

Overview of DAKOTA Project (from the software perspective)

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NREL

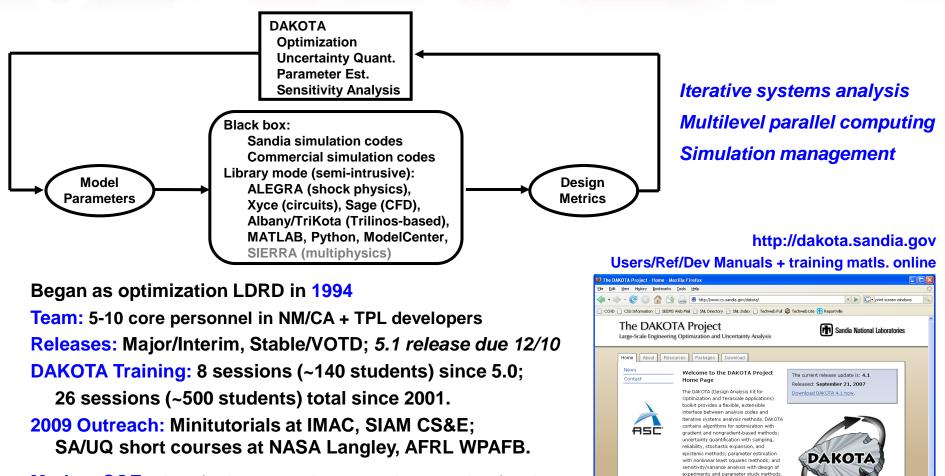
December 14, 2010

- Capability overview
- Advanced deployment efforts

Sandia is a multi program laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.



DAKOTA Project



These capabilities may be used on their own or as components within advanced strategies such as hybrid optimization, surrogate-based optimization, mixed

nteger nonlinear programming, or

FAQ

Privacy and Security - Site Conta-

ocumentation

computational models on high performance computers

Package:

optimization under uncertainty. By employing object-oriented design to implement abstractions of the key components required for iterative systems analyses, the DAKOTA toolkit provides a flexible and extensible problem-solving environment for design and performance analysis of

Download

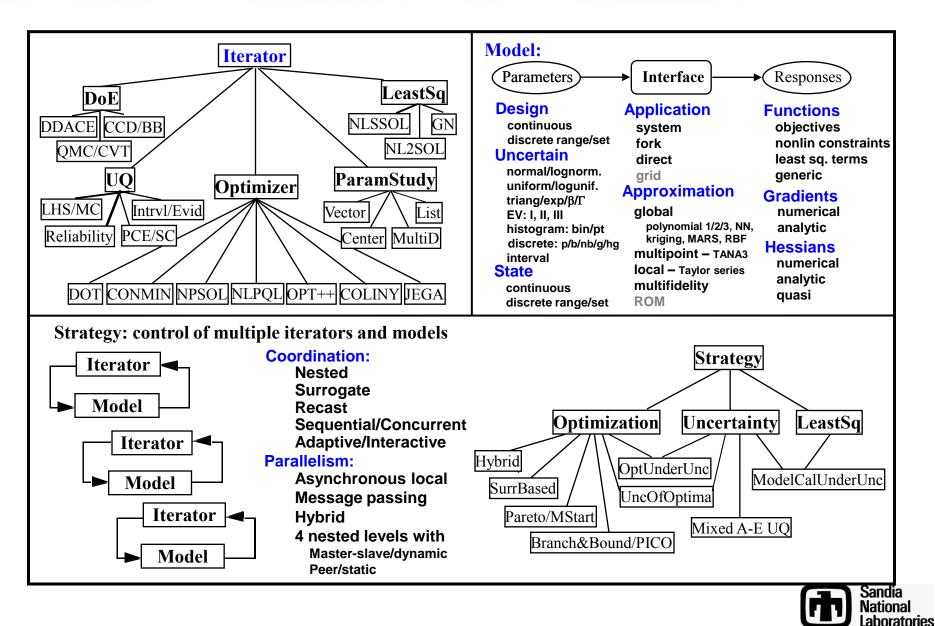
License Release Notes Registration

Modern SQE: Linux/Unix, Mac, Windows; Nightly builds/testing; subversion, TRAC, Cmake; Top 2008 SQE score

