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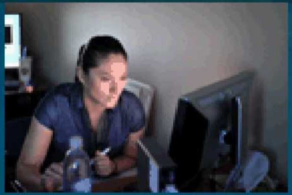
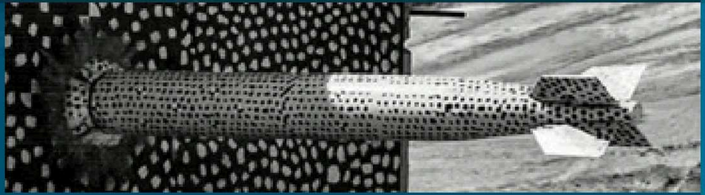
Survey of Sensitivity Analysis Methods During the Simulation of Residual Stresses in Simple Composite Structures





PRESENTED BY

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Presentation Outline

- Motivation and Objectives
- Validation Experiments
- Finite Element Methods
- Solution Verification and Mesh Optimization
- Sensitivity Study Methods Survey
- Discussion of Results and Conclusions
  - Ideal Sensitivity Study Methodology
  - Critical Parameters for Residual Stress Predictions

Introduction

Motivation

- Residual stresses should be considered when designing composite parts
- Computational simulation of process-induced stress state is an alternative to experimental measurements
  - Experimental approaches become impractical with increasing part complexity
- Sandia's simplified residual stress modeling approach has been validated
  - CTE mismatch and polymer shrinkage
  - Experimentally measured stress-free temperature
  - Requires the definition of 20+ material parameters
- Experimental characterization of many material properties not feasible
  - Sensitivity analysis methods can be employed to determine parameters critical to a simulated response
    - Critical parameters should be rigorously characterized, non-critical parameters can be approximated
- Many sensitivity analysis methods exist in the literature offering trade-offs between complexity and cost
  - Sampling methods are simple to implement, but computationally expensive
  - Surrogate methods are complex, but usually require fewer samples

Objectives

- Develop a residual stress case study that will be:
  - Low-cost to model → Sensitivity studies will require thousands of simulations
  - Reasonable to physically implement → nominal model validation is important
- Complete a survey of common sensitivity analysis methods
  - Determine the ideal approach during the simulation of a composite's manufacturing process
    - Metric for comparison will be computational cost
  - Demonstrate how simulations can assist with allocating sparse experimental resources
  - Determine the material parameters most critical to predictions of a composite's process-induced stress state

Validation Experiment

Test Description

- Bi-material, CFRP/aluminum strip
  - Visually obvious post-fabrication residual stresses
  - Efficient and low-cost to model
- Dimensions:
  - In plane dimensions: 25.4 mm x 304.8 mm
  - Thickness: 1.6 mm (0.8 mm aluminum, 0.8 mm CFRP)
- Materials:
  - 8-harness satin weave, CFRP prepreg, $[0_2]_s$
  - Aluminum 6063-T6
  - Composite co-bonded to aluminum during an autoclave cure
- Process-induced stresses manifest as out-of-plane warpage/curling along the strip's length
  - CFRP and aluminum dissimilar CTE's
  - Irreversible strain due to polymer shrinkage
- Measurement procedure:
  - Granite table, guarantees flatness
  - Digital height gage, ±0.01 mm
- One strip was manufactured and measured: 15.4 mm
  - Limited experimental rigor expended, sensitivity study survey not a validation exercise
    - Qualitative nature of the experiment indicates if the model captures the correct physical trends

Finite Element Methods

Analysis Software and Element Formulation

- Analysis Software:
  - All simulations were processed with Sandia's SIERRA SolidMechanics/Implicit ("Adagio")
    - Lagrangian, three dimensional code for FEA of solid structures
    - Suitable for implicit, quasi-static analyses
  - DAKOTA used to facilitate sensitivity study survey
    - Interface between SIERRA/SolidMechanics and iterative analysis methods
    - Available algorithms for sensitivity analysis, uncertainty quantification, and gradient and non-gradient based optimization

- Element Formulation:
  - 8-noded hexahedral elements were used for all modeled components
  - Adagio's default element formulation was used for simplicity and to reduce cost
    - Single point Gaussian quadrature
    - Hourglass modes are controlled through the definition of an hourglass stiffness

