



**LSTC**  
Livermore Software  
Technology Corp.

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# New Developments in LS-OPT Version 4

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# LS-OPT Capabilities

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- ◆ Design of Experiments
  - ◆ D-Optimality, Latin Hypercube, Space Filling
  
- ◆ Metamodels
  - ◆ Polynomials, Radial Basis Function networks, Feedforward Neural networks, Kriging, User-defined metamodels
  - ◆ Used for variable screening, optimization, prediction, reliability and outlier analysis
  
- ◆ Pre/Post-processor interfaces
  - ◆ ANSA, META-Post, Truegrid, User-defined
  
- ◆ Job distribution
  - ◆ PBS, SLURM, NQE, NQS, LSF, User-defined, Blackbox, Honda, LoadLeveler

# LS-OPT Optimization Capabilities

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## ◆ Optimization solvers

- ◆ NSGA-II (Non-dominated sorting Genetic Algorithm)
  - Multi-Objective global optimization
- ◆ Adaptive simulated annealing
  - Single objective global optimization. Very fast
- ◆ LFOPC
  - Original algorithm, highly accurate for single objective

## ◆ Reliability-based Design Optimization

## ◆ Topology optimization

- ◆ LS-DYNA explicit and implicit (linear + nonlinear)
- ◆ Multi-case design
- ◆ Large number of elements (1e6 tested)
- ◆ General and extruded geometries
- ◆ Non-cuboidal design domains

# LS-OPT development: 4.0

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## ◆ Next Generation Postprocessor (Viewer)

- ◆ New architecture
  - Split windows, vertically/horizontally
  - Detachable windows
  - Spreadsheet type point listing
- ◆ Correlation Matrix
  - Scatter plots, Histograms and Correlation values
  - Interactive: Display histograms or correlation bars
- ◆ Visualization of Pareto Optimal Front
  - 4D plotting (already in Version 3.4)
  - Multi-axis plot for higher dimensions
  - Hyper-Radial Visualization
  - Self Organizing Maps (Version 4.1)
- ◆ Virtual histories
  - Plot history at any point in the design space (Version 4.1)

# Outlook: LS-OPT development: 4.0

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## ◆ META Post interface

- ◆ Allows extraction of results from any package (Abaqus, NASTRAN, ...) supported by META Post (ANSA package)

## ◆ LS-OPT/Topology

- ◆ Nonlinear topology optimization
- ◆ LS-DYNA based
- ◆ Multiple load cases
- ◆ Linear as well as non-linear
- ◆ Design part selection
- ◆ Job distribution (queuing) as in LS-OPT

