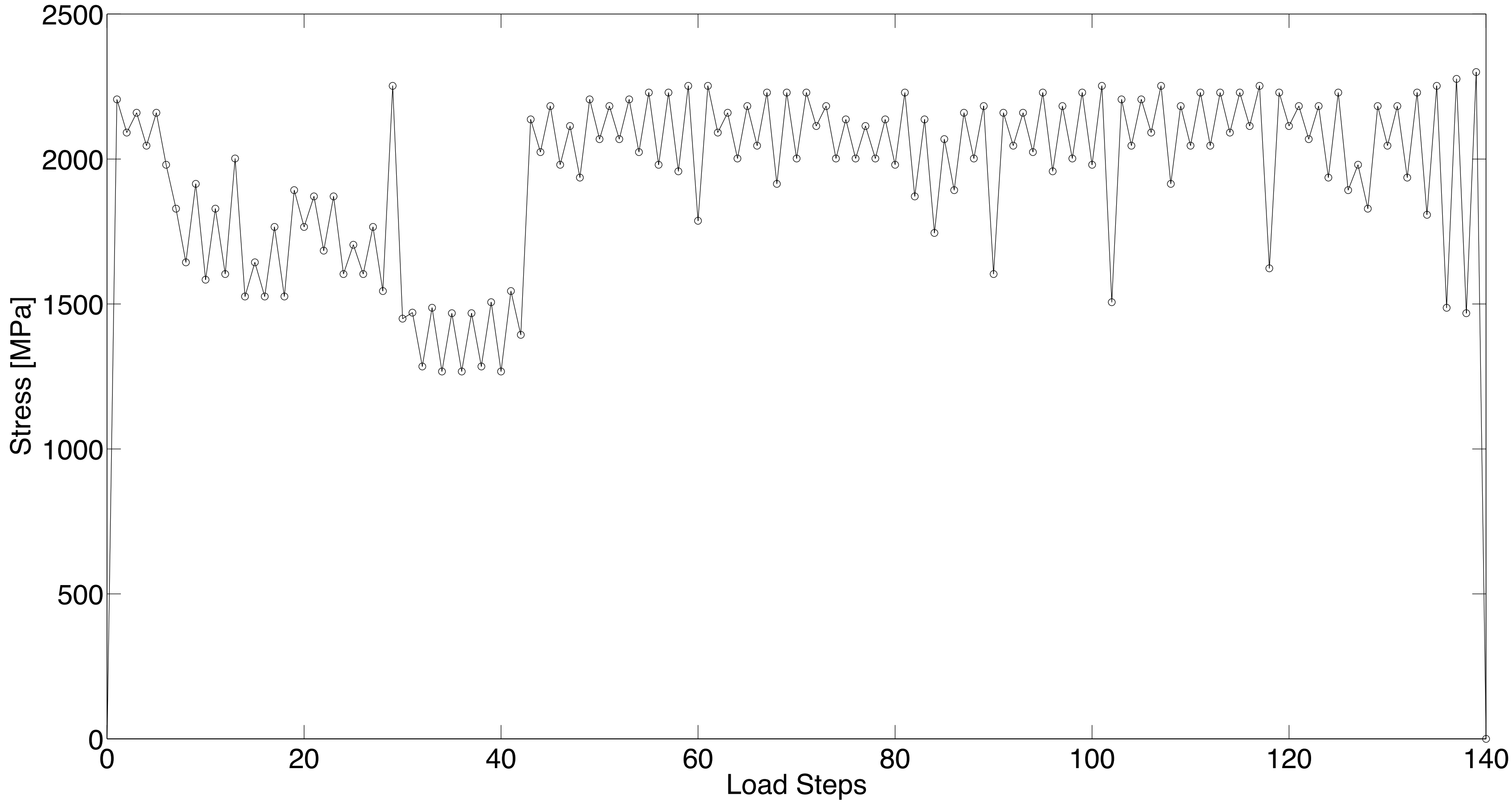
$$\frac{da}{dN} = C_1\left[(\Delta K)(1-R)^{(m-1)}\right]^{n_1} \qquad \Delta K < b$$

$$b = \frac{\log_{10}(C_1) - \log_{10}(C_2)}{n_2 - n_1}$$

$$\frac{da}{dN} = C_2\left[(\Delta K)(1-R)^{(m-1)}\right]^{n_2} \qquad \Delta K \geq b$$