GNU LGPL: free downloads worldwide

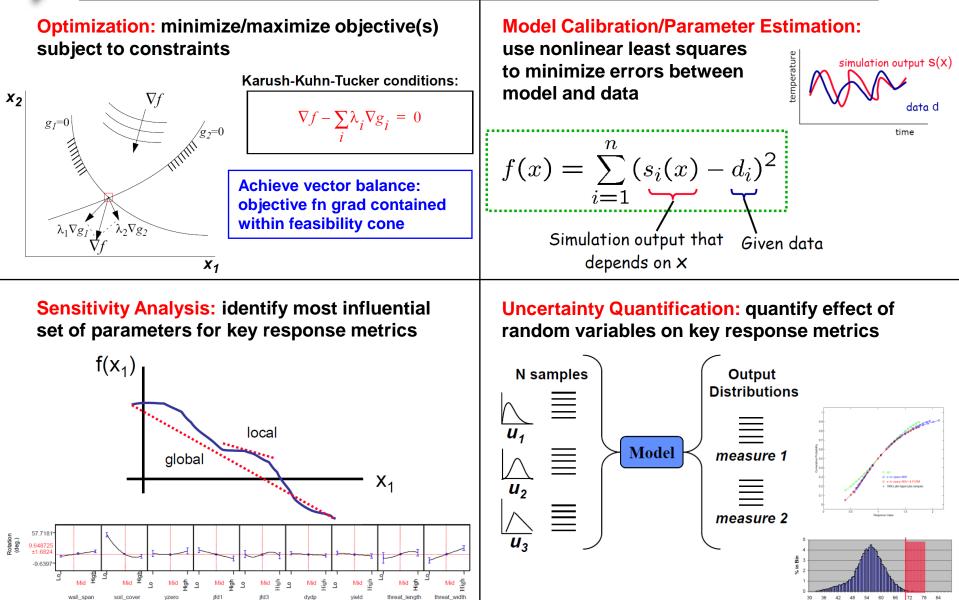
(~6500 total ext. registrations, ~3500 distributions last yr.) Community development: open checkouts now avail (→ PSAAP) Community support: dakota-users, dakota-developers

C++ Framework



Core Methods





Uncertainty Quantification Algorithms @ SNL: New methods bridge robustness/efficiency gap

	Production	New	Under dev.	Planned	Collabs.
Sampling	Latin Hypercube, Monte Carlo	Importance, Incremental		Bootstrap, Jackknife	FSU
Reliability	<i>Local:</i> Mean Value, First-order & second-order reliability methods (FORM, SORM)	Global: Efficient global reliability analysis (EGRA) Reseach: Tailor	ing & Adaptivity	gradient- enhanced EGRA	<i>Local:</i> Notre Dame, <i>Global:</i> Vanderbilt
Stochastic expansion	Adv. Deployment Fills Gaps	Tailored polynomial chaos & stochastic collocation with extended basis selections	p-adaptive, adjoint gradient- enhanced	h-adaptive, hp-adaptive, discrete, multi- physics	Stanford, Purdue, Austr. Natl., FSU
Other probabilistic		Random fields/ stochastic proc.		Dimension reduction	Cornell, Maryland
Epistemic	Interval-valued/ Second-order prob. (nested sampling)	Opt-based interval estimation, Dempster-Shafer	Bayesian	Imprecise probability	LANL, Applied Biometrics
Metrics & Global SA	Importance factors, Partial correlations	Main effects, Variance-based decomposition	Stepwise regression		UNM

Generalized Polynomial Chaos Expansions

Approximate response w/ spectral proj. using orthogonal polynomial basis fns

$R = \sum_{j=1}^{P} \alpha_{j} \Psi_{j}(\boldsymbol{\xi})$
$\overline{j=0}$

- $$\begin{split} \Psi_0(\boldsymbol{\xi}) &= \psi_0(\xi_1) \ \psi_0(\xi_2) &= 1 \\ \Psi_1(\boldsymbol{\xi}) &= \psi_1(\xi_1) \ \psi_0(\xi_2) &= \xi_1 \\ \Psi_2(\boldsymbol{\xi}) &= \psi_0(\xi_1) \ \psi_1(\xi_2) &= \xi_2 \\ \Psi_3(\boldsymbol{\xi}) &= \psi_2(\xi_1) \ \psi_0(\xi_2) &= \xi_1^2 1 \\ \Psi_4(\boldsymbol{\xi}) &= \psi_1(\xi_1) \ \psi_1(\xi_2) &= \xi_1\xi_2 \\ \Psi_5(\boldsymbol{\xi}) &= \psi_0(\xi_1) \ \psi_2(\xi_2) &= \xi_2^2 1 \end{split}$$
- Nonintrusive: estimate α_j using sampling (expectation), pt collocation (regression), tensor-product quadrature, Smolyak sparse grids, or cubature (numerical integration)

