



Dakota as a Solution Verification and Uncertainty Quantification Tool

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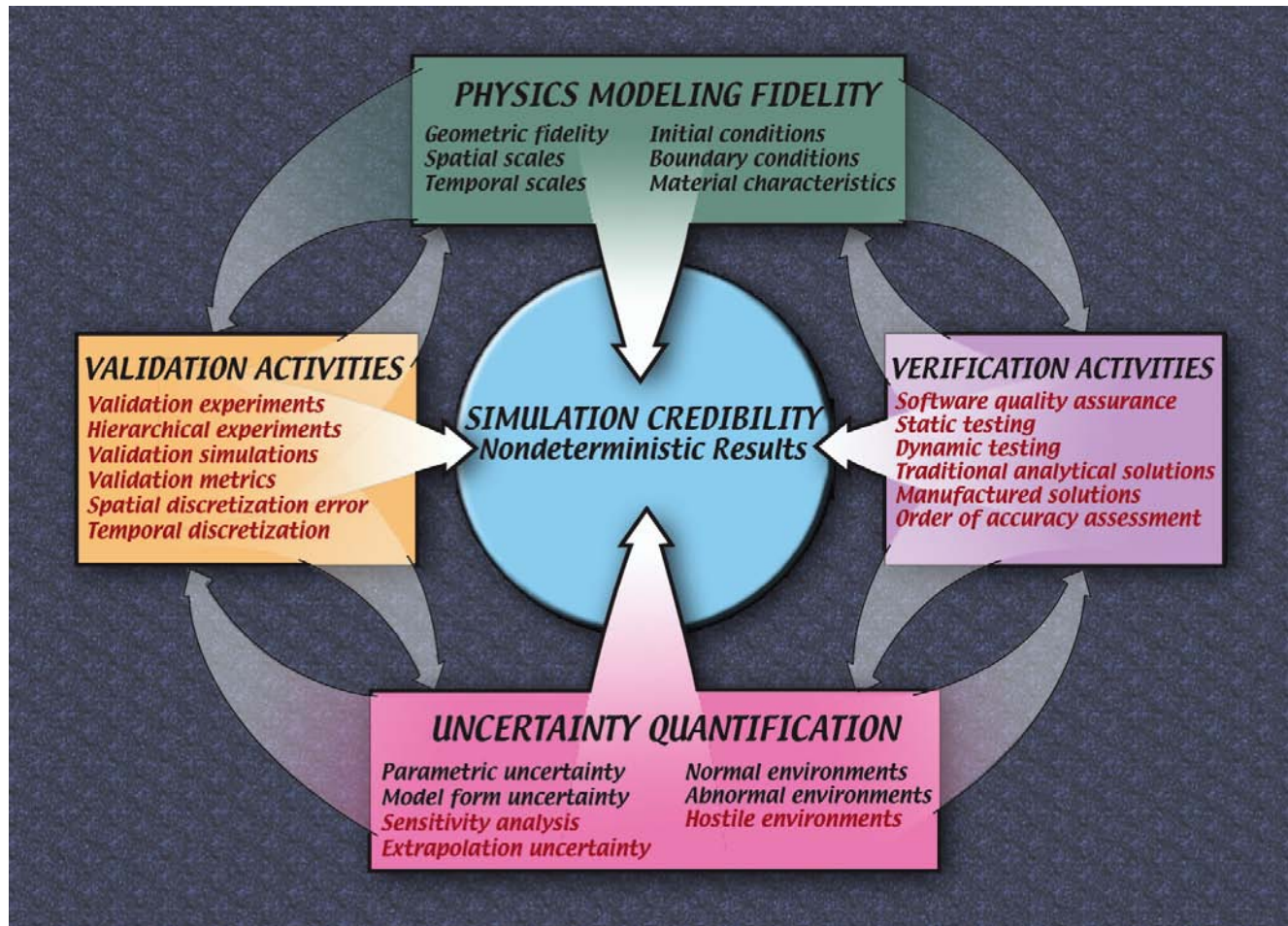
Outline

- Why perform Verification of your solution and What is Uncertainty Quantification?
- DAKOTA Overview
- Overview of Dakota Tools Using Analytical Beam Equation
 - Dakota Input Deck
 - Parameter Studies
 - Uncertainty Quantification
 - Mixed Aleatoric/Epistemic Uncertainty
- Case Study: Electrostatic Activation of Thin Film MEMS Device
 - Solution Verification
 - Aleatoric Uncertainty

Why perform Solution V&V and UQ?

- Verification
 - Determine if you are solving what you believe you are solving
 - Quantify how well you are solving the problem
- Uncertainty Quantification
 - Epistemic
 - Lack of knowledge
 - Reducible
 - Aleatoric
 - Variability inherent in the environment or problem definition
 - Irreducible, can't be reduced by further knowledge

Overview of V&V and UQ

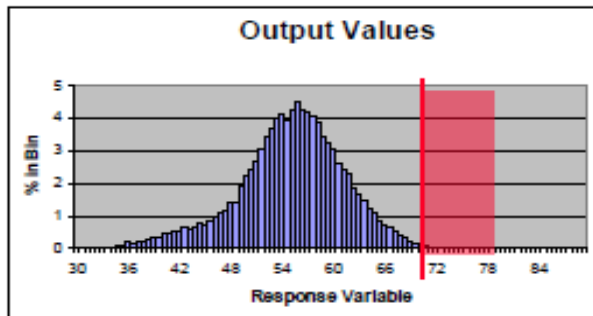


Toolkit for Large-Scale Optimization & UQ



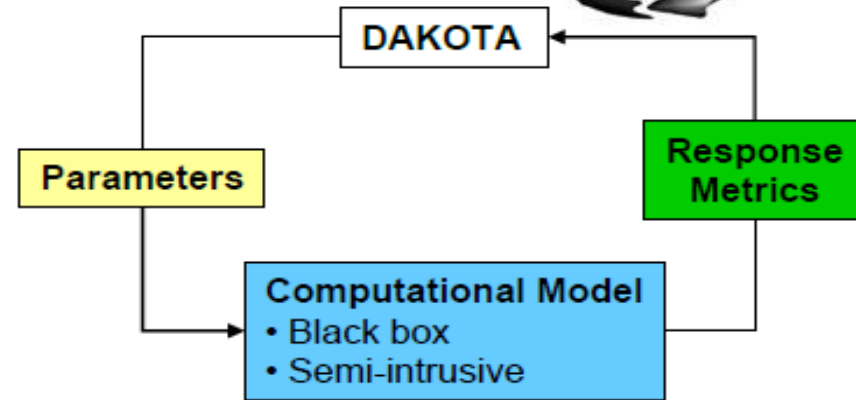
DAKOTA allows analysis of fundamental science and engineering questions with computational models:

- **Sensitivities:** What are the crucial parameters?
- **Uncertainties:** How safe, reliable, robust, variable is my system?
- **Optimization:** What is the best performing design?
- **Calibration:** What parameter values or models best match experimental data?



