This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

SAND2018-5144C



Explore and predict with confidence



Dakota Optimization and UQ Explore and Predict with Confidence

Brian M. Adams, J. Adam Stephens *Optimization and Uncertainty Quantification* **Patricia D. Hough** *Quantitative Modeling and Analysis*

http://dakota.sandia.gov

2018 SIAM Conference on Uncertainty Quantification April 16—19, 2018 Garden Grove, CA





Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

SNL Mission: Advanced Science and Engineering for National Security



- Nuclear Weapons
- Defense Systems and Assessments
- Energy and Climate
- Global Security

Strong research foundations span many disciplines



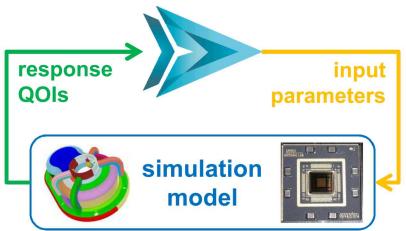
Dakota Mission:

To serve Sandia's mission through state-of-the-art research and robust, usable software for optimization and uncertainty quantification.

Dakota Team: has balanced strengths in algorithm research, software design and development, and application deployment and support

Dakota: Algorithms for Design Exploration and Uncertainty Quantification

- Suite of iterative mathematical and statistical methods that interface to computational models
- Makes sophisticated parametric exploration of black-box simulations practical for a computational design-analyze-test cycle:
 - Sensitivity Analysis
 - Uncertainty Quantification
 - Design Optimization
 - Model Calibration
- Goal: provide scientists and engineers (analysts, designers, decision makers) richer perspective on model predictions

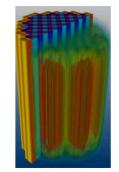




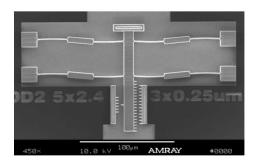
Practical Design Exploration and UQ for Diverse Simulations



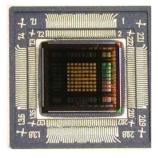
- Applied to many science and engineering domains mechanics, structures, shock, fluids, electrical, radiation, bio, chemistry, climate, infrastructure, etc.
- Diverse, often costly, simulation codes: finite element, coupled multi-physics, discrete event, Matlab, Python models



UQ and Bayesian inference for nuclear reactor core analysis



Reliability-based design optimization of micro-electromechanical systems (MEMS)



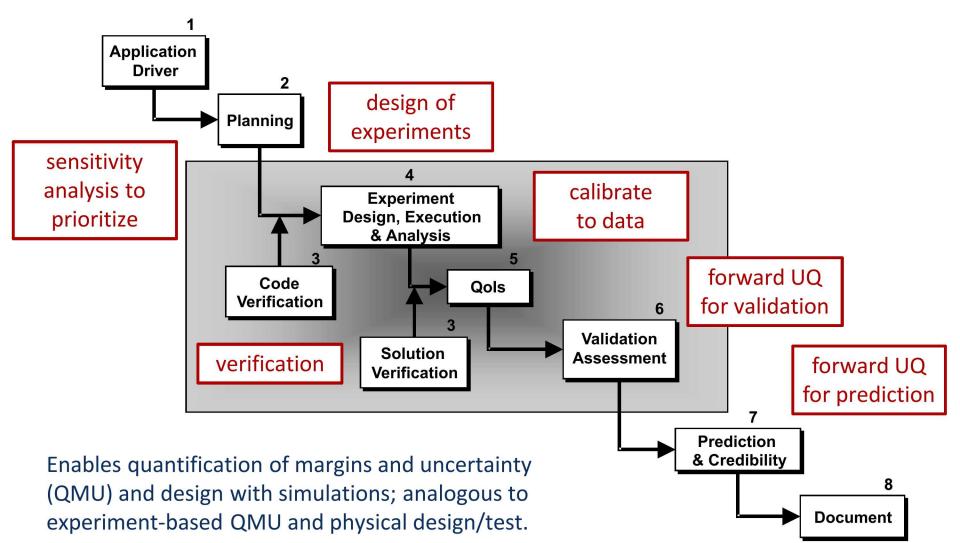
UQ for qualification of electrical circuits in harsh environments