using

$$\begin{array}{lll} \alpha_{j} & = & \displaystyle \frac{\langle R, \Psi_{j} \rangle}{\langle \Psi_{j}^{2} \rangle} & = & \displaystyle \frac{1}{\langle \Psi_{j}^{2} \rangle} \int_{\Omega} R \, \Psi_{j} \, \varrho(\boldsymbol{\xi}) \, d\boldsymbol{\xi} \\ \\ & & \\ \hline & & \\ \hline & & \\ \langle \Psi_{j}^{2} \rangle \, = & \displaystyle \prod_{i=1}^{n} \langle \psi_{m_{i}^{j}}^{2} \rangle \end{array}$$

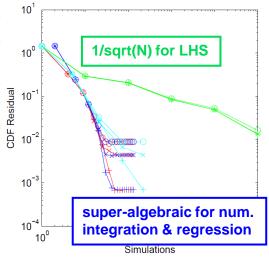
Generalized PCE (Wiener-Askey + numerically-generated)

• Tailor basis: optimal basis selection leads to exponential convergence rates

Distribution	Density function	Polynomial	Weight function	Support range
Normal	$\frac{1}{\sqrt{2\pi}}e^{\frac{-x^2}{2}}$	Hermite $He_n(x)$	$e^{\frac{-x^2}{2}}$	$[-\infty,\infty]$
Uniform	$\frac{1}{2}$	Legendre $P_n(x)$	1	[-1, 1]
Beta	$\frac{(1-x)^{\alpha}(1+x)^{\beta}}{2^{\alpha+\beta+1}B(\alpha+1,\beta+1)}$	Jacobi $P_n^{(\alpha,\beta)}(x)$	$(1-x)^{\alpha}(1+x)^{\beta}$	[-1,1]
Exponential	e^{-x}	Laguerre $L_n(x)$	e^{-x}	$[0,\infty]$
Gamma	$\frac{x^{\alpha}e^{-x}}{\Gamma(\alpha+1)}$	Generalized Laguerre $L_n^{(\alpha)}(x)$	$x^{lpha}e^{-x}$	$[0,\infty]$

Additional bases generated numerically via Golub-Welsch

- Tailor expansion type/order/range:
 - Total order \rightarrow tensor and sum of tensor expansions
 - Dimension p-refinement: anisotropic tensor/sparse grids
 - Domain h-refinement: discretization of random domain



ASCR Wind Turbine UQ

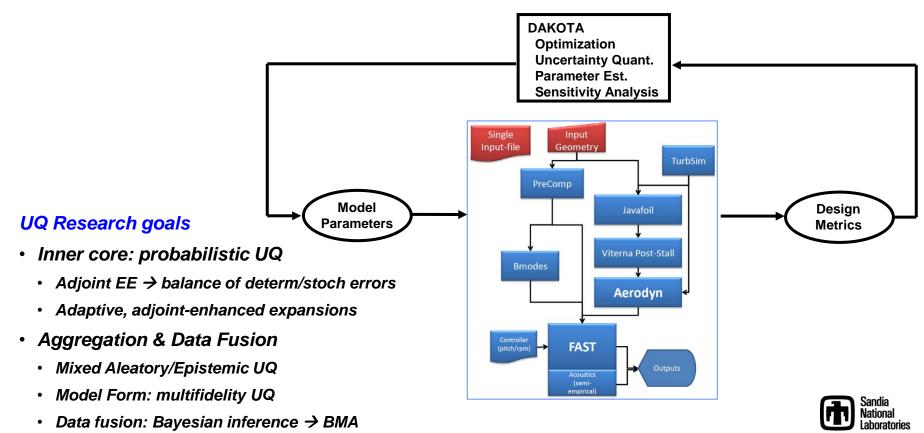
New DOE ASCR Project (Office of Science): FY2010-2012