Example: Assessing probability of failure from distribution (uncertainty) of output values

Broad deployment via open source model:
Over 4,000 download registrations spanning
government, industry, academia



DAKOTA analysis "strategies" rely on iterative analysis with a computational model for the phenomenon of interest

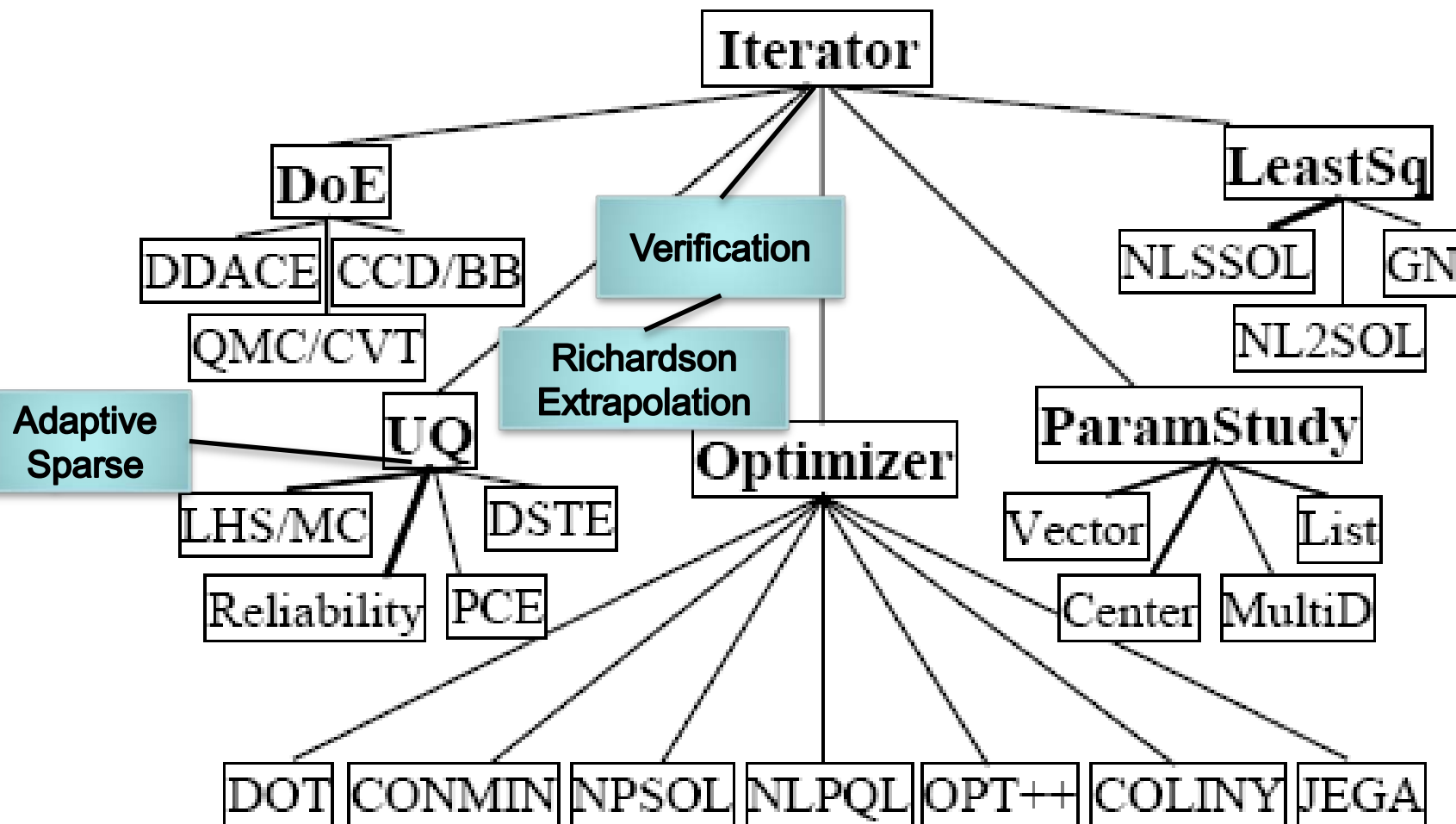
Strategies can be combined for more advanced capabilities, e.g.,

- *Model calibration under uncertainty*
- *Uncertainty of optima*

Multi-level parallelism supports large-scale applications and architectures



Dakota Features



Dakota Input Deck

Strategy,

single_method

tabular_graphics_data

Method,

multidim_parameter_study

partitions = 3 3

Model,

single

primary_variable_mapping = 'v1' 'v2'

primary_response_mapping = 0. 1. 0. 1.

Variables,

interval_uncertain

num_intervals 1 1

interval_probs 1. 1.

interval_bounds 1. 10. 1. 10.