Material Models and Nominal Property Values

- Aluminum 6063-T6
  - Linear-elastic model (no yielding or failure expected)
    - Requires: density, Young's modulus, and Poisson's ratio
  - Isotropic CTE
  - Material properties taken from literature
- Uncured CFRP
  - Same linear-elastic model as aluminum
  - Same Isotropic CTE as aluminum
  - Material properties define a compliant and incompressible , isotropic-elastic solid
    - E = 0.1 GPa, ν = 0.499
- Cured CFRP
  - Linear-elastic orthotropic model
    - Requires: density, nine regular elastic constants, and material orientation
  - Orthotropic CTE's
  - Material properties taken from a combination of testing, micromechanical modeling, and literature

Nominal Aluminum Properties

Density, ϱ (kg/m^3)	2,700
Young's Modulus, E (GPa)	68.9
Poisson's Ratio, ν	0.33
Coefficient of Thermal Expansion, CTE (1/°C)	23.4e-06

Uncured Composite Properties

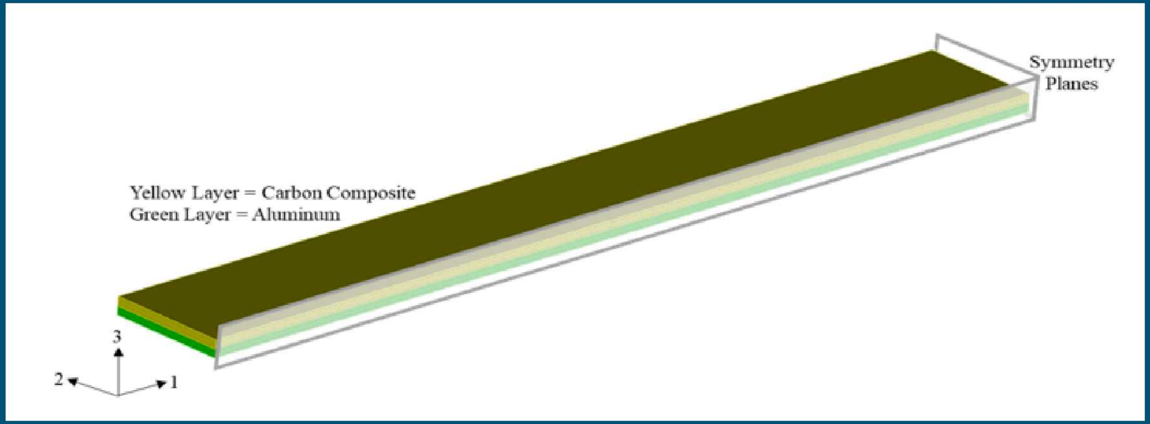
Density, ϱ (kg/m^3)	1,600
Young's Modulus, E (GPa)	0.1
Poisson's Ratio, ν	0.499
Coefficient of Thermal Expansion, CTE (1/°C)	23.4e-06

Nominal Cured Composite Properties

Density, ϱ (kg/m^3)	1,600	
Elastic Moduli, E_{11}, E_{22}, E_{33} (GPa)	63.86, 62.74, 8.59	
Poisson's Ratios, ν_{12}, ν_{13}, ν_{23}	0.0480, 0.4075, 0.0548	
Shear Moduli, G_{12}, G_{13}, G_{23} (GPa)	3.44, 3.27, 3.25	
Glass Transition Temperature, T_g (ºC)	125.1	
Stress-Free Temperaure, T_{sf} (ºC)	143.3	
	Glassy Region	Rubbery Region
Coefficient of Thermal Expansion, CTE_{11} (1/ºC)	3.40e-06	1.13e-06
Coefficient of Thermal Expansion, CTE_{22} (1/ºC)	3.36e-06	1.13e-06
Coefficient of Thermal Expansion, CTE_{33} (1/ºC)	7.20e-05	2.83e-04

Model Geometry and Boundary Conditions

- Aluminum/CFRP modeled as separate, homogenized material layers
- CFRP layer merged to aluminum layer
  - Merging approximates perfect bonding, delamination is not modeled
- Boundary conditions:
  - Quarter model symmetry conditions assumed for computational efficiency
  - Two isothermal temperature cycles approximate the CFRP's curing:
    - Ambient (20°C) to stress-free temperature (143.3°C)
    - Stress-free temperature to ambient
  - CFRP's curing/stiffness change approximated with element activation



