

Recent developments in MADS algorithms:  
ABAGUS and *Squads*

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# Model analysis and decision support (MADS) for complex problems

## Complex problems:

- Large number of model parameters
- Nonlinear and hysteretic parameter correlations
- Multiple maxima/minima
- Flat response surface regions (portions of parameter space with low parameter sensitivity)
- Long execution times
- Require efficient and robust model analyses strategies

# Model analysis and decision support (MADS) for complex models

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- Model analysis
  - Calibration/parameter estimation
  - Uncertainty quantification
  - Parameter sensitivities and correlations
  - Predictive analysis
  - Model selection
  - Model averaging

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  - Model selection
  - Model averaging
- Decision support
  - Robust and/or optimal decisions

## ABAGUS features:

- “Agent-based” model analysis
- Extends Particle Swarm Optimization (PSO) to uncertainty and sensitivity analysis
- Collects all model evaluation results in KD-Tree for efficient restart and hierarchical analysis
- Response surface sculpting discourages reinvestigation of “collected” regions of the parameter
- Discretized parameter space
- Automated discretization refinement

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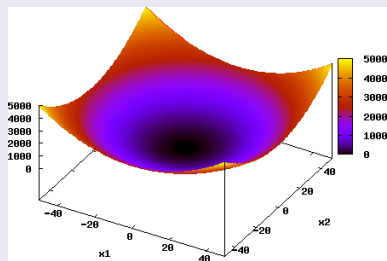
## ABAGUS uses:

- Identify acceptable parameter ranges
- Sensitivity analysis
- Identify parameter correlations
- Parameter uncertainty analysis
- Predictive analysis
- Decision support
- Information for these are contained in the results from a single ABAGUS run

Harp, D.R. and V.V. Vesselinov (2011), An agent-based approach to global uncertainty and sensitivity analysis, *Computers & Geosciences*, doi:10.1016/j.cageo.2011.06.025.

# Monte Carlo vs ABAGUS: Estimation of probability of success/failure based

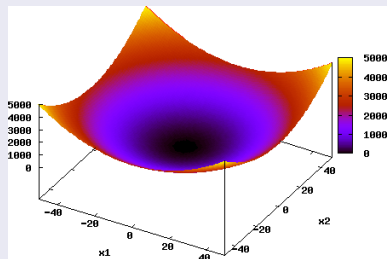
Example: parabola function



$$f(x_1, x_2) = x_1^2 + x_2^2$$

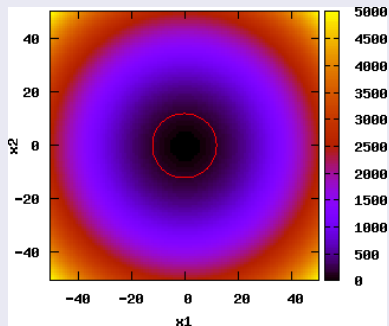
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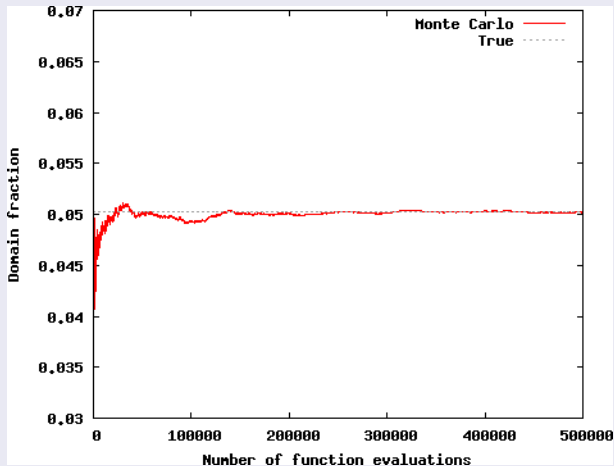
Goal: estimate area where  $f(x_1, x_2) \leq 160$ , (red circle)



- $f(x_1, x_2) \leq 160$  is approximately 5% of domain
- $x$  uniformly distributed
- Domain:  $x = [-50 : 50]$