Responses,

number_response_functions = 2

response_descriptors 'r1' 'r2'

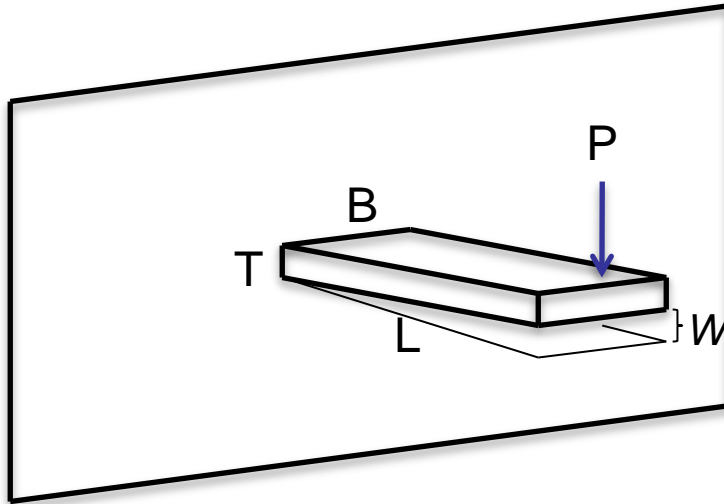
Interface,

asynchronous

evaluation_concurrency = 3

analysis_driver = './simulation.py'

Example Problem: Analytical Beam



$$\frac{\partial^2}{\partial x^2} \left(EI \frac{\partial^2 w}{\partial x^2} \right) = q$$

$$I = \frac{BT^3}{12}$$

$$W = \frac{4PL^3}{EBT^3}$$

Parameters	UQ Type	Nominal Value	Std Dev Range	%
Youngs Modulus (E,Pa)	Epistemic	2.00E+11	2.00E+10	10.00%
Beam Width (b,m)	Aleatoric	0.15	0.015	10.00%
Beam Length (l,m)	Epistemic	0.5	0.05	10.00%
Beam Thickness (t,m)	Aleatoric	0.006	0.0006	10.00%
Load (P,N)	Epistemic	2000	200	10.00%
Density(rho,kg/m ³)	-	7874	-	-

Example Problem: Parameter Study

- List

- Arbitrary set of points
 - Length of beam



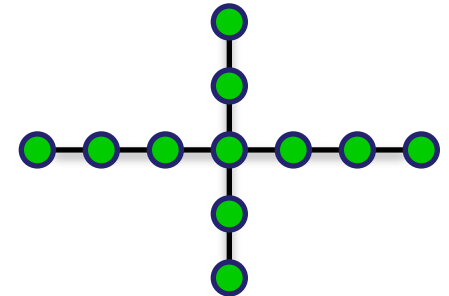
- Vector

- Ordered set of points in 1 dimension
 - Load on beam tip



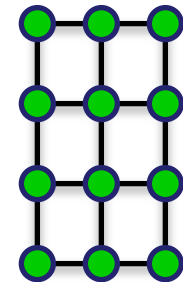
- Centered

- Evaluate 2 dimensions about 2 central values
 - Length of beam and Load on beam tip



- Multi-dimensional

- Explore a full grid of points
 - Length of beam and Load on beam tip



Example Problem: Dakota Set-up

```
method,  
  list_parameter_study  
  list_of_points = 0.25 0.5 0.6 0.7 0.75 1.0
```

```
variables,  
  discrete_state_set_real = 1  
  set_values = 0.25 0.5 0.6 0.7 0.75 1.0  
  descriptors = 'L'
```

```
method,  
  centered_parameter_study  
  step_vector = 0.05 200  
  steps_per_variable = 2
```

```
variables,  
  continuous_design = 2  
  initial_point = 0.5 2000  
  descriptors = 'L' 'P'
```

```
method,  
  vector_parameter_study  
  final_point = 4000  
  num_steps = 9
```

```
variables,  
  continuous_design = 1  
  initial_point = 1000  
  descriptors = 'P'
```

```
method,  
  multidim_parameter_study  
  partitions = 2
```

```
variables,  
  continuous_design = 2  
  initial_point = 0.5 2000  
  upper_bounds = 0.75 3000  
  lower_bounds = 0.25 1000  
  descriptors = 'L' 'P'
```

Example Problem: Dakota Set-up

```
method,  
  nond_polynomial_chaos  
  quadrature_order 4 4  
  sample_type lhs  
  seed = 1729 rng rnum2  
  samples = 1000  
variables,  
  normal_uncertain = 2  
  mean              = 0.15    0.006  
  std_deviations = 0.015    0.0006  
  descriptors       = 'B'     'T'
```

```
method,  
  nond_polynomial_chaos  
  sparse_grid_level = 2  
  sample_type lhs  
  seed = 1729 rng rnum2  
  samples = 1000  
variables,  
  normal_uncertain = 3  
  mean              = 0.5    0.15    0.006  
  std_deviations = 0.05    0.015    0.0006  
  descriptors       = 'L'    'B'     'T'
```