Residual Stress Sensitivity Study

Variable Amplitude Loading

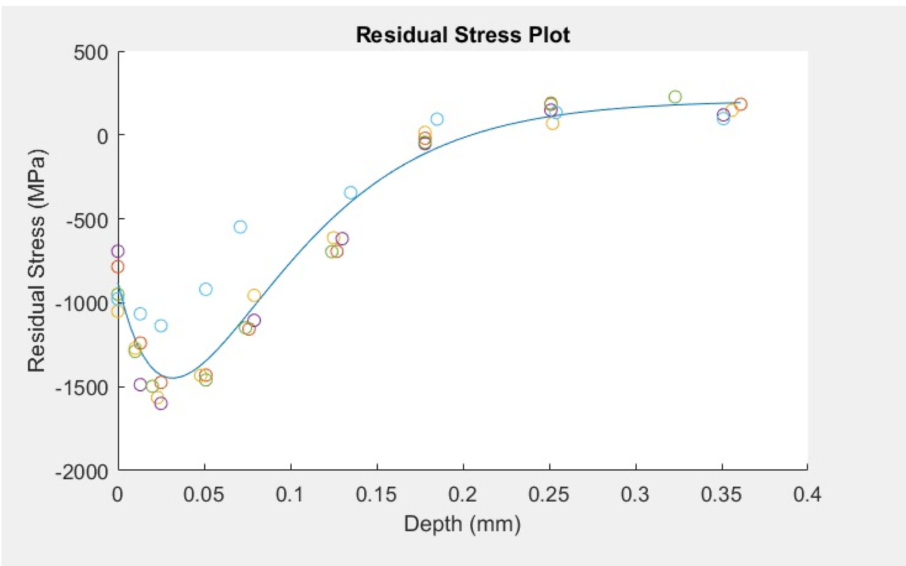


Previous RS Sensitivity Study

- Shot Peening Residual Stress Profile (Random)

Mean and Standard Deviation Parameters

	Mean	St dev
ss	-879.16	58.58
si	205.68	9.448
c2	20.872	1.050

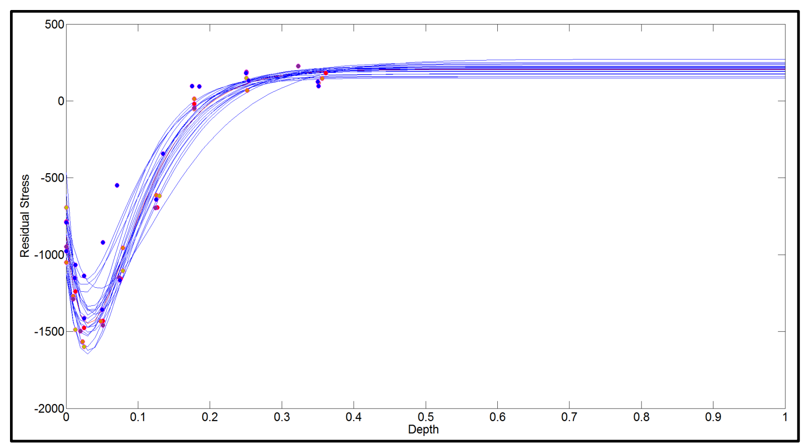


$$\sigma(x) = (ss - si + c_1 x)Exp[-C_2 x] + si$$

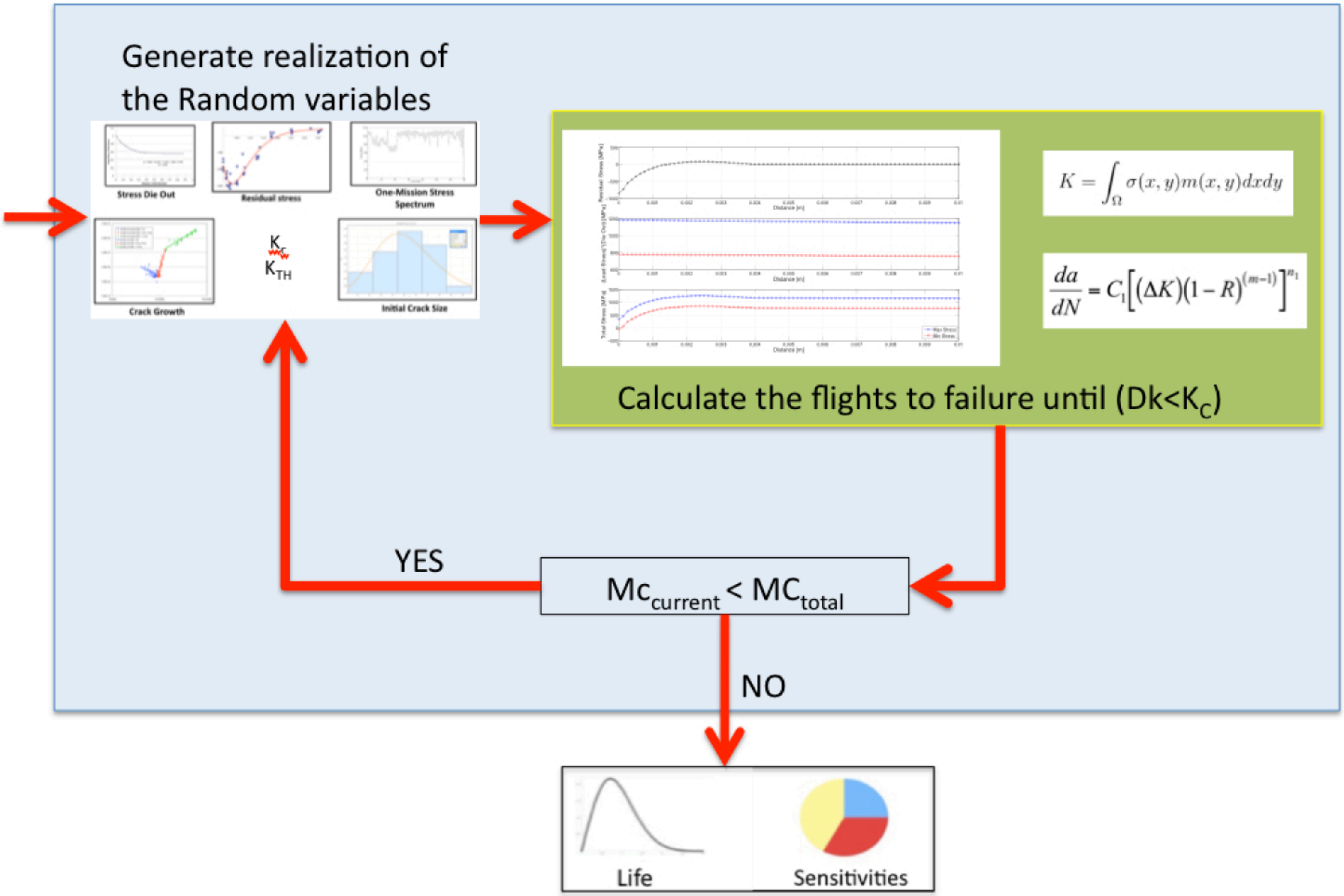
$$C_1 = \frac{\{(\sigma_s - \sigma_i)(1 - Exp[-C_2 B]) + \sigma_i B C_2\}C_2}{(C_2 B + 1)Exp[-C_2 B] - 1}$$