# Monte Carlo estimation of probability of success/failure

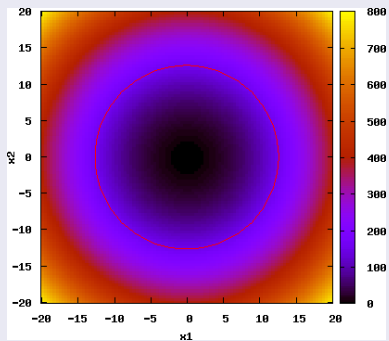
Estimation of parameter space with  $f(x_1, x_2) \leq 160$



- Probability of success/failure (i.e. domain fraction) estimated by fraction of random samples in “red circle”
- Monte Carlo uses an Improved Distance Latin Hypercube Sampling

# ABAGUS estimation of probability of success/failure

Before exploration

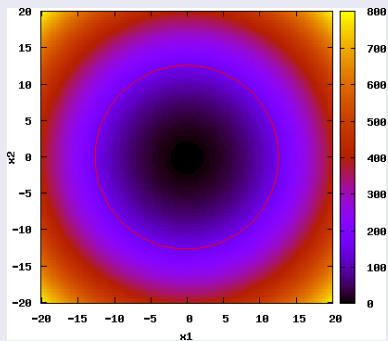


- $f(x_1, x_2) = 160$  indicated by red circle
- Zoomed into  $x_1, x_2 = [-20 : 20]$



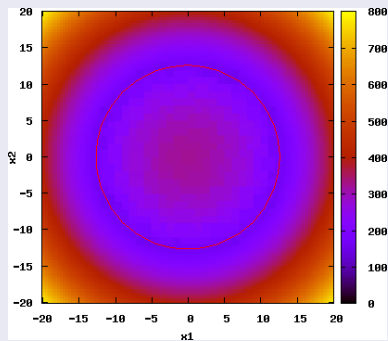
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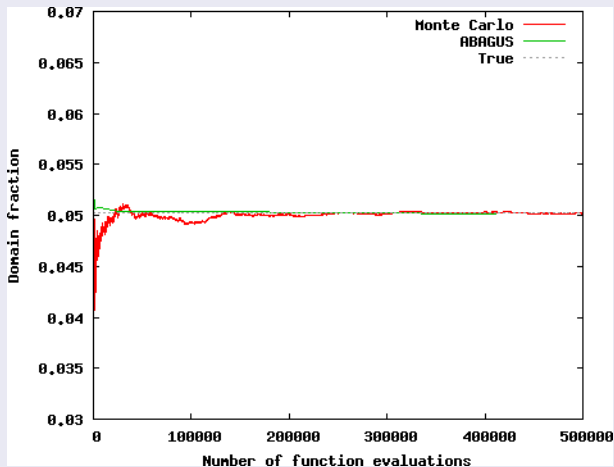
After exploration



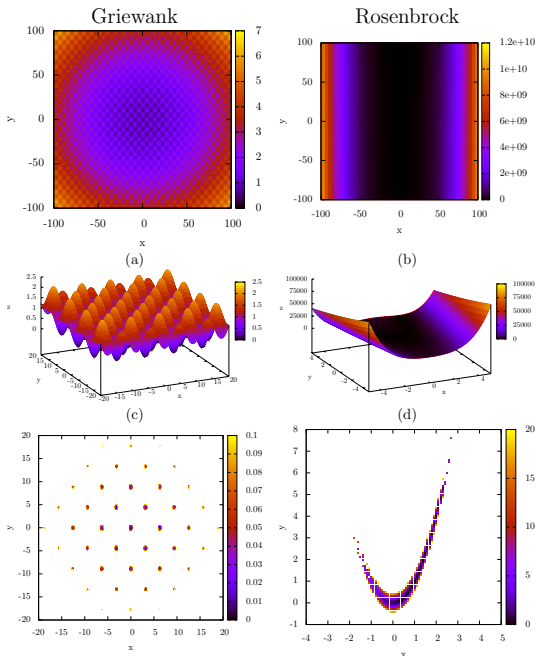
- Response surface sculpted
- "Acceptable" parameter sets collected