Element Activation

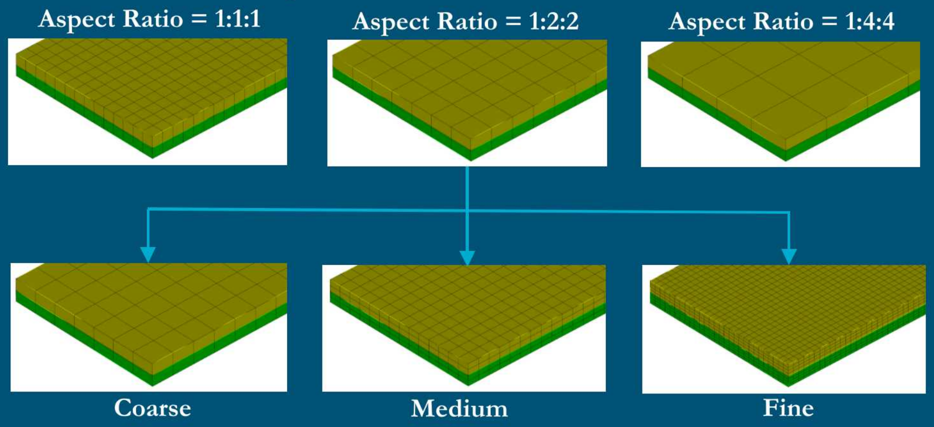
- CFRP's stiffness change due to the matrix material's polymerization reaction is approximated with Adagio's element activation
  - The stress/strain/deformation output of one simulation sets the initial stress/strain/deformation state of a subsequent simulation
  - An uncured composite material is simulated as compliant in one simulation and stiff in a subsequent simulation
- Bi-material strip processing modeled as two subsequent simulations:
  - Simulation #1:
    - Aluminum modeled as stiff, ***CFRP modeled as compliant with uncured material properties***
    - Model is isothermally heated to stress-free temperature
    - Stress/strain/displacement data written to an output file
  - Simulation #2:
    - Input geometry, stress/strain/displacement states from output of simulation #1
    - ***CFRP assigned actual material properties (ACTIVATION)***
    - Model is isothermally cooled to room temperature, residual stresses form due to CTE mismatch

Simulation #	**Components Modeled with *Actual* Material Properties**	**Components Modeled with *Compliant* Material Properties**	**Applied Temperature Boundary Conditions**
1	Aluminum Layer	Composite Layer	Heating from 20ºC to 143.3ºC
2	Aluminum Layer, Composite Layer	None	Cooling from 143.3ºC to 20ºC

Solution Verification, Mesh Optimization, Nominal Model Validation

- Mesh study considered hex element size and aspect ratio
  - What is the largest element providing confident predictions?
- 3 element lengths and 3 aspect ratios
  - 9 models processed according to described FE methods
  - 3 separate mesh studies based on the 3 aspect ratios
- Richardson's extrapolation estimated "exact" out-of-plane displacement
  - Approximates a higher order estimate of a continuum value given discrete solutions → discretization errors
- Summary of results:
  - Extrapolated exact solutions do not differ significantly
    - 1:4:4 can be used with a reasonable expectation of model accuracy
  - Medium, 1:2:2 mesh size offers best combination of computational efficiency and model accuracy
    - Lowest discretization error with fewer than 36 solution cores
    - Exact solution and shape of deformation agree well enough with experiment to satisfy physics

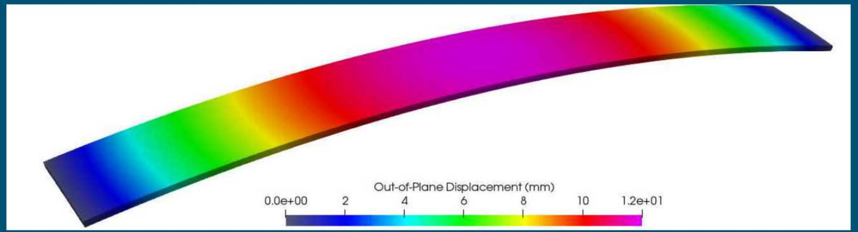
3 Element Aspect Ratios and 3 Levels of Refinement