Correlation Parameters

	ss	si	c2
ss	1	-0.214	0.402
si	-0.214	1	-0.796
c2	0.402	-0.796	1



Residual Stress Sensitivity Study



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Sensitivity Results

$$\bar{S}_\theta = \frac{\partial P}{\partial \theta} \cdot \theta$$

$$S_i = \frac{V_{X_i}\left(E_{X\sim i}(Y/X_i)\right)}{V(Y)}$$

Input variable	Sensitivity Value	Importance	Sensitivity Value	Importance
C2	0.30	1	0.473479	1
Si	0.18	2	0.329348	2
Paris	0.16	3	0.150957	4
Ss	0.09	4	0.198532	3
ai	0.04	5	0.092150	5
Loading	0.01	6	0.014135	6
W	0.0026	7	0.003211	7
Kic	0.0009	8	0.001111	8
t	0.000009	9	1.11E-05	9

Results are problem dependent

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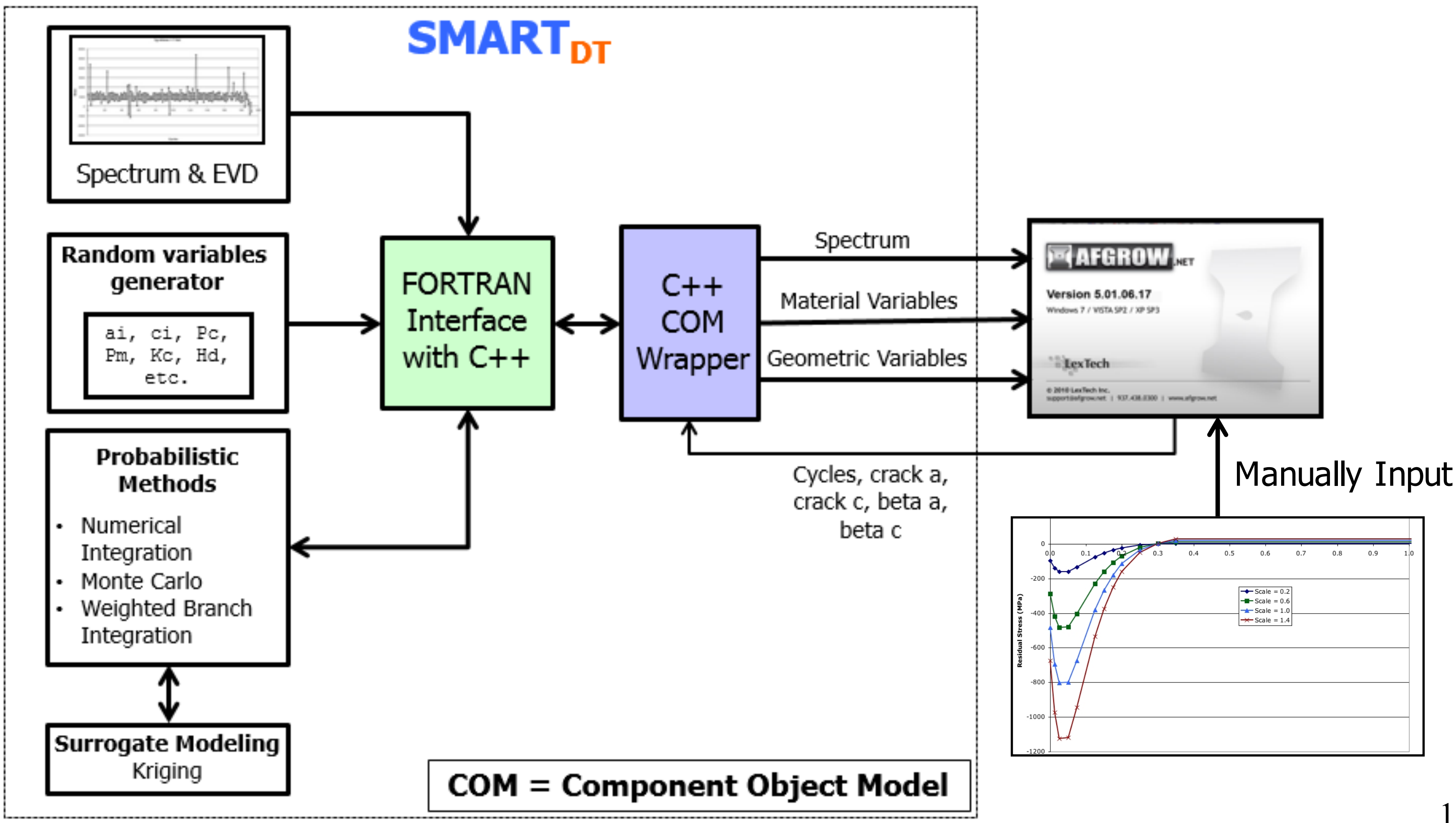
Residual Stress Effect on SFPOF Using Deterministic Residual Stress Profile