Adjoint-based UQ for robust design of satellite radiation shields

Supports Credible Prediction





Many Methods in One Tool



 Sensitivity Analysis Designs: param. sweeps, MC/LHS, DACE, sparse grid, one-at-a-time Analysis: correlations, scatter, Morris effects, Sobol indices 	 Uncertainty Quantification MC/LHS/Adaptive sampling Local/global reliability Stochastic expansions Epistemic and interval methods Multi-fidelity/multi-level
Optimization	Calibration
Gradient-based local	 Tailored gradient-based
Derivative-free local	Use any optimizer
Global/heuristics	Bayesian inference
 Surrogate-based, multi-fidelity 	

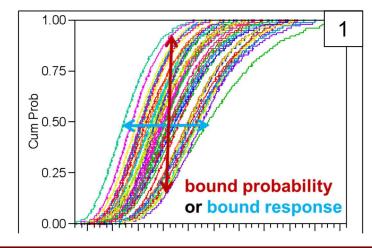
- ✓ One flexible simulation interface, many methods: once interface created, apply appropriate algorithm depending on question at hand
- ✓ Scalable parallel computing from desktop to HPC

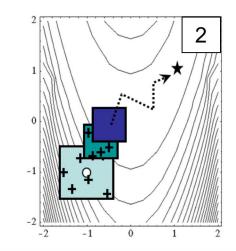
Engineering Needs Drive Dakota R&D



Advanced approaches help you solve practical problems:

- Characterize parameter uncertainty → Bayesian calibration
- Hybrid analysis goals → mix methods, surrogates, and models
- Mixed uncertainty characterizations → epistemic and mixed UQ approaches [1]
- Costly or noisy simulations → surrogate-based optimization [2] and UQ
- Build in safety or robustness → mixed deterministic/probabilistic methods [3]





min $f(d) + Ws_u(d)$ 3 s.t. $g_l \leq g(d) \leq g_u$ $h(d) = h_t$ $d_l \leq d \leq d_u$ $a_l \leq A_i s_u(d) \leq a_u$ $A_e s_u(d) = a_t$

Dakota History and Resources

- Genesis: 1994 optimization LDRD
- Modern software quality and development practices
- Released every May 15 and Nov 15
- Established user support process and mailing list







Mike Eldred, Founder

Lab mission-driven algorithm R&D deployed in production software

- Extensive website: documentation, training slides/videos, downloads
- Open source to facilitate collaboration; widely downloaded

Dakota Capability Directions





2016—2020 Strategic Plan stewards Dakota's research program while improving production deployment and impact

R&D Challenges



Tackle design exploration and UQ computational challenges (focusing on DOE national security mission):

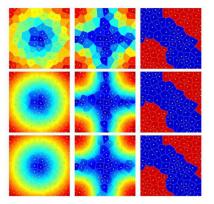
- Severely constrained simulation budgets
- High-dimensional parameter spaces
- Non-smooth, multi-modal, or unreliable quantities of interest
- Quantifying small probabilities

Active Algorithm R&D



- Core UQ: robust, scalable, adaptive sampling and stochastic expansions
- Multi-fidelity, multi-level optimization, inference, UQ methods
- Calibration: usable, robust deterministic and Bayesian methods
- Optimization: new gradient-based and discrete optimization methods
- Algorithms and interfaces that directly treat functional (time/space) data
- Scalability in number of parameters / responses and to next-generation architectures and parallelism models
- Reduced-order models: surrogates, active subspace, random field models

Discontinuity-detecting piecewise local surrogate models (Ebeida)



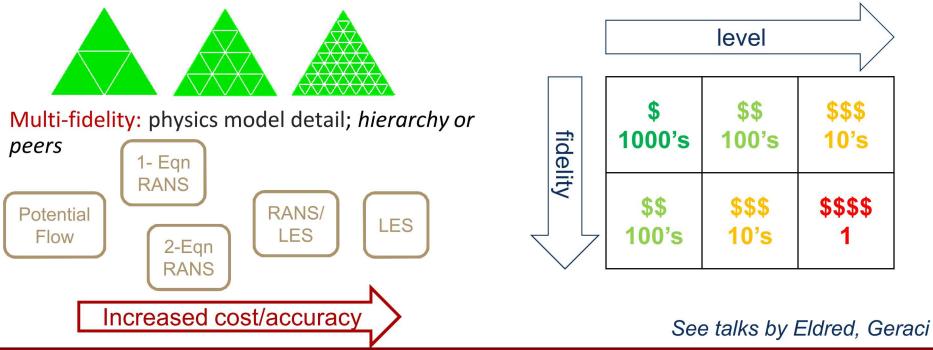
Multi-level/Multi-fidelity Methods



Goal: Use models of varying fidelities and/or levels to converge more quickly

- ML/MF sampling, stochastic expansions, optimization, calibration
- Automatically balance evaluations of each model