Summary of Mesh Convergence Study Results

Aspect Ratio	Mesh Refinement Level	Run Time (min) /Solution Cores	Predicted Deflection (mm)	Error (%)	Exact Solution (mm)
1:1:1	Coarse	01:14.3/1	14.02	20.2	11.666
	Medium	04:51.7/4	12.16	4.3	
	Fine	24:32.7/36	11.77	0.9	
1:2:2	Coarse	00:33.7/1	12.75	9.4	11.652
	Medium	**01:04.4/4**	**11.90**	**2.2**	
	Fine	03:24.3/36	11.71	0.5	
1:4:4	Coarse	00:25.2/1	9.33	20.3	11.702
	Medium	00:40.1/4	10.94	6.5	
	Fine	00:59.7/36	11.46	2.1	

Representative Deformation Prediction



Sensitivity Analysis Methods

Survey Overview

- Sandia's residual stress modeling method requires the characterization of at least 20 parameters
  - Sparse experimental resources → Rigorous characterization not possible
  - Sensitivity analyses can assist in prioritizing/allocating experimental resources
    - Different methods offer trade-offs between complexity and efficiency
- Survey of DAKOTA's sensitivity analysis methods was completed with the verified bi-material strip model
  - What model parameters affect the residual stress predictions?
  - Which method is best for process modeling of composites?
- Six methods were examined:
  - Parameter study (centered parameter study)
  - Design of Experiments (Box-Behnken Design)
  - Sampling Methods (Monte Carlo, Latin HyperCube)
  - Surrogate Methods (Gaussian process, Polynomial Chaos Expansion)
- Approach to completing the survey:
  - Step 1: Define parameter space
    - Nominal values ± 3 standard deviations *or* ± percentage of the nominal
  - Step 2: Complete sensitivity studies with the six methods
  - Step 3: Complete N-way ANOVA to find critical parameter list

Sensitivity Study Parameter Space

	Parameter	Minimum Value	Maximum Value
Composite Properties	E_{11} (GPa)	57.5	70.2
	E_{22} (GPa)	56.5	69.0
	E_{33} (GPa)	7.7	9.4
	ν_{12}	0.043	0.053
	ν_{13}	0.367	0.449
	ν_{23}	0.367	0.448
	G_{12} (GPa)	3.1	3.8
	G_{13} (GPa)	2.9	3.6
	G_{23} (GPa)	2.9	3.6
	T_g (°C)	110.9	141.8
	T_{sf} (°C)	140.6	146.1
	CTE_{11} (1/°C, rubbery)	0.294e-6	1.913e-6
	CTE_{22} (1/°C, rubbery)	0.357e-6	2.794e-6
	CTE_{33} (1/°C, rubbery)	268.1e-6	290.9e-6
	CTE_{11} (1/°C, glassy)	3.060e-6	3.708e-6
	CTE_{22} (1/°C, glassy)	2.585e-6	4.165e-6
	CTE_{33} (1/°C, glassy)	67.8e-6	76.5e-6
Aluminum Properties	E (GPa)	57.0	85.6
	ν	0.264	0.396
	CTE (1/°C)	18.7e-6	28.1e-6

Parameter Study Method: Centered Parameter Study (CPS)