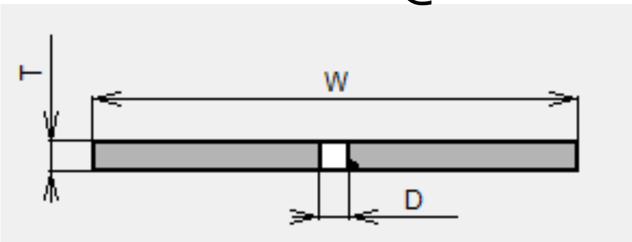
Residual Stress Effect on SFPOF

➢ SMART-AFGROW interface.

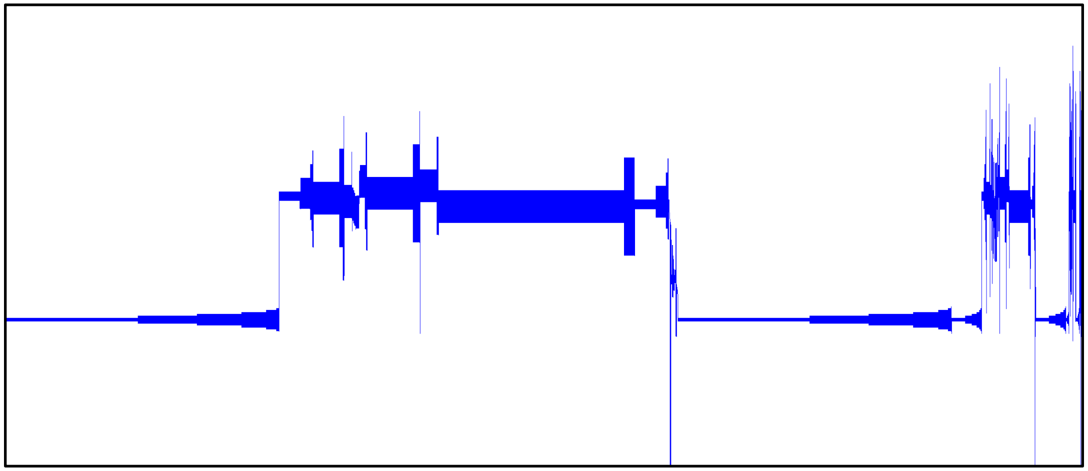


Input Parameters
Deterministic RS Example