# ABAGUS estimation of probability of success/failure

Estimation of parameter space with  $f(x_1, x_2) \leq 160$

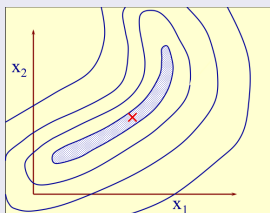


# ABAGUS results on more complicated response surfaces...



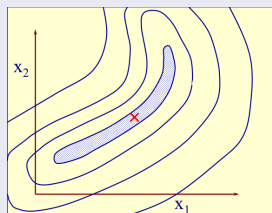
# ABAGUS as predictive analyzer

Identify “plausible”  
region based on 1<sup>st</sup>  
criterion

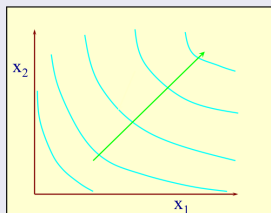


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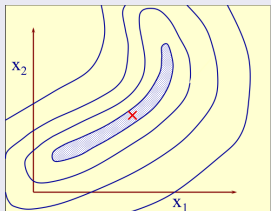


Gradient contours of 2<sup>nd</sup> criterion

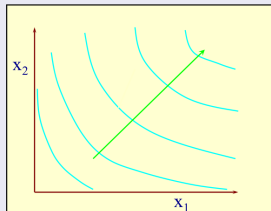


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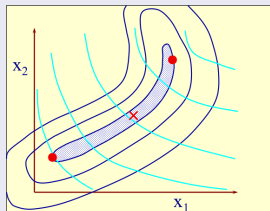
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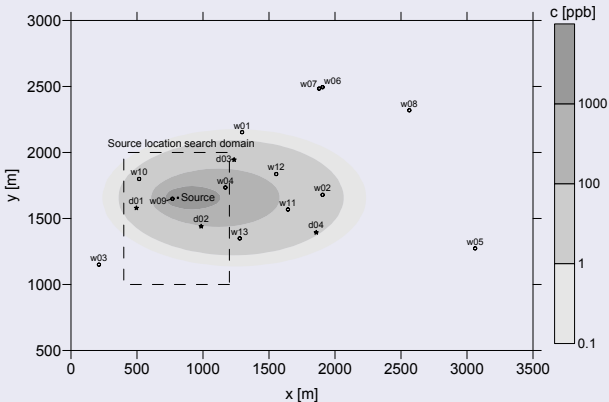
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Max/min values of 2<sup>nd</sup> criterion within 1<sup>st</sup> criterion

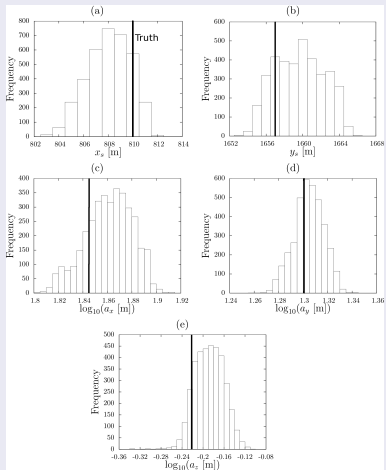


## Contaminant plume in aquifer...



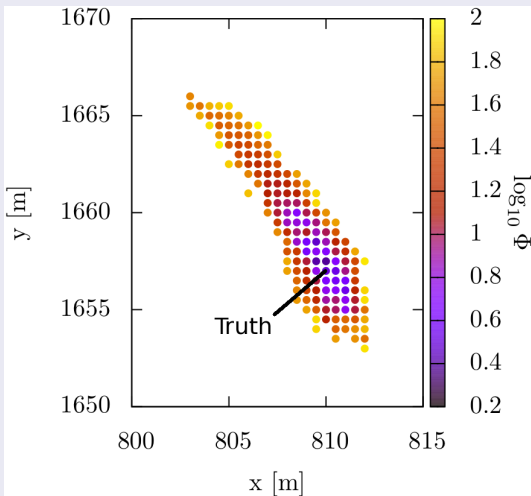
- w wells (circles) - existing wells
- d wells (stars) - proposal wells
- Uncertain parameters: source location ( $x_s, y_s$ ) dispersivities ( $a_x, a_y, a_z$ )