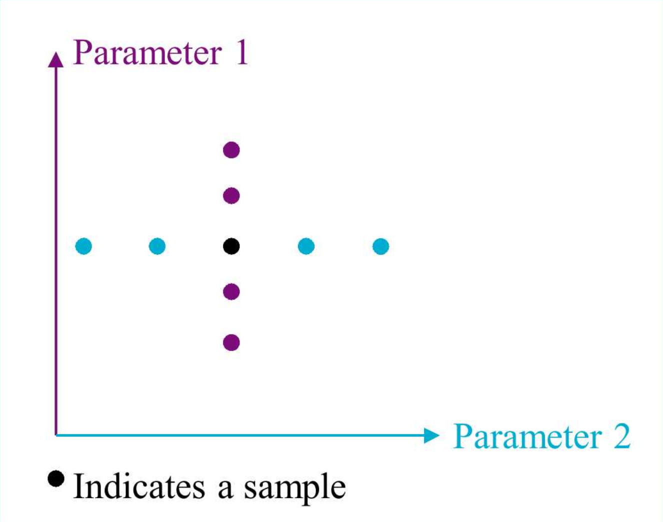
- One parameter study method was selected for consideration → CPS
  - DAKOTA also has multi-dimensional and vector parameter studies
  - CPS is cheapest, quantifies relationships between multiple model inputs and the simulated response
- General CPS approach: *"One-at-a-Time"*
  - Step 1: Define the parameter space and an initial value set
  - Step 2: Process a simulation with the initial value set
  - Step 3: For each parameter, process simulations at *s* steps ± the initial value. Values for all other model parameters held constant.
  - Step 4: Apply the ANOVA to the ensemble of predictions to determine the critical parameter list
- Bi-material strip CPS process:
  - Step 1: 20-dimensional parameter space, initial values defined by nominal properties
  - Step 2: Simulation processed with nominal material properties
  - Step 3: Starting with *s*=1 and step size= (max value – nominal value)/*s*, independently process simulations along each dimension.
  - Step 4: ANOVA applied to resulting 41 predictions to generate critical parameter list
  - Step 5: Repeat steps 3-4 with incrementally increasing *s* until critical parameter list is converged

Samples Required for CPS:

(n=dimensions, s=steps)

$$Samples_{CPS} = 1 + 2\sum_{i=1}^{s} n_s$$

Sample 2-Dimensional CPS Parameter Space



Design of Experiments: Box-Behnken Design (BBD)

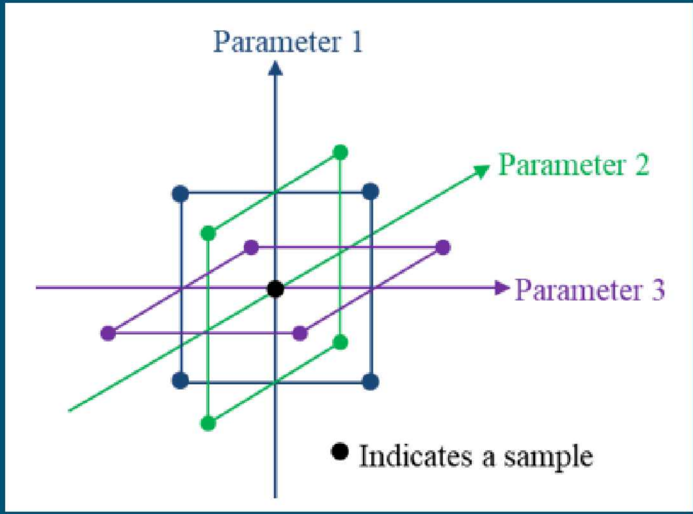
- One DOE method was selected for consideration → BBD
  - BBD does not sample outside of parameter space, requires fewer samples than other DOE methods
- General BBD approach:
  - Step 1: Define the parameter space with minimum, maximum, mean values
  - Step 2: Parameter combinations are created at the center and midpoints of the process space edges.
  - Step 3: A simulation is processed at each parameter combination
  - Step 4: Apply the ANOVA to the ensemble of predictions to determine the critical parameter list
- Bi-material strip BBD process:
  - Step 1: 20-dimensional parameter space
  - Step 2: BBD specified 761 parameter combinations
  - Step 3: 761 simulations were processed
  - Step 4: ANOVA applied to resulting 761 predictions to generate critical parameter list

Samples Required for BBD:

(k=number of parameters)

$$Samples_{BBD} = 1 + 2k(k-1)$$

Sample 3-Dimensional BBD Parameter Space



Sampling Methods: Monte Carlo (MC)