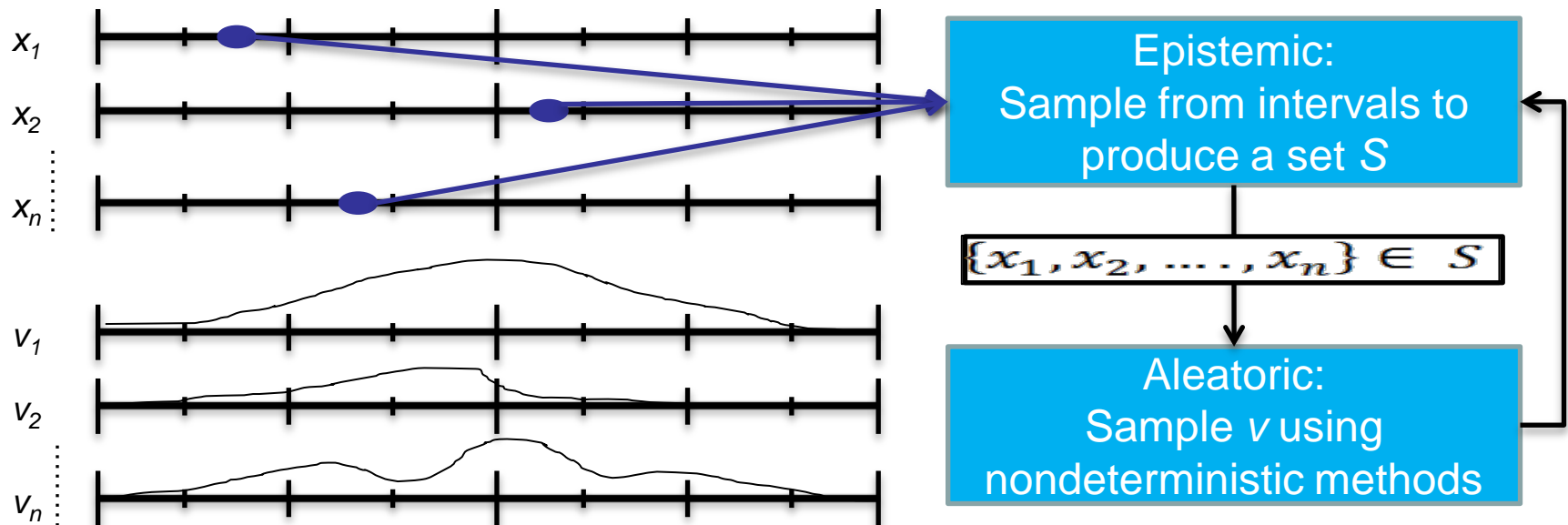
$$W = \frac{4PL^3}{EBT^3}$$

Example Problem: UQ Method Comparison

	Monte Carlo	LHC	Tensor	Sparse	Sparse 2
Simulations	6400	1280	16	5	17
Mean of W	1.668E-001	1.661E-001	1.660E-001	1.659E-001	1.660E-001
RMS error	-	4.24E-003	4.54E-003	5.35E-003	4.53E-003
% Error	-	0.4241%	0.4540%	0.5347%	0.4529%
Workload	-	20.000%	0.250%	0.078%	0.266%

Example Problem: Mixed Aleatoric and Epistemic Uncertainty

- Nested Model
 - Outer loop iterates over Epistemic
 - Inner loop iterates over Aleatoric
- Optimization, parameter studies, or sampling of Epistemic variables
- PCE, parameter studies, or sampling of Aleatoric variables



Example Problem: Dakota Set-up

```
strategy,  
  single_method  
  method_pointer = 'EPISTEMIC'  
method,  
  id_method = 'EPISTEMIC'  
  model_pointer = 'EPIST_M'  
  multidim_parameter_study  
  partitions = 2 2 2  
model,  
  id_model = 'EPIST_M'  
  nested  
  variables_pointer = 'EPIST_V'  
  sub_method_pointer = 'ALEATORY'  
  responses_pointer = 'EPIST_R'  
  primary_variable_mapping = 'L' 'P' 'E'  
  primary_response_mapping = 1. 0. 0. 0. 0. 0.  
                             0. 1. 0. 0. 0. 0.  
                             0. 0. 0. 1. 0. 0.  
                             0. 0. 0. 0. 1. 0.  
variables,  
  id_variables = 'EPIST_V'  
  interval_uncertain = 3  
  num_intervals = 1 1 1  
  interval_probs = 1.0 1.0 1.0  
  interval_bounds = 0.4 0.6 1600 2400 1.8e11 2.2e11  
responses,  
  id_responses = 'EPIST_R'  
  num_response_functions = 4  
  response_descriptors = 'mean_W' 'STD_W' 'mean_Weight' 'STD_beta_Weight'  
  no_gradients  
  no_hessians
```

```
method,  
  id_method = 'ALEATORY'  
  model_pointer = 'ALEAT_M'  
  nond_sampling sample_type lhs  
  seed = 84952 samples = 5  
  num_response_levels = 1 1  
  response_levels = 0.2 3  
  compute_reliabilities  
  complementary_distribution  
model,  
  id_model = 'ALEAT_M'  
  single  
  variables_pointer = 'ALEAT_V'  
  interface_pointer = 'ALEAT_I'  
  responses_pointer = 'ALEAT_R'  
variables,  
  id_variables = 'ALEAT_V'  
  continuous_design = 3  
  normal_uncertain = 2  
interface,  
  id_interface = 'ALEAT_I'  
  fork  
  asynchronous_evaluation_concurrency = 5  
  analysis_driver = './list.py'  
responses,  
  id_responses = 'ALEAT_R'  
  num_response_functions = 2  
  response_descriptors = 'W' 'Weight'  
  no_gradients  
  no_hessians
```

Case Study: Electrostatic Activation of Radio Frequency Capacitive Switch

- Coupled Physics
 - Electrostatics
 - Solid Mechanics
 - Contact
- Instability
- Loosely coupled
 - Iteration on non-linear loop
- Quasi-static

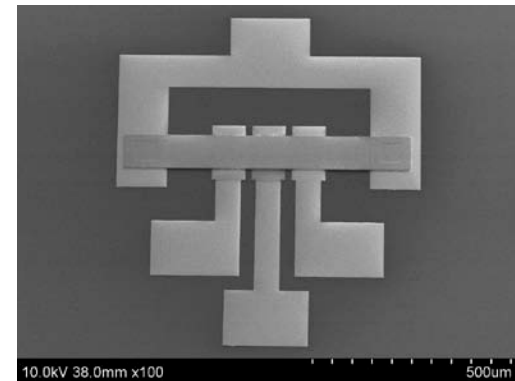
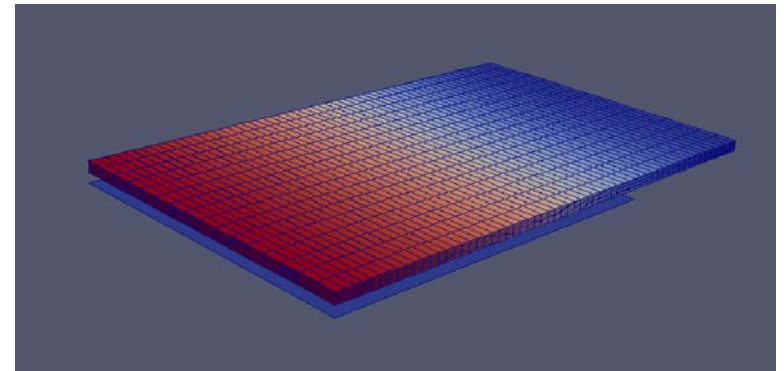


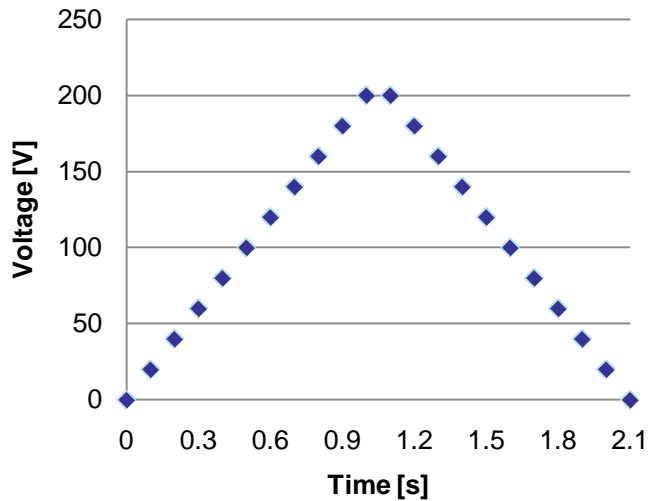
Image courtesy of NNSA sponsored Center for PRISM