Multi-level: hierarchy of numerical approximation accuracies, *e.g., mesh resolution, solver tolerance*



Inference: Bayesian Calibration



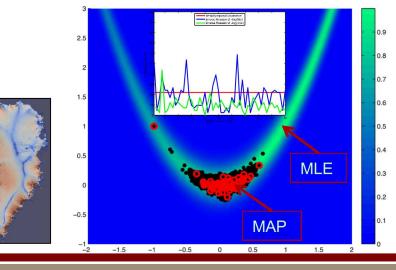
Goal: Obtain statistical characterization of parameters consistent with data

- MCMC with QUESO/DRAM and DREAM
- Adaptive, surrogate-based inference, including with ML/MF PCE
- Mutual information guided calibration of low-fi to high-fi model
- Usability: chain post-processing, statistics, credible/prediction intervals,
 KDE-smoothed posteriors, mutual information

Emerging capabilities

- Discrepancy models
- Metropolis-adjusted Langevin Algorithm
- Non-MCMC-based approaches
- Automated diagnostics and filtering
- Coupling with forward UQ methods

See talks by Jakeman, Maupin, Perego, Wildey



Random Field Modeling

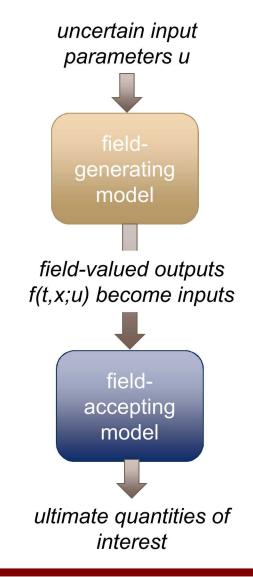
Goal: perform UQ with field-valued (time- or spacevarying) input uncertainties f(t, x), e.g., boundary conditions

- Generate realizations of *f(t; u)*: either sample the field-generating model or use offline data
- Approximate uncertainty in *f(t; u)*, e.g., by PCA + GP, or a Karhunen–Loève expansion with normal coefficients ω

$$\hat{f}(t,\omega) = \boldsymbol{\mu}_{f}(t) + \sum_{i=1}^{P} c_{i}(\omega) \varphi_{i} \quad (t)$$

• Propagate: perform UQ over ω , generating realizations of the approximate field $\hat{f}(t, \omega)$ and propagate through the field-accepting model





Other Development Areas



- Modular architecture
 - Ease Dakota development and give greater control to advanced users
 - Example 1: Surrogate model
 - Example 2: Optimizer traits and APIs
- Usability and user resources
 - Example 1: GUI
 - Example 2: Output database
 - Example 3: dakota.interfacing Python module
 - Example 4: Examples repo
- Improved user community engagement
 - Example 1: Dakota user-stakeholder meetings
 - Example 2: Surveys and interviews

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Thanks for your attention!

briadam@sandia.gov jasteph@sandia.gov pdhough@sandia.gov Other team members presenting at SIAM UQ: Eldred, Geraci, Jakeman, Khalil, Maupin, Swiler



BACKUP (ADDITIONAL DETAILS)

HPC Integration



Dakota readily integrates into HPC environments

Massively Serial

Dakota runs in parallel and drives a large number of serial simulations

Evaluation Tiling

Dakota runs serially as part of a submitted job and "tiles" intermediate-sized parallel simulations across the job