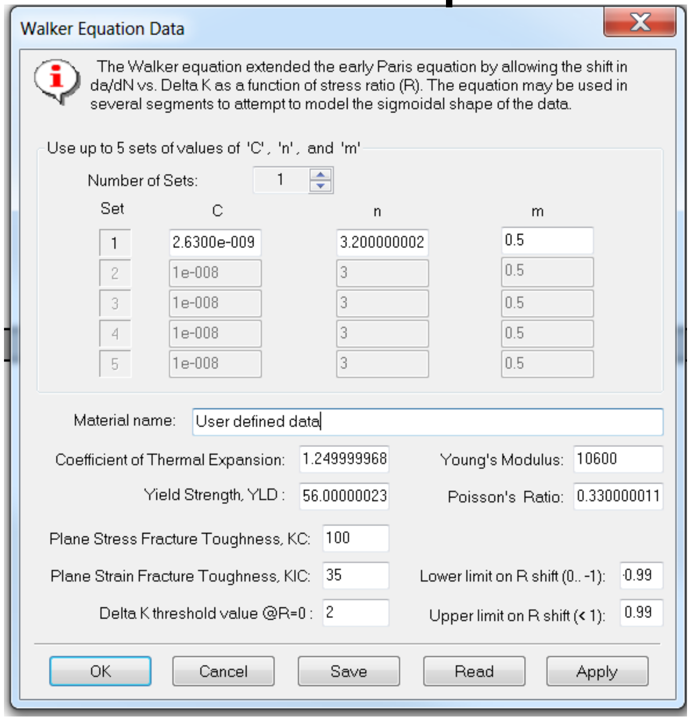
Corner crack @ hole



Parameter	Value
T	0.09 in
W	4.0 in
D	0.25 in

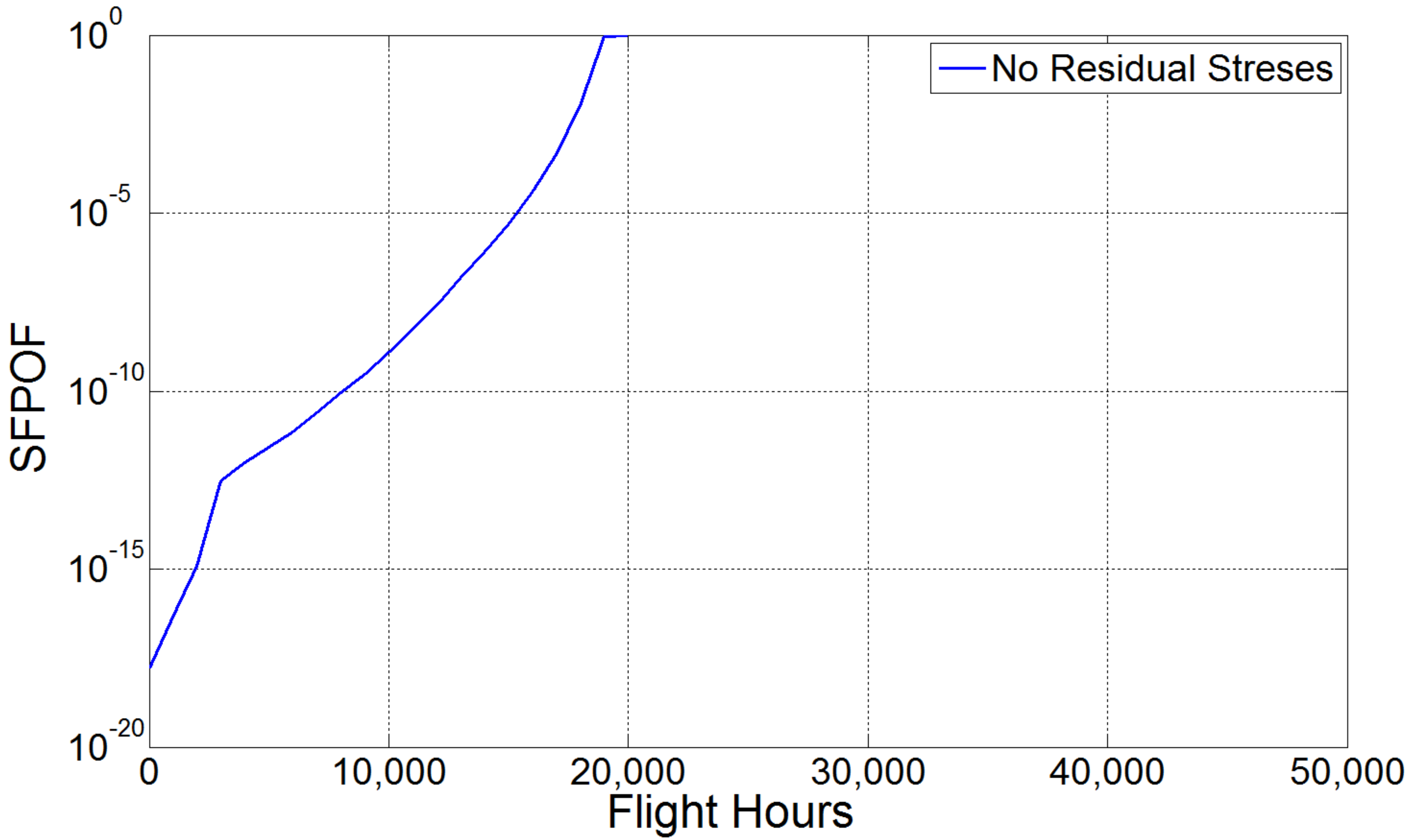


Mat. Prop.