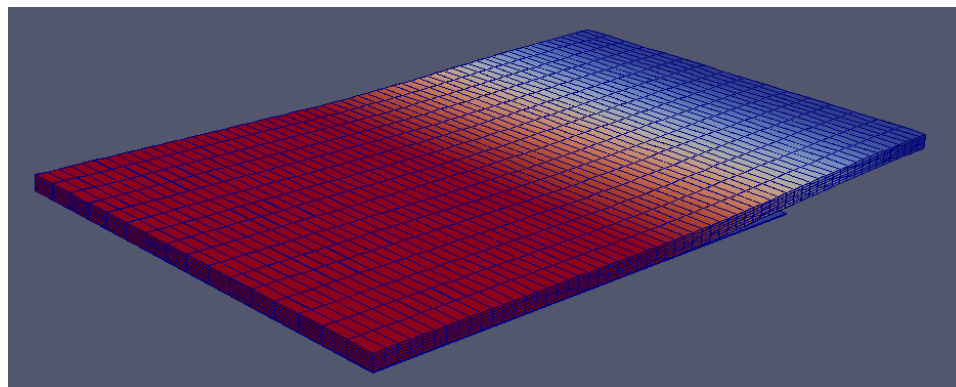
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Case Study: Beam Properties and Load Conditions

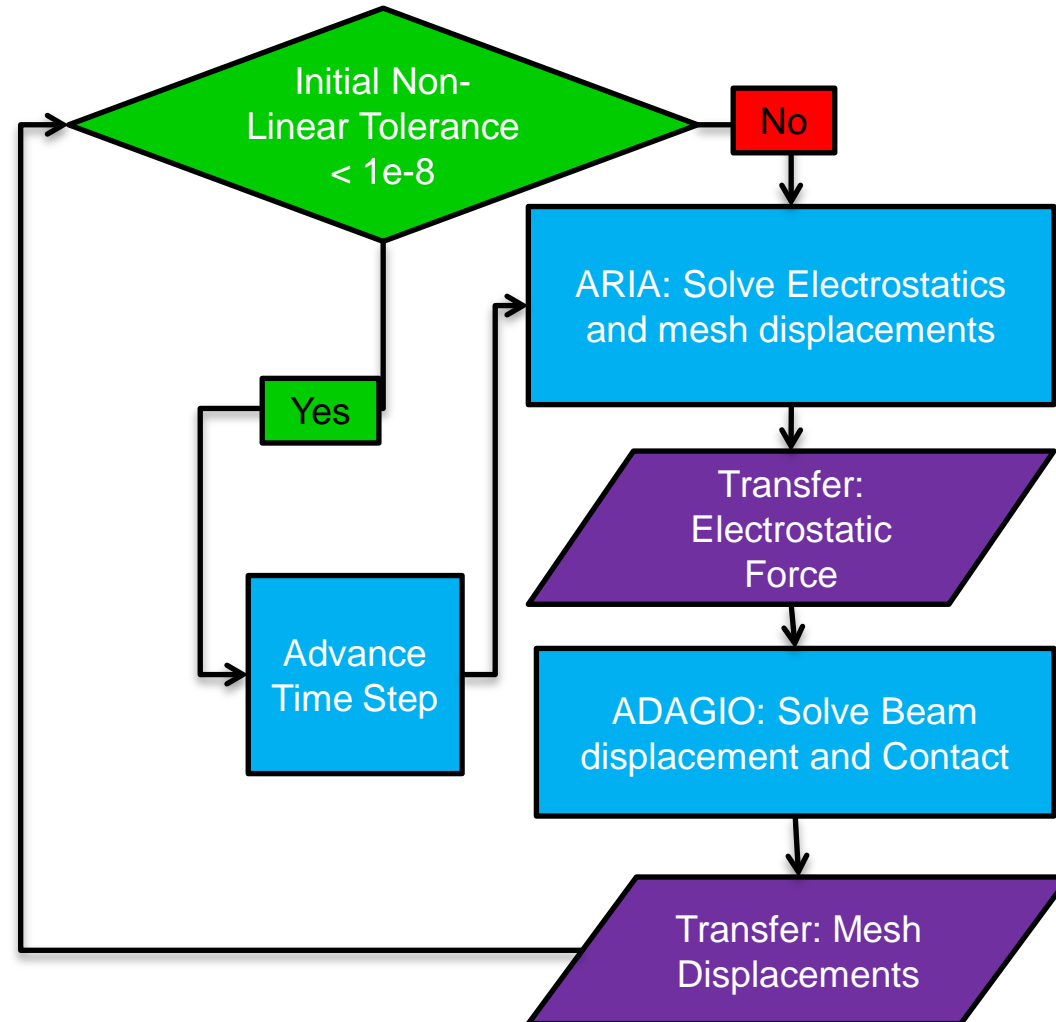
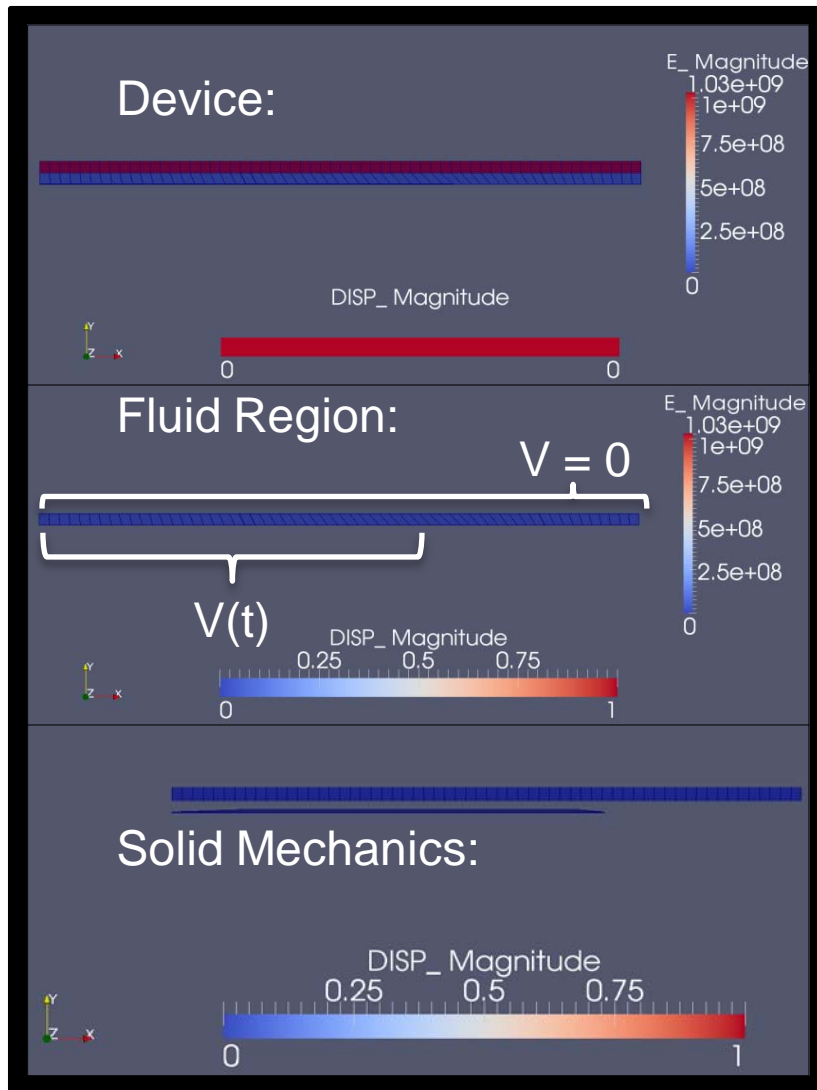
Voltage Load Boundary Condition