## Parameter histograms produced from ABAGUS:



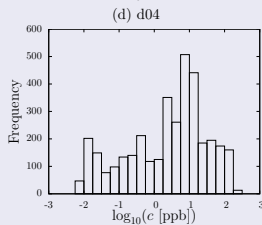
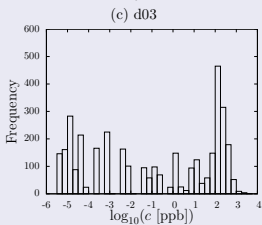
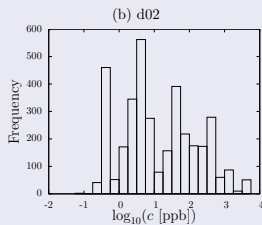
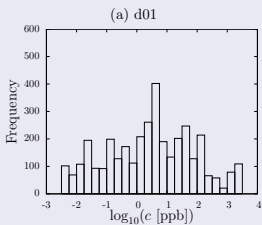


## Plausible source locations collected by ABAGUS:



- Min OF at each source location plotted

## Predictive analysis of concentrations at proposal wells:



## *Squads*

- Global optimization with local optimization speedup
- Global strategy: Adaptive Particle Swarm Optimization (APSO)
- Local strategy: Levenberg-Marquardt (LM)
- Adaptive rules balance strategies

Vesselinov, V.V. and D.R. Harp, Adaptive hybrid optimization strategy for calibration and parameter estimation of physical model, *Computers & Geosciences*, In Review.

## *Squads* is compared to:

- Levenberg-Marquardt (LM) - local strategy
- Particle Swarm Optimization (PSO) Standard 2006 - global strategy
- TRIBES Adaptive PSO - global strategy
- hPSO (PSO + simplex) - alternative hybrid strategy

# Squads comparisons

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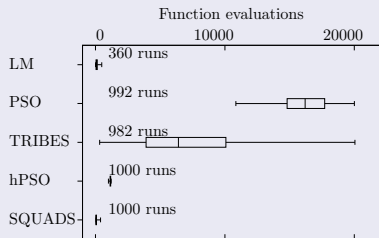
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## Comparison details:

- 2D, 5D, and 10D Rosenbrock and Griewank test functions
- Domain:  $\mathbf{x} = [-100 : 100]$
- 20,000 allowable function evaluations for each optimization run
- 1000 runs per strategy for each test function
- Success: all parameters within 0.1 of optimal parameters

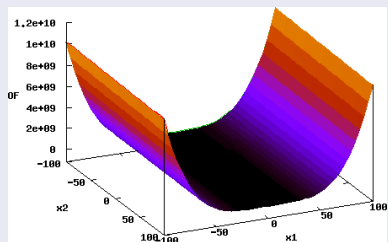
# Squads: Rosenbrock comparisons

## 2D Rosenbrock

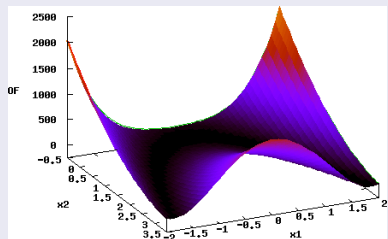


- Boxes indicate 25<sup>th</sup> to 75<sup>th</sup> percentile range for number of evaluations needed to achieve success
- Vertical lines in boxes indicate median value
- “Whiskers” indicate max and min values
- Number of successful runs out of 1000 are indicated above boxes

## 2D Rosenbrock function

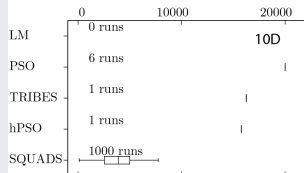
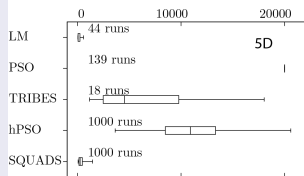
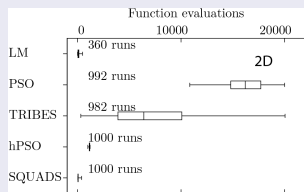