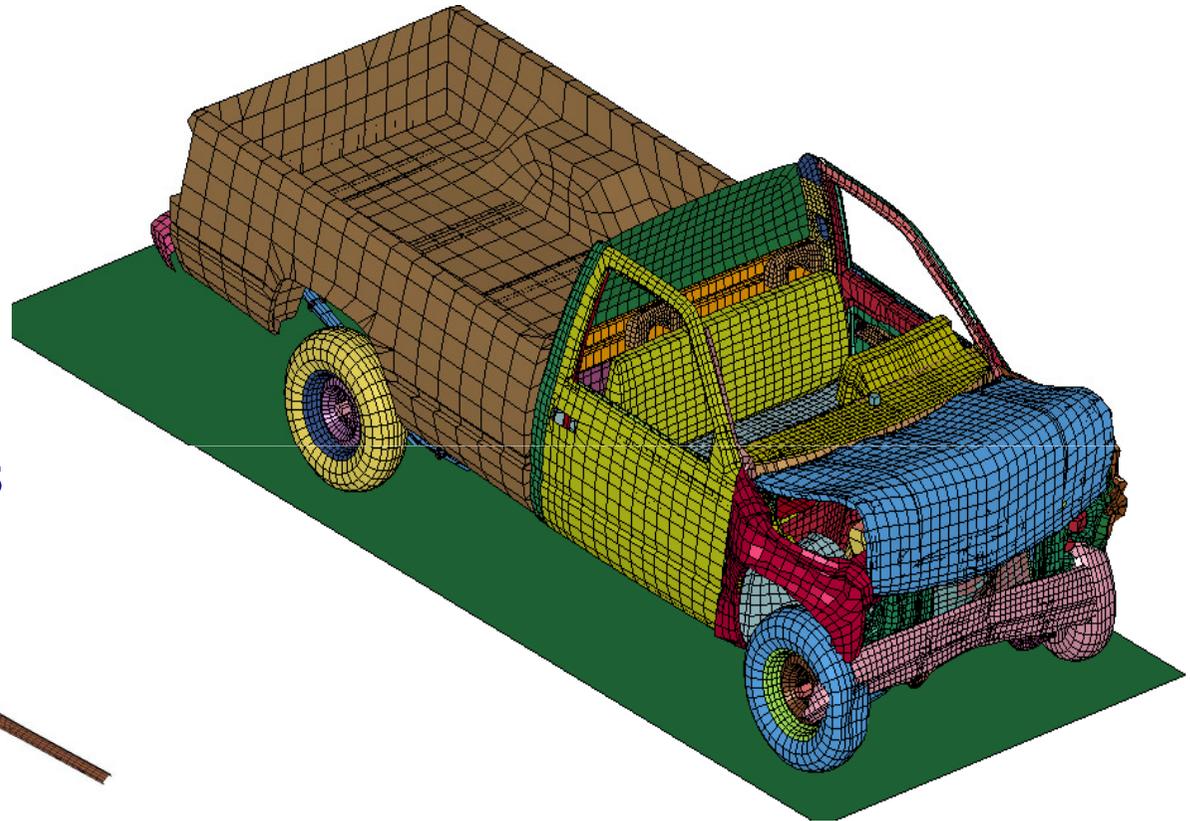
# Multi-Objective Optimization: Example

C2500 PICKUP TRUCK MODEL - (NGAC V6)  
Time - 0



Thickness design variables

C2500 PICKUP TRUCK MODEL - (NGAC V6)  
Time - 0



# Design criteria

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## Minimize

- ◆ Mass
- ◆ Acceleration

## Maximize

- ◆ Intrusion
- ◆ Time to zero velocity

9 thickness variables of main crash members

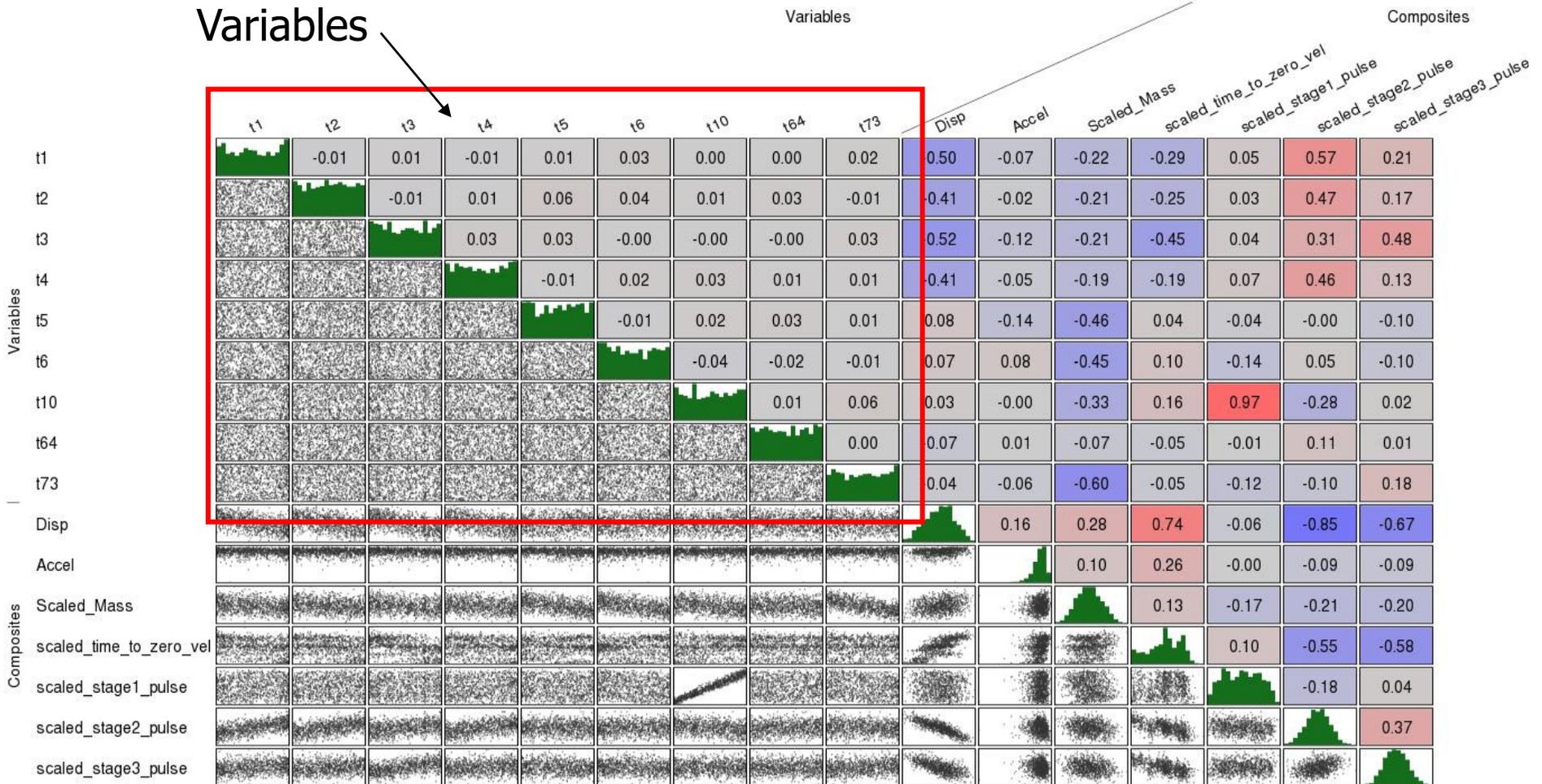
◆ Intrusion	<	721
◆ Stage 1 pulse	<	7.5g
◆ Stage 2 pulse	<	20.2g
◆ Stage 3 pulse	<	24.5g

# Simulation statistics

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- ◆ 640-core HP XC cluster (Intel Xeon 5365 80 nodes of 2 quad-core)
- ◆ *Queuing* through LSF
- ◆ Elapsed time per generation ~ 6 hours
- ◆ Total of 1,000 crash runs
  
- ◆ Strategy: Single stage run
- ◆ Sampling scheme: *Space Filling* (MinMax distance) using 1000 points
- ◆ Surrogate model: *Radial Basis Function Network*
- ◆ Optimization solver: *NSGA-II* to find *Pareto Optimal Frontier*

# Correlation Matrix of 1000 simulation points



# Stochastic input

The image displays two screenshots of a software interface for defining statistical distributions. The top screenshot shows a 'Truncated Normal' distribution with a mean of 1.08 and standard deviation of 0.06. The bottom screenshot shows a 'Uniform' distribution with a mean of 0 and standard deviation of 0.05. Both screenshots include a 'Statistical Distributions' list and a 'Distribution Name' field.

**Truncated Normal Distribution Parameters:**

Parameter	Value
Type	Truncated Norm
Mean	1
Standard Dev	0.1
Lower Bound	1
Upper Bound	2

**Uniform Distribution Parameters:**

Parameter	Value
Type	Uniform
Lower	-0.1
Upper	0.1

# Variables and distributions

File View Task Help

Info Strategy Solvers Dist Variables Sampling Histories Responses Objective Constraints Algorithms Run Viewer DYNA Stats