Parameters	UQ Type	Nominal Value	Std Dev Range	%
Young's Modulus (E) [Pa]	Epistemic	1.6E+11	5.00E+10	31.25%
Beam Width (T) [um]	Aleatoric	120	2	1.67%
Beam Length (Lb) [um]	Epistemic	400	2	0.50%
Electrode Length (Le) [um]	Aleatoric	270	1	0.37%
Beam Thickness (t) [um]	Aleatoric	4	0.6	15.00%
Gap Thickness (g) [um]	Aleatoric	3.8	0.3	7.89%
Dielectric Thickness (d) [um]	Aleatoric	0.15	0.02	13.33%
Density (rho) [kg/m ³]	-	8800	-	-

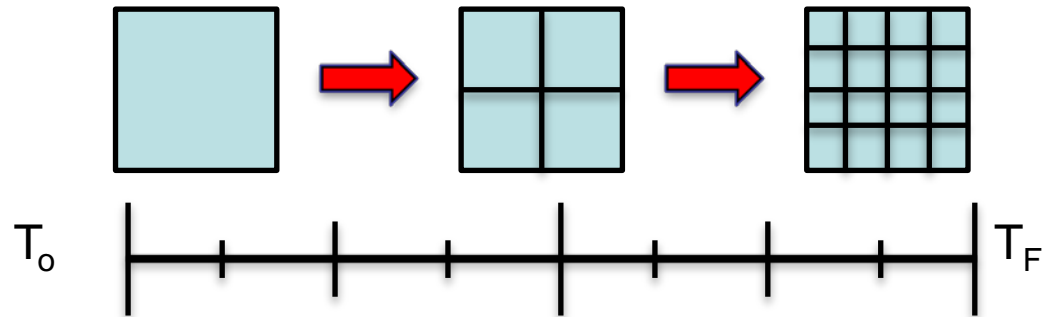


Case Study: Boundary Conditions and Solution Procedure



Case Study: Verification

- Code Verification (Algorithm)
 - Code solves equations correctly
 - Analytical Solutions
 - Method of Manufactured Solutions
- Solution Verification (Numeric's)
 - Simulations are refined to acceptable level of error
 - Discretization
 - Temporal
 - Tolerance



Quantify!

Case Study: Solution Verification

Discretization Set-up

```
method,  
  list_parameter_study  
  list_of_points = 1 2 3 4 5 6 7 8  
  
variables,  
  discrete_state_set_real = 1  
  set_values = 1 2 3 4 5 6 7 8  
  descriptors = 'Mesh_multiplier'
```