Global minimum:  $x = 1$

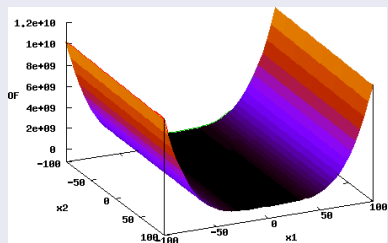


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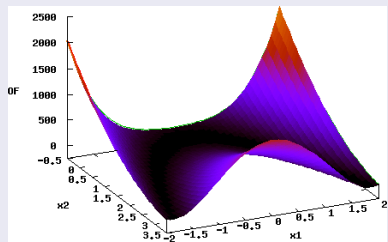
## Function evaluation boxplots



## 2D Rosenbrock function



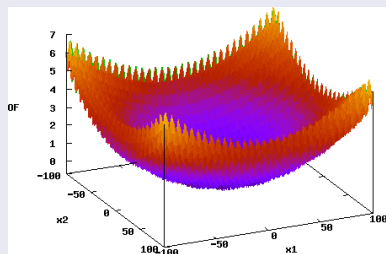
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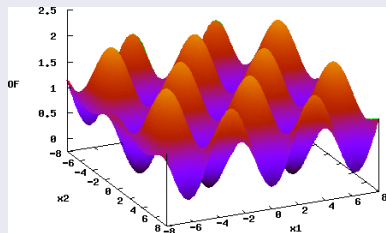
## Griewank Function:

- Ideal for comparison of hybrid methods
- Becomes more difficult for global methods with increased dimensionality
- Becomes easier for local methods with increased dimensionality
- Hybrid methods should have a well balanced act

## 2D Griewank function



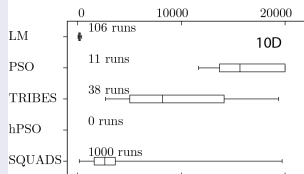
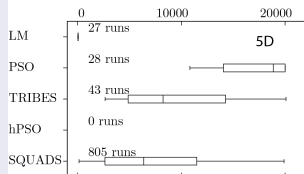
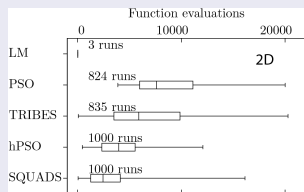
Global minimum:  $\mathbf{x} = \mathbf{0}$



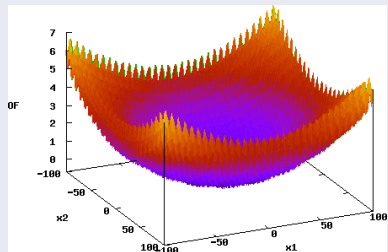


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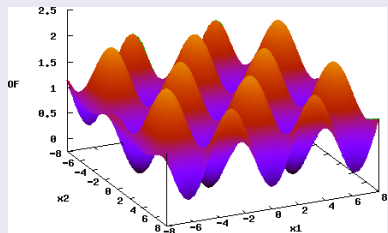
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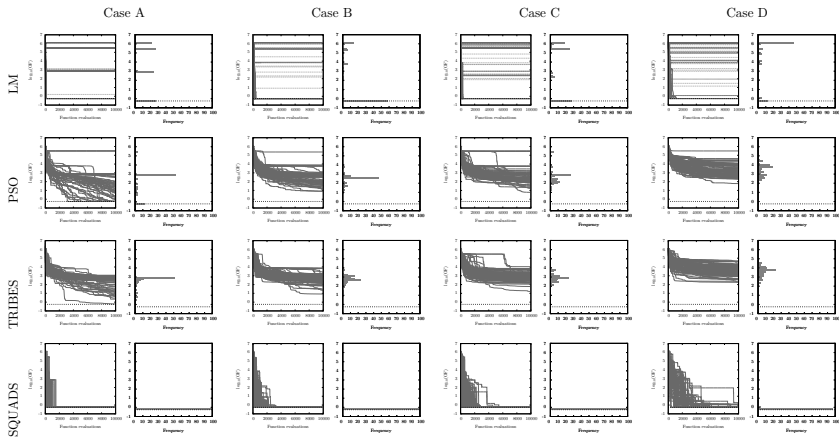
## 2D Griewank function



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# SQUADS application



- ABAGUS presents efficient approach for model-based uncertainty analyses
- *Squads* provides an efficient and robust optimization strategy