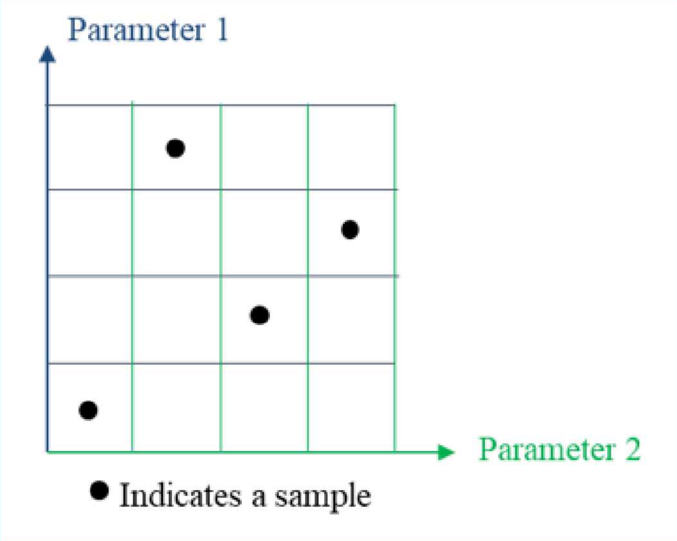
- Two sampling methods were considered → MC and LHS
  - MC is simple and easy to implement with any deterministic FE code
  - LHS is more complex, but provides better parameter space coverage with fewer samples
- Monte Carlo (MC)
  - Completely random sampling
    - No guarantee that any number of samples will cover parameter space
    - Convergence is assured, but a prohibitive number of samples may be required
  - General approach:
    - Step 1: Define the parameter space with minimum, maximum values
    - Step 2: Define the desired number of samples, N
    - Step 3: Process N simulations
    - Step 4: Apply the ANOVA to the N predictions to determine the critical parameter list
  - Bi-material strip MC process:
    - Step 1: 20-dimensional parameter space
    - Step 2: Initial samples size = 22, or $n+2$
    - Step 3: Process 22 simulations
    - Step 4: ANOVA applied to resulting 22 predictions to generate critical parameter list
    - Step 5: Repeat steps 2-4 with incrementally increasing N until critical parameter list is converged

Sampling Methods: Latin HyperCube Sampling (LHS)

- Latin HyperCube Sampling (LHS)
  - Stratified sampling technique
    - If N samples are desired, each parameter space dimension is divided into N segments of equal probability
      - Relative length of segments governed by probability distributions
    - N samples placed throughout parameter space grid → *One, and only one, sample can be placed in each bin*
      - Better coverage of parameter space!
  - General approach:
    - Step 1: Define the parameter space and probability distributions for each parameter
    - Step 2: Define the desired number of samples, N → Stratify parameter space
    - Step 3: Process N stratified simulations
    - Step 4: Apply the ANOVA to determine the critical parameter list
  - Bi-material strip LHS process:
    - Step 1: 20-dimensional parameter space, uniform distributions for all parameters
    - Step 2: Initial samples size = 22, or $n+2$
    - Step 3: Process 22 simulations
    - Step 4: ANOVA applied to resulting 22 predictions to generate critical parameter list
    - Step 5: Repeat steps 2-4 with incrementally increasing N until critical parameter list is converged

Sample 2-Dimensional LHS Parameter Space

(2 parameters and 4 samples)



Surrogate Methods: Polynomial Chaos Expansion (PCE)

- Two surrogate methods were considered → PCE and GP
- General surrogate model approach:
  - Minimally sample the parameter space to find a numerical function defining the relationship between the desired model output and the design variables
  - Sample the surrogate model 1000's of time at negligible cost
- Polynomial Chaos Expansion (PCE) → *Stochastic expansion method*
  - Multivariate orthogonal polynomials build the functional relationship between a response function and its random inputs
    - Polynomials are tailored to the specific input parameter distribution types → Legendre polynomial represent uniform distributions
  - Polynomial coefficients found through regression
    - LHS samples of the parameter space build a response function set that is fit with polynomials of varying order → Cross-validation determines best polynomial order

- General Approach:
  - Step 1: Define the parameter space and probability distributions for each parameter
  - Step 2: Define the desired number of LHS samples (*N*), stratify parameter space, process *N* stratified simulations
  - Step 4: Build the PCE surrogate using cross-validation to determine the best polynomial order
  - Step 5: Sample the surrogate model 1000's of times
  - Step 6: Apply the ANOVA to the surrogate samples to determine the critical parameter list