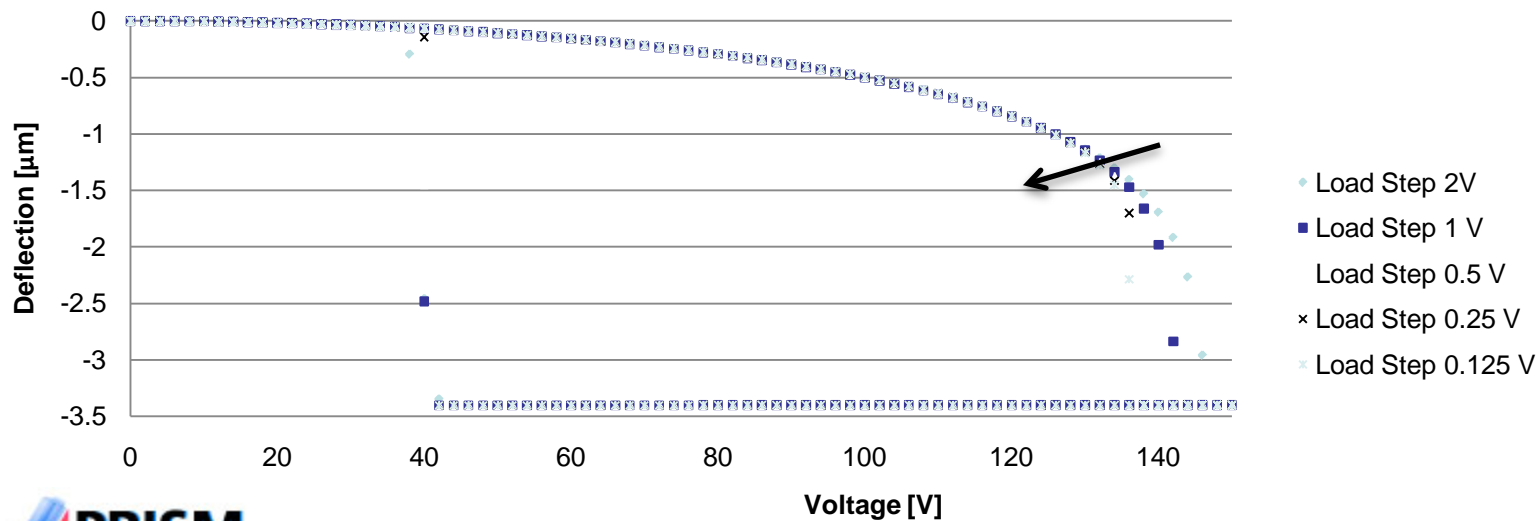
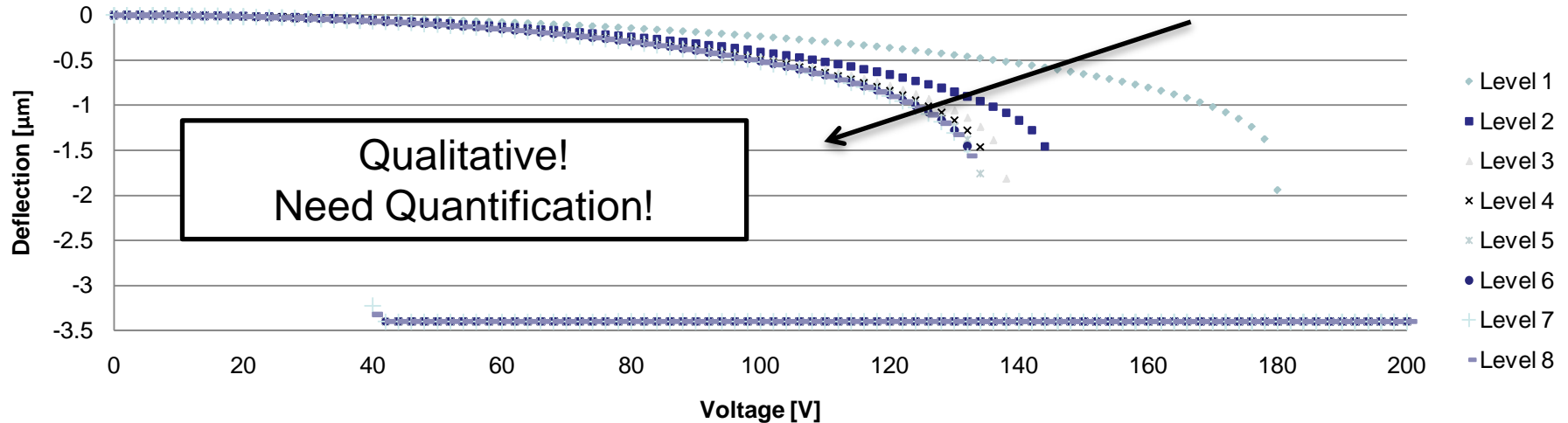
```
method,  
  list_parameter_study  
  list_of_points = 2 1 0.5 0.25 0.125  
  
variables,  
  discrete_state_set_real = 1  
  set_values = 2 1 0.5 0.25 0.125  
  descriptors = 'V_step'
```

New Richardson Extrapolation Iterator!

```
method,  
  richardson_extrap  
  estimate_order  
  refinement_rate = 2  
variables,  
  continuous_state = 1  
  initial_state = 1  
  descriptors = 'Mesh_multiplier'
```

```
method,  
  richardson_extrap  
  estimate_order  
  refinement_rate = 2  
variables,  
  continuous_state = 1  
  initial_state = 1  
  descriptors = '1/V_step'
```

Case Study: Solution Verification Discretization and Temporal



Case Study: Solution Verification - Convergence

$$p = \frac{\ln \left| \frac{\varepsilon_{32}}{\varepsilon_{21}} \right| + q(p^*)}{\ln |r_{21}|}$$

$$C = \frac{(\varphi_{fine} - \varphi_{medium})}{h_{medium}^p - h_{fine}^p}$$

$$\varphi_{extrap,coarse} = \varphi_{coarse} + C * h_{coarse}^p$$

$$r = \frac{h_{coarse}}{h_{fine}}$$

$$\varepsilon_{21} = \varphi_2 - \varphi_1$$

$$s = \sin \left(\frac{\varepsilon_{32}}{\varepsilon_{21}} \right)$$

$$q(p^*) = \ln \left(\frac{r_{21}^{p^*} - s}{r_{32}^{p^*} - s} \right)$$

Uniform refinement ratio:

$$q(p^*) = 0$$

Case Study: Solution Verification

Discretization

Delta [V]	Mesh Factor	Pull-in	Rate	Extrapolated	Numerical Error [V]	% Error of Extrapolated
0.1	1	180.4	2.24	142.68	37.72	26.43%
0.1	2	145.9	2.45	136.97	8.93	6.52%
0.1	3	138.6	2.82	135.06	3.54	2.62%
0.1	4	135.9	2.42	133.98	1.92	1.43%
0.1	5	134.7	3.07	133.61	1.09	0.81%
0.1	6	134.0	1.87	133.04	0.96	0.72%
0.1	7	133.6	-	-	-	-
0.1	8	133.3	-	-	-	-

Discretization Error!
Can be used to bound results.

Delta [V]	Mesh Factor	Pull-in	Rate	Extrapolated	Num Error [V]	Error [%]
2	4	148	0.74	140.19	7.81	5.57%
1	4	143	0.42	136.14	6.86	5.04%
0.5	4	140	0.58	135.95	4.05	2.98%
0.25	4	137.75	0.78	135.48	2.27	1.68%
0.125	4	136.25	-	-	-	-
0.0625	4	135.375	-	-	-	-

Case Study: Solution Verification

- Large Error (5.6%, 7.81 V) for Pull-in voltage
- Dependence on load step size
 - Quasi-static problem
 - Convergence issue!
- Options to proceed
 - Improve simulation (Best Option)
 - Refine problem statement
 - Work with Code developers to improve capabilities, resolve convergence issues
 - Simulate using fine discretization/load step (Duct Tape)
 - Document shortcomings of simulation
 - Quantify!
 - Minimize effects of shortcomings

Case Study: Uncertainty Quantification

Aleatoric Uncertainty

- Level 1 – Sparse Grid Integration of Polynomial Chaos Expansion
 - Effect Screening
- 6 uncertain parameters
 - Assume Normal distribution
 - Assumed form of distribution can be treated as an epistemic error!