Short term:

• MATLAB management of NREL design tool ensemble ("EOLO", Sandia wind group)

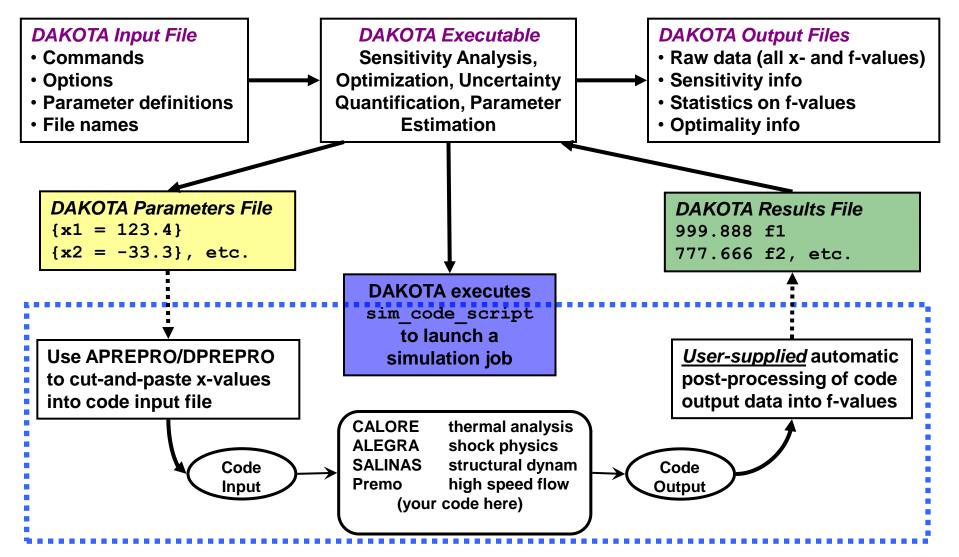
Longer term:

• CFD with Joe (Stanford) and FSI with SIERRA/Aria (Sandia)





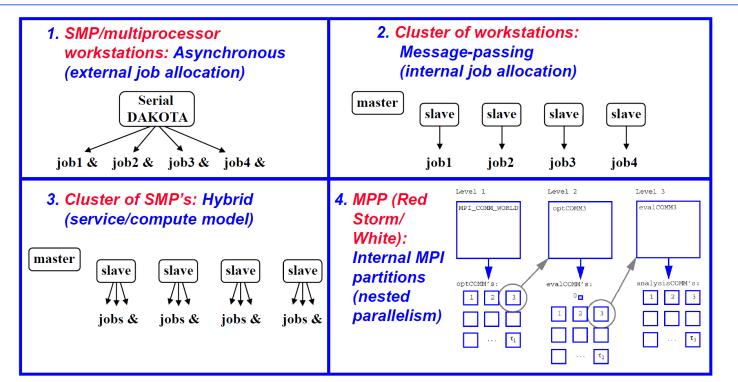
Simulation Management (Black Box case)





Parallelism Options: Multicore Desktops to MPP

- 1. Algorithmic coarse-grained: concurrency in data requests:
 - Iterators: Gradient-based, Nongradient-based, Surrogate-based
 - Strategies with concurrent Iterators: Multi-start, Pareto, Hybrid
 - Nested Models: OUU/MCUU, Mixed UQ
- 2. Algorithmic fine-grained: computing the internal linear algebra of an opt. algorithm in parallel
- 3. *Fn eval coarse-grained:* concurrent execution of separable simulations within each fn. eval.
- 4. Fn eval fine-grained: parallelization of the solution steps within a single analysis code





Deployment

Impact Sandia missions

- Technology insertion
 - ASC milestones
 - Early adopters

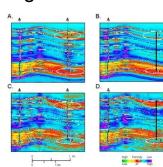
Partnerships

- Government: LLNL, LANL, ORNL, INL, NASA, DOD
- Industry: Lockheed Martin, Goodyear, Exxon Mobil
- University: MIT, Cornell, CU Boulder, Vanderbilt, USC, FSU, Notre Dame, VPISU, UNM
 - CSRI students/postdocs, faculty sabbaticals
 - ASC PSAAP: UT Austin (Bayesian), Purdue (cubature),
 UIUC (adaptive collocation), Caltech (global opt.), Michigan (gradient-enhanced interpolation), Stanford (adaptive collocation)