- Bi-Material Strip PCE process:
  - Step 1: 20-dimensional parameter space, uniform distributions for all parameters
  - Step 2: Initial samples size = 21, or $n+1$ → response function set size = 21
  - Step 4: PCE surrogate built considering polynomial orders 1-5
  - Step 5: 10000 samples were taken of the PCE surrogate
  - Step 6: ANOVA applied to resulting 10000 predictions to generate critical parameter list
  - Step 7: Repeat steps 2-6 with incrementally increasing *N* until critical parameter list is converged

Surrogate Methods: Gaussian Process (GP)

- Gaussian Process (GP)
  - All finite dimensional distributions must have a multivariate normal, or Gaussian, distribution
    - *Example*: Given a stochastic process, X, that is a function of the variables within a set T, for any choice of distinct values of T, the corresponding vector $\boldsymbol{X}$ must have a multivariate normal distribution
    - Normal distribution can be described by the finite dimensional distribution's mean and covariance functions → the Gaussian distribution is defined

- General Approach:
  - Step 1: Define the parameter space and probability distributions for each parameter
  - Step 2: Define the desired number of LHS samples (N), stratify parameter space, process N stratified simulations
  - Step 4: Assume response function set adheres to a Gaussian distribution and build the GP surrogate
  - Step 5: Sample the surrogate model 1000's of times
  - Step 6: Apply the ANOVA to the surrogate samples to determine the critical parameter list

- Bi-Material Strip GP process:
  - Step 1: 20-dimensional parameter space, uniform distributions for all parameters
  - Step 2: Initial samples size = 21, or $n+1$ → initial response function set size = 21
  - Step 4: GP surrogate was built
  - Step 5: 10000 samples were taken of the GP surrogate
  - Step 6: ANOVA applied to resulting 10000 predictions to generate critical parameter list
  - Step 7: Repeat steps 2-6 with incrementally increasing N until critical parameter list is converged

Results and Conclusions

Comparison of Sensitivity Analysis Methods

- Surrogate methods require the fewest samples for a converged list of critical parameters
  - GP may be preferred, slightly easier to implement
- Sampling methods are the least efficient approaches → 4-8x more expensive than surrogate methods
  - MC/LHS are simple to implement with any deterministic FE code
  - Merit consideration when lacking access to iterative analysis tools
- BBD is more efficient than the sampling methods, but twice as expensive as the surrogate methods
  - DOE methods are less complex than surrogates, can be implemented with any deterministic FE code
  - Should be considered as preferred alternative to sampling methods when lacking access to iterative analysis tools
- CPS provides a reasonable critical parameters list at a low number of samples, but seems to omit some of the less influential critical parameters
  - Should be considered when a measure of sensitivity is required, but only a handful of samples are computationally affordable

Summary of Sensitivity Study Survey

		Model Parameters																			
Method	Sample #	E_{11}	E_{22}	E_{33}	v_{12}	v_{13}	v_{23}	G_{12}	G_{13}	G_{23}	$\alpha_{11,G}$	$\alpha_{22,G}$	$\alpha_{33,G}$	$\alpha_{11,R}$	$\alpha_{22,R}$	$\alpha_{33,R}$	T_g	T_{sf}	E_{Al}	v_{Al}	α_{Al}
CPS	41	■									■			■			■	■	■		■
	81	■	■								■			■			■	■	■		■
	121	■	■								■			■			■	■	■		■
MC	22	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■	■	■
	44	■						■			■			■		■	■	■	■	■	■
	88	■	■								■			■			■	■	■		■
	176	■						■			■			■		■	■	■	■		■
	352	■						■			■			■			■	■	■		■
	704	■	■		■				■		■			■		■	■	■	■		■
	1408	■	■								■			■			■	■	■		■
	2816	■	■		■						■	■		■			■	■	■	■	■
	5632	■	■		■						■	■		■			■	■	■	■	■
LHS	22										■						■	■			■
	44	■	■							■	■			■			■	■	■		■
	88	■	■								■			■			■	■	■		■
	176	■	■								■			■			■	■	■	■	■
	352	■	■								■	■		■			■	■	■		■
	704	■	■		■						■			■			■	■	■	■	■
	1408	■	■		■						■	■		■			■	■	■	■	■
	2816	■	■		■						■	■		■			■	■	■	■	■
BBD	**761**	■	■		■						■	■		■			■	■	■		■
PCE	21	■	■			■			■		■			■			■	■	■		■
	42	■	■		■	■		■	■	■	■	■	■	■			■	■	■		■
	84	■	■								■	■		■			■	■	■	■	■
	168	■	■		■						■	■		■	■		■	■	■		■
	336	■	■		■						■	■		■	■		■	■	■	■	■
	672	■	■		■						■	■		■	■		■	■	■	■	■
GP	21				■		■					■	■	■		■					■
	42	■						■	■			■		■	■	■		■		■	■
	84	■	■	■	■	■	■	■	■	■	■	■	■	■		■	■	■	■		■
	168	■	■	■	■	■		■	■	■	■	■		■	■		■	■	■	■	
	336	■	■		■						■	■		■	■		■	■	■	■	■
	672	■	■		■						■	■		■	■		■	■	■	■	■