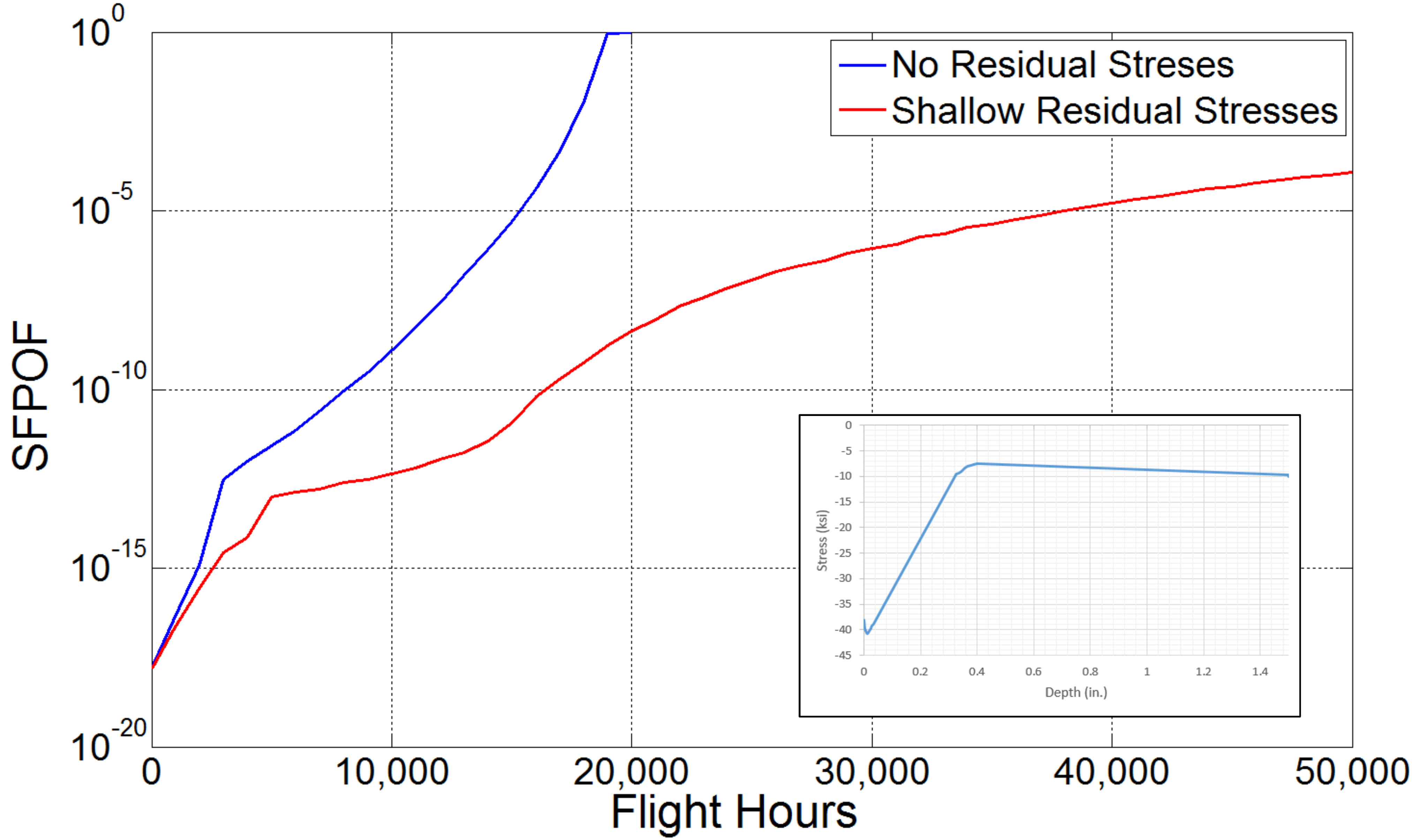


Random Variables	Value
Fracture Toughness Distribution (Normal)	Mean = 34.5ksi√in, Standard Deviation = 3.8 ksi√in.
Initial & Repair Lognormal Size Distribution (a & c) (Lognormal)	Mean = 0.01 in, Standard Deviation = 0.001 in.
Extreme Value Distribution (Gumbel)	Location = 14.5, Scale = 0.8, and Shape = 0.0
Inspections (5,000 & 10,000)	POD Lognormal Mean = 0.07in, Standard Deviation = 0.06)