Address core usability barriers

- JAGUAR
- Library embedding

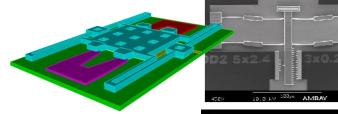


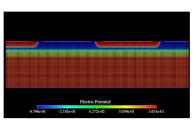


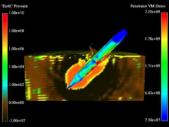
Jan/Feb 2010: 92% of DAKOTA invocations on SNL clusters were UQ or param studies, but new methods starting to reduce LHS dominance

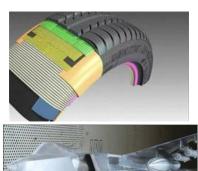


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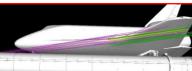












Deployment Initiative: JAGUAR User Interface

- Eclipse-based rendering of full DAKOTA input spec.
- Automatic syntax updates
- Tool tips, Web links, help
- Symbolics, sim. interfacing

- Flat text editor for experienced users
- Keyword completion
- Automatically synchronized with GUI widgets
- Simplified views for high-use applications ("Wizards")

🔗 Resource - proj1/mydak.i - Jaguar	🗖 Resource - JAGUAR/jaguar/misc_files/constropt.i - Jaguar 💦 🔲 🔀	🗖 Dakota LHS Wizard 📃 🗖 🔀					
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Problem definition and execution	# DAKOTA INPUT FILE - dakota_textbook.in strategy	✓ Uniform Uncertainty ✓ samples 100 60					
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To define a problem for DAKOTA to solve, you must first define a model, a variable set, an interface set and a response set. Then you must	single_method method						
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Impact: streamline problem set-up for user base, spanning novices to experts							
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Deployment Initiative: Embedding

Make DAKOTA natively available within application codes

- Streamline problem set-up, reduce complexity, and lower barriers
 - A few additional commands within existing simulation input spec.
 - Eliminate analysis driver creation & streamline analysis (e.g., file I/O)
 - Simplify parallel execution
- Integrated options for algorithm intrusion

SNL Embedding

- Existing: Xyce, Sage, Albany (TriKOTA)
- New: ALEGRA, SIERRA (TriKOTA) → STK

External Embedding

- Existing: ModelCenter, university applications
- New: QUESO (UT Austin), R7 (INL)
- Expanding our external focus:
 - GPL \rightarrow LGPL; svn restricted \rightarrow open network

barriers barriers t spec. g., file I/O) An end of the optimization of the optimiz

ModelEvaluator Levels

Non-intrusive

ModelEvaluator: systems analysis

- · All residuals eliminated, coupling satisfied
- DAKOTA optimization & UQ

Intrusive to coupling

ModelEvaluator: multiphysics

- Individual physics residuals eliminated; coupling enforced by opt/UQ
- DAKOTA opt/UQ & MOOCHO opt.

Intrusive to physics

ModelEvaluator: single physics

Impact: eliminate custom set-up and support fully integrated opt. and UQ studies

Concluding Remarks

DAKOTA provides a variety of core algorithms for iterative analysis:

- Optimization

-- Sensitivity Analysis

- Calibration

-- Uncertainty quantification

As well as advanced capabilities for

- Multilevel parallel computing
- Manage multiple iterative methods, models of varying fidelity, nesting, recasting, etc.
- Emerging UQ methods: adaptive, adjoint-enhanced, multi-{fidelity,physics,scale}, mixed UQ
- Emerging algs. in other areas: OUU, SBO, MINLP, SA w/ PCE/SC, Nond. calibration

Advanced deployment initiatives will "lower the bar" for adoption

- JAGUAR -- Library embedding

Expanding from NNSA to include energy missions: Wind, NE

Some lessons learned in open source framework development

- Bound your mission space and manage scope creep
 - Focus on your core strengths and provide flexible APIs for others to use
 - Be selective on strategic partnerships
- Establish a support hierarchy and manage it effectively
 - Small teams may need to rely on community support for bottom tier
- Utilize modern CS tools (svn/git, cmake/scons, Trac) to simplify collaborative development
- Manage quality through sponsorship and review of external contributions