Parameters	UQ Type	Nominal Value	Std Dev Range	%
Beam Width (T) [um]	Aleatoric	120	2	1.67%
Beam Length (Lb) [um]	Epistemic	400	2	0.50%
Electrode Length (Le) [um]	Aleatoric	270	1	0.37%
Beam Thickness (t) [um]	Aleatoric	4	0.6	15.00%
Gap Thickness (g) [um]	Aleatoric	3.8	0.3	7.89%
Dielectric Thickness (d) [um]	Aleatoric	0.15	0.02	13.33%

Case Study: Uncertainty Quantification Aleatoric Uncertainty – Results

Statistics derived analytically from polynomial expansion:

Moments for each response function:

Pull_in: Mean = $1.4941666667e+02$ Std. Dev. = $3.5132665237e+01$ Coeff. of Variation = $2.3513217114e-01$

Pull_out: Mean = $3.5666666667e+01$ Std. Dev. = $7.5346975166e+00$ Coeff. of Variation = $2.1125320140e-01$

Pull_in total Sobol indices:

$7.8748822717e-03$ Lb
 $2.4305192197e-05$ Le
 $7.1209419612e-01$ t
 $2.8000661641e-01$ g
 $0.0000000000e+00$ d
 $0.0000000000e+00$ T

Pull_out total Sobol indices:

$1.3210815254e-02$ Lb
 $3.6696709039e-04$ Le
 $6.0489387312e-01$ t
 $1.9076417227e-01$ g
 $1.9076417227e-01$ d
 $0.0000000000e+00$ T

Case Study: Uncertainty Quantification

Aleatoric Uncertainty - Results

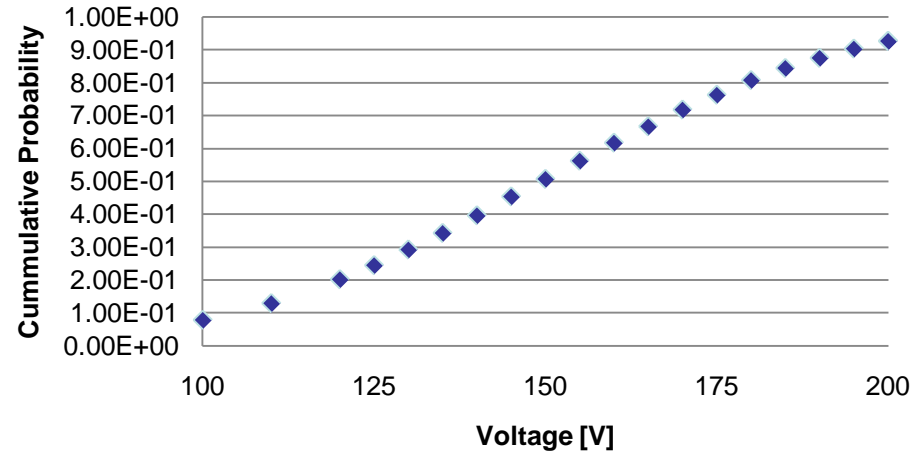
CDF: Pull-in

Polynomial Chaos coefficients for Pull_in:

coefficient u1 u2 u3 u4 u5 u6

```

-----
1.4941666667e+02 He0 He0 He0 He0 He0 He0
-3.1176914536e+00 He1 He0 He0 He0 He0 He0
1.7320508076e-01 He0 He1 He0 He0 He0 He0
2.9646936323e+01 He0 He0 He1 He0 He0 He0
1.8590678668e+01 He0 He0 He0 He1 He0 He0
0.0000000000e+00 He0 He0 He0 He0 He1 He0
0.0000000000e+00 He0 He0 He0 He0 He0 He1
    
```



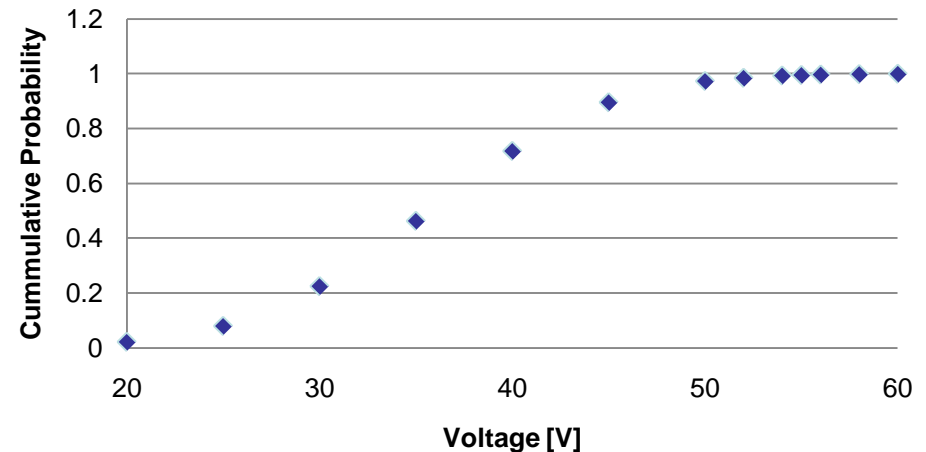
Polynomial Chaos coefficients for Pull_out:

coefficient u1 u2 u3 u4 u5 u6

```

-----
3.5666666667e+01 He0 He0 He0 He0 He0 He0
-8.6602540378e-01 He1 He0 He0 He0 He0 He0
1.4433756730e-01 He0 He1 He0 He0 He0 He0
5.8601052323e+00 He0 He0 He1 He0 He0 He0
3.2908965344e+00 He0 He0 He0 He1 He0 He0
3.2908965344e+00 He0 He0 He0 He0 He1 He0
0.0000000000e+00 He0 He0 He0 He0 He0 He1
    
```

CDF: Pull-out



Dakota: V&V and UQ tool

- Demonstrated solution verification using parameter studies
- Determined parameter relevance in uncertainty quantification using Sparse Grid PCE
- Evaluated PCE Response metrics to determine relative importance of parameters
 - Use to determine further course of action

<http://dakota.Sandia.gov>

Special Thanks

- Brian Carnes, Sandia V&V and UQ
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