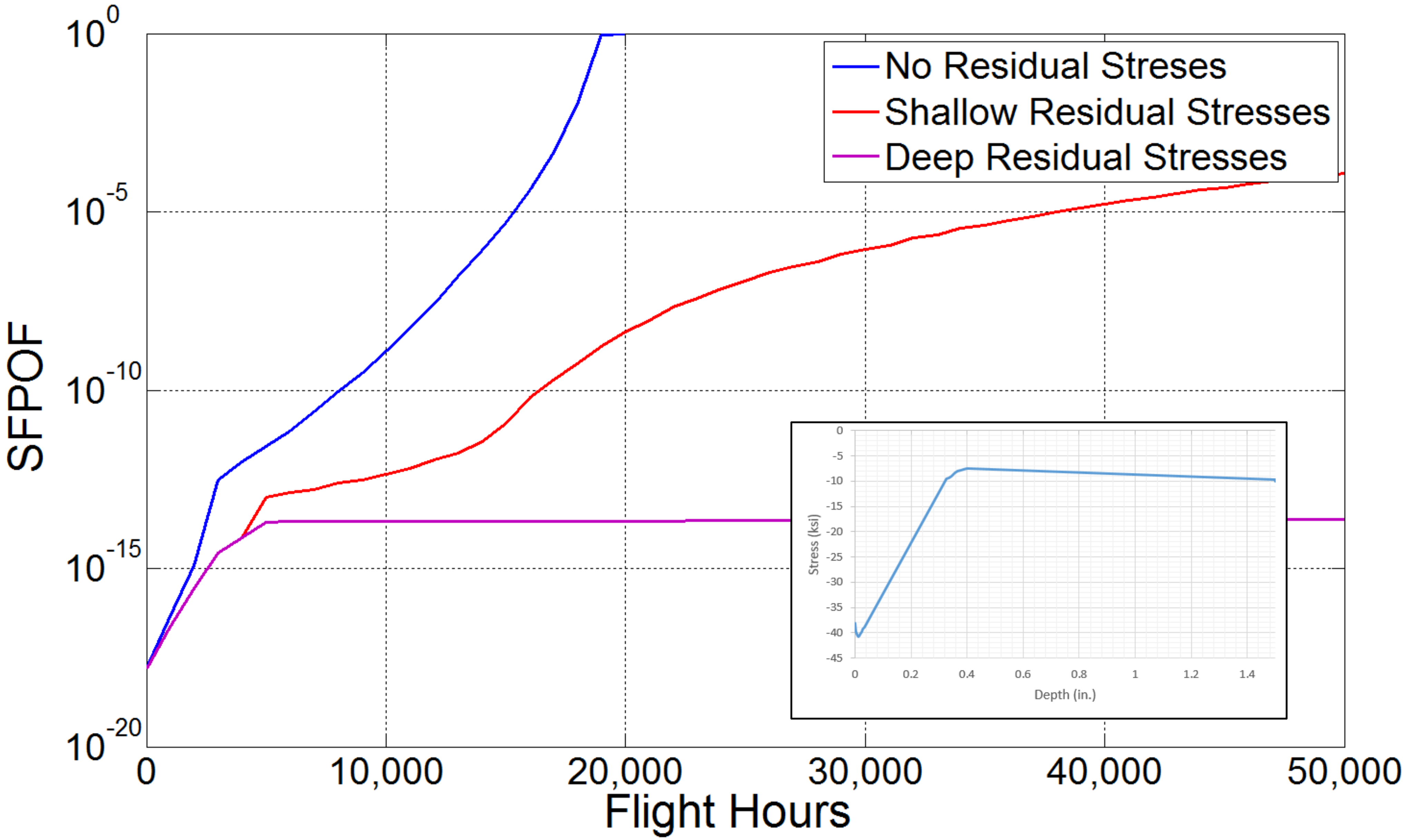
Results without Inspections



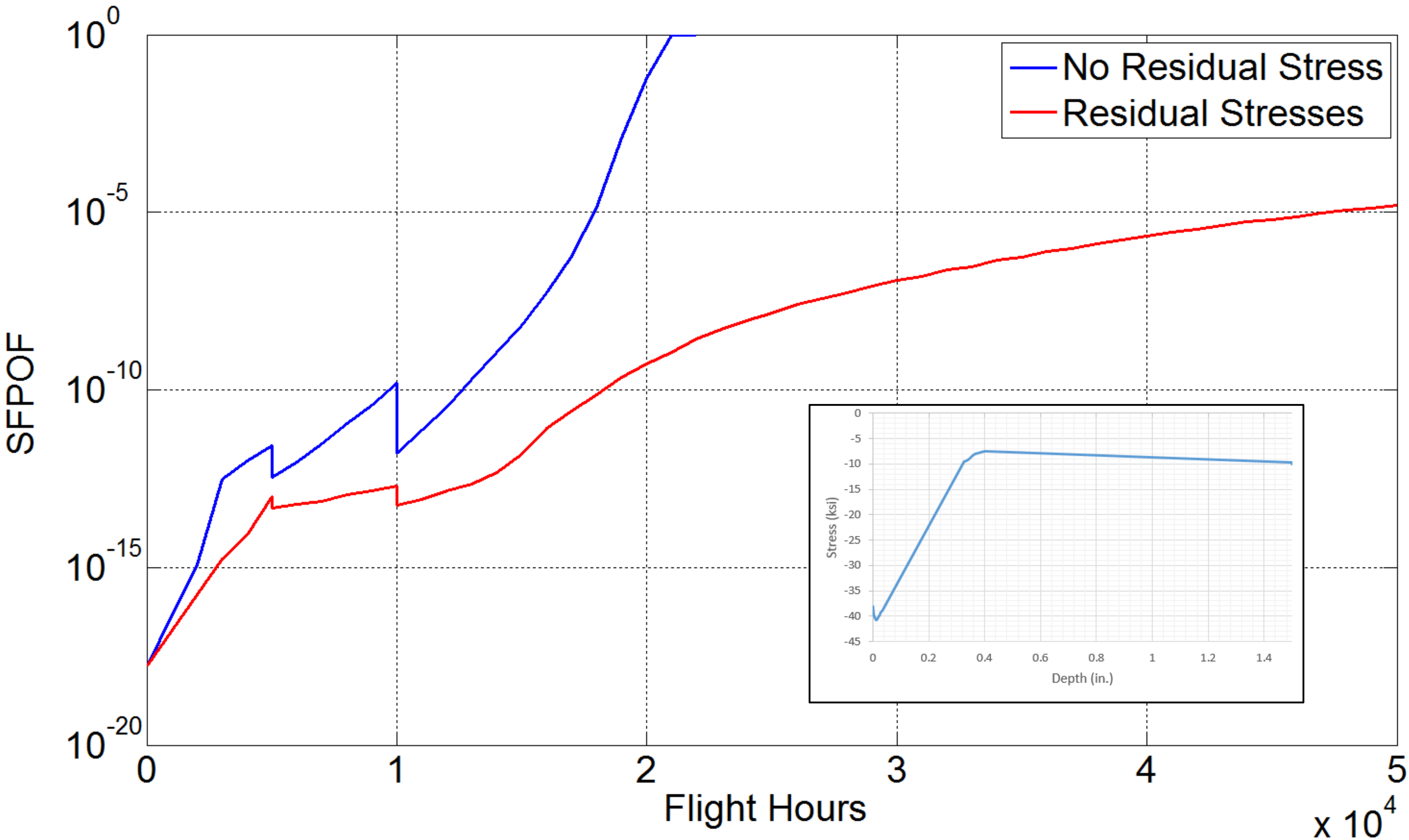
Results without Inspections



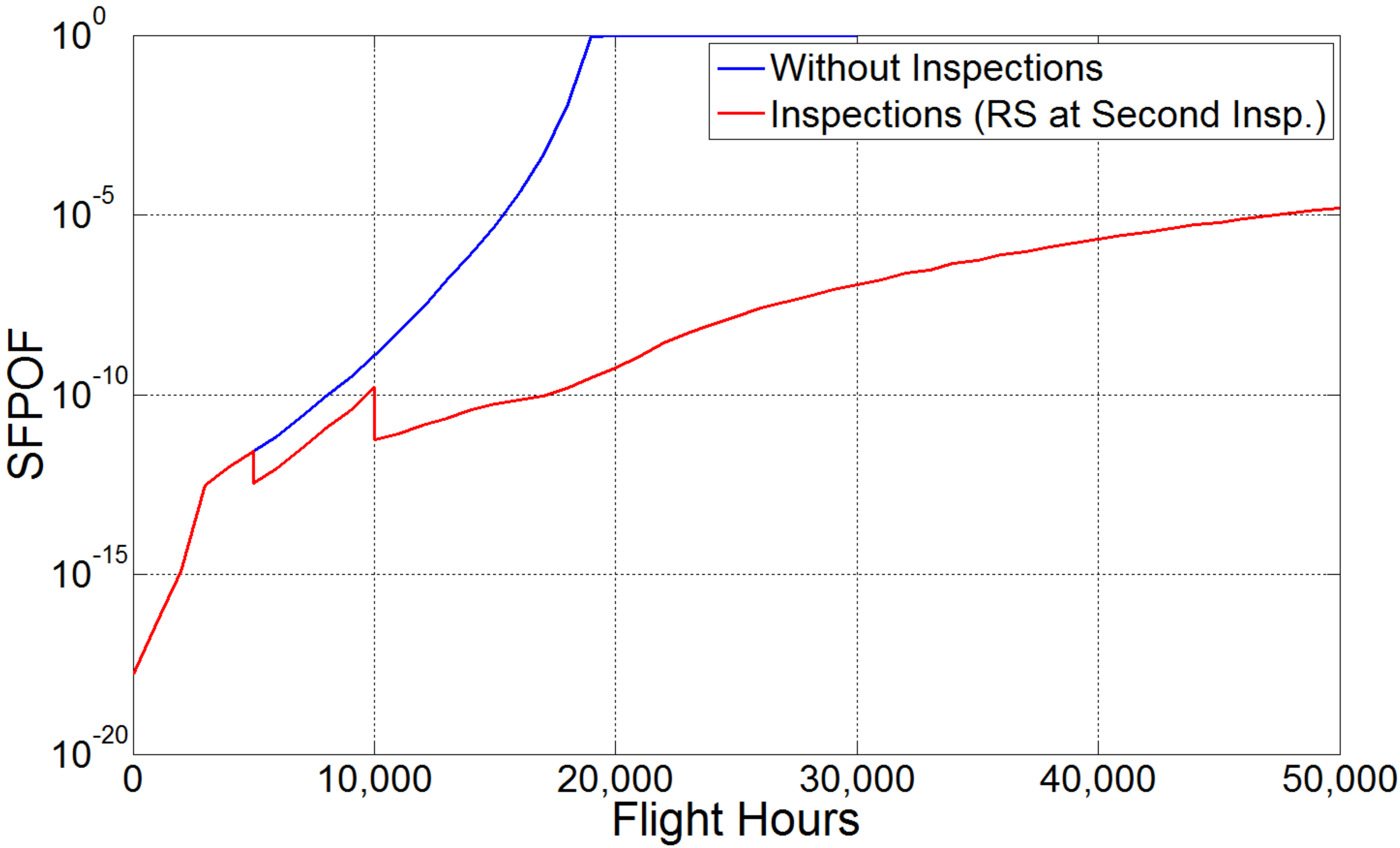
Results without Inspections



Results with Inspections



Inducing RS at the Second Inspections



SMART Internal Crack Growth Code

An Ultrafast Crack Growth Lifing Algorithm for Probabilistic Damage Tolerance Analysis

Harry Millwater, Nathan Crosby
University of Texas at San Antonio

Juan D. Ocampo
St. Mary's University, San Antonio

The Aircraft Airworthiness & Sustainment (AA&S) Conference
Jacksonville, FL. May– 2018.

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Purpose

- ✓ Probabilistic damage tolerance analysis requires very small probabilities, e.g., 1E-9
- ✓ Previous methods allow for a deterministic crack growth curve and do not consider randomness in crack growth rate properties.
- ✓ Surrogate models, e.g., Kriging, can be used to speed up the analysis but are still very time consuming.
- ✓ Hence an ultrafast crack growth lifing code was developed.

Ultrafast Approach

1) Create an equivalent constant amplitude from an arbitrary spectrum
2) Use an *internal* adaptive time stepping RK algorithm to grow the crack
3) Collect the top 100 (or so) damaging realizations for further examination and potential reanalysis

Thank you!!

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