Three common use cases

- Example interface scripts provided
- Python modules in development

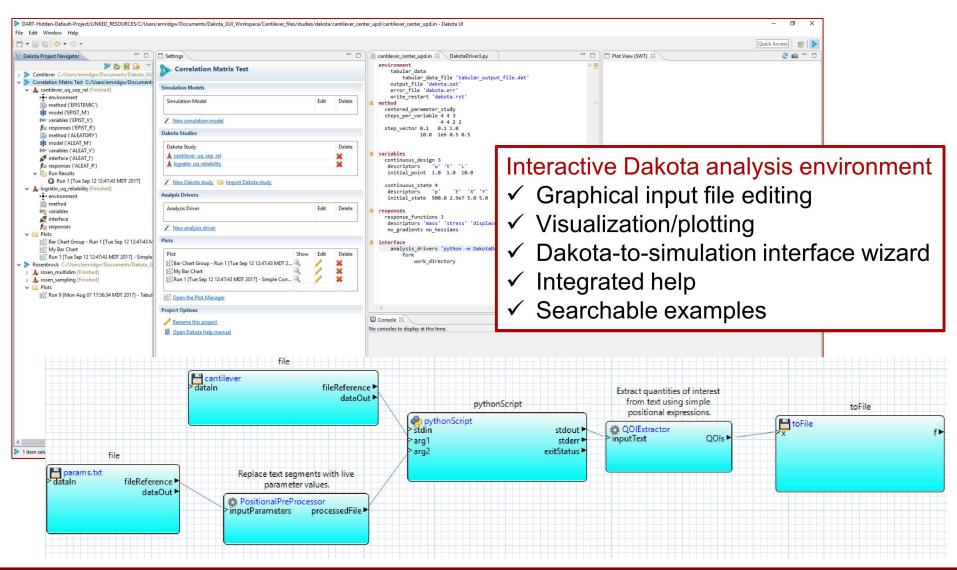
Evaluation Submission

Dakota runs serially on the login node and submits large parallel simulations as separate jobs.



Graphical User Interface

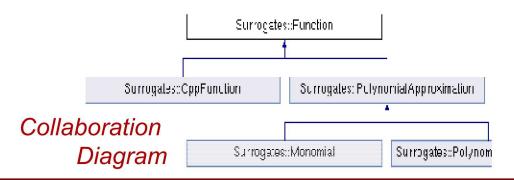




Dakota Modularization: Surrogate Model Library

Initial prototype demonstrated

- Modularize foundational utilities and surrogate models
- Progress on unifying Dakota, Surfpack, Pecos
- Increasing unit testing, coverage, and software quality
- Python interfaces to C++ components for ease of use by advanced users
- Jupyter-based interactive Python tutorial demonstrates more usable coordination of model components with Python





Building an monomial approximation of a function $f(x): \mathbb{R}^d o \mathbb{R}^q$

Environment setup

```
In [7]: # Reload all modules (except those excluded by %aimport) every time b
executing the Python code typed.
# Only necessary when using notebook
%load_ext autoreload
%autoreload
from approximations_cpp import *
```

The autoreload extension is already loaded. To reload it, use: %reload_ext autoreload

Specifying the function variables

$$=(x_1,\ldots,x_d)\in\mathcal{X}\subseteq\mathbb{R}^d$$

Let us consider a function of two variables defined on the unit square, i.e. $\mathcal{X} = [0,1]^d$

x

```
In [8]: num_vars = 2
variables = BoundedVariables()
ranges = define_homogeneous_ranges(num_vars, 0., 1.);
variables.set ranges(ranges)
```

Defining the function we want to approximate

Dakota provides a consistent interface to all functions and approximations. A standard python function can be wrappe the PyFunction class. For example here we create a wrapper of the function

$$f(x) = (f_1, f_2)^T, \quad f_j = \sum_{i=1}^d (jx_i^2 + (j+1)x_i) + j$$





dakota.interfacing

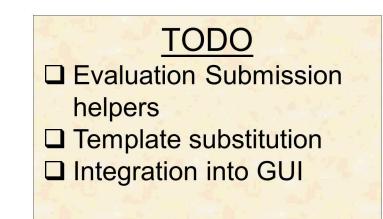
Tools for Python-based black-box simulation interfacing

Read params files/write results files

```
1 #!/usr/bin/env python
2
3 import dakota.interfacing as di
4 from rosenbrock import rosenbrock_function
5
6 params, results = di.read_parameters_file()
7
8 x1 = params['x1']
9 x2 = params['x2']
10
11 results['f'].function = rosenbrock_function(x1, x2)
12
13 results.write()
14
```

Evaluation tiling helper

1	#!/bin/bash
2	
2	params=\$1
4	results=\$2
5	
6	# For dynamic scheduling:
6 7	<pre>mpitile -np 2 text_book_simple_par \$params \$results</pre>
8	





Promote User and Development Community Engagement



- Web resources:
 - Interactive user forums
 - Capability maturity ratings and test linkage
 - Community repository of code, examples, scripts
- Training materials: presentations, videos, exercises
- New graphical user interface for Dakota analysis



- Improved modularity so users can extend, contribute components, e.g.,
 - Surrogate model module with Python bindings
 - More usable simulation interfacing that encourages best practices
- Communicate development practices to encourage contribution, e.g., principles, code standards, easier build/test on new platforms
- Portability to and scalability on new high-performance computers





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