Material Parameter Criticality

- Summary of critical parameters:
  - All methods selected as critical: E_{11}, E_{22}, $\alpha_{11,G}$, $\alpha_{11,R}$, T_g, T_{sf}, E_{Al}, α_{Al}
    - In-plane mechanical/thermal properties of CFRP and aluminum properties should be critical
      - Residual stress development governed by in-plane CFRP/Al contraction mismatch
    - T_g and T_{sf} should be critical
      - T_{sf} indicates when residual stresses begin to develop
      - T_g governs rate of stress development
  - All methods, *except* CPS, selected as critical: ν_{12} , $\alpha_{22,G}$
  - All methods, *except* CPS and BBD, selected as critical: ν_{Al}
  - *Only* surrogate methods selected: $\alpha_{22,R}$
    - ν_{12} , $\alpha_{22,G}$, ν_{Al}, $\alpha_{22,R}$ may be less influential
- PCE surrogate can determine Sobol indices
  - Sensitivity indices → *rank critical parameters by relative influence*
  - Parameters selected by some, but not all, methods as critical of the lowest indices
  - The most significant indices govern the development of thermal strains
  - α_{Al} is most significant by a large margin
    - In-plane CTE of CFRP ≪ CTE of aluminum → aluminum thermal contractions drive residual stress development

PCE Sobol Indices

Parameter	Sobol Index
α_{Al}	98.003763%
T_{sf}	1.091548%
T_g	0.363556%
$\alpha_{11,G}$	0.354474%
E_{Al}	0.059520%
$\alpha_{11,R}$	0.056149%
E_{11}	0.027971%
E_{22}	0.001954%
ν_{12}	0.000305%
ν_{Al}	0.000301%
$\alpha_{22,G}$	0.000295%
$\alpha_{22,R}$	0.000018%
ν_{13}	0.000000%
E_{33}	0.000000%
$\alpha_{33,R}$	0.000000%
G_{23}	0.000000%
$\alpha_{33,G}$	0.000000%
ν_{23}	0.000000%
G_{13}	0.000000%
G_{12}	0.000000%

Final Summary and Conclusions

- Residual stresses should be considered when designing composite parts
  - Finite element simulation of residual stresses may be preferred to experimental measurement
- Sandia's process modeling approach requires 20+ material parameters
  - Sparse experimental resources can make rigorous characterization impractical
  - Sensitivity surveys can be used to allocate experimental resources
- A survey of DAKOTA's sensitivity survey capabilities was completed with a process model of a mesh-optimized, bi-material CFRP/Aluminum strip
  - What is the ideal sensitivity study approach?
    - *GP/PCE* surrogates demonstrated the best computational efficiency
    - *BBD* approach should be used if there is no access to an iterative analysis toolkit
    - *CPS* should be used if parameter sensitivity is desired for an expensive model
    - Suggested methodology can be applied generally, not just to process modeling of composites
  - Which model parameters are most critical to a composite's residual stress predictions?
    - In-plane mechanical and thermal properties → in-plane contractions govern residual stress development at the bi-material interface
    - Stress-free and glass transition temperatures → T_g and T_{sf} govern when and with what rates residual stresses develop

Thank you!