Design Variables

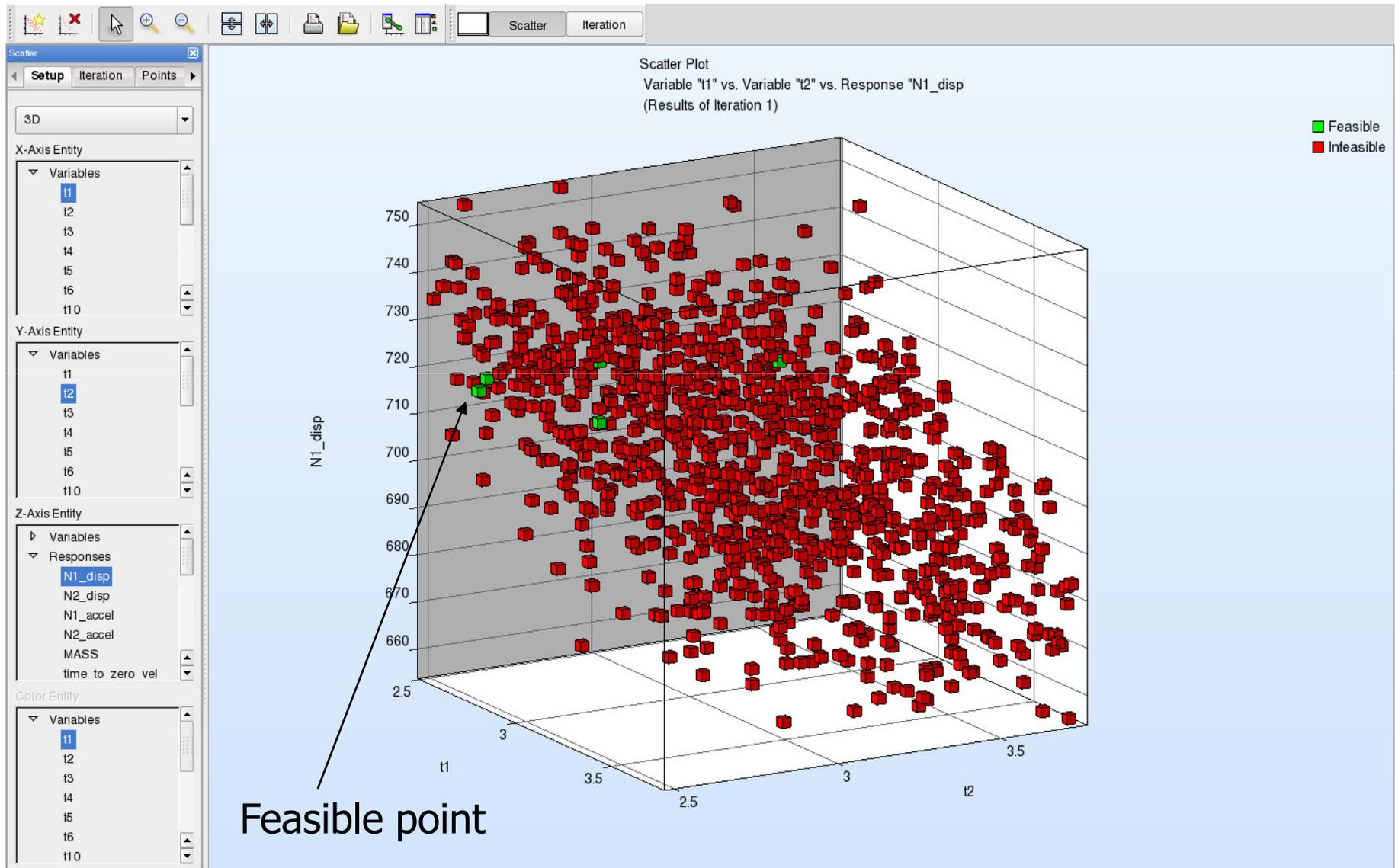
Type	Name	Starting	Init. Range	Minimum	Maximum	Distribution
Variable	t1	3.137		2.5	3.765	Uniform
Variable	t2	3.112		2.48	3.75	Uniform
Variable	t3	2.997		2.4	3.6	Uniform
Variable	t4	3.072		2.4	3.6	Uniform
Variable	t5	3.4		2.72	4.08	Uniform
Variable	t6	3.561		2.85	4.27	Truncatec
Variable	t10	2.7		2.16	3.24	Truncatec
Variable	t64	1.262		1	1.51	Truncatec
Variable	t73	1.99		1.6	2.4	Truncatec

Saddle Direction  
Minimize

Cases  
 All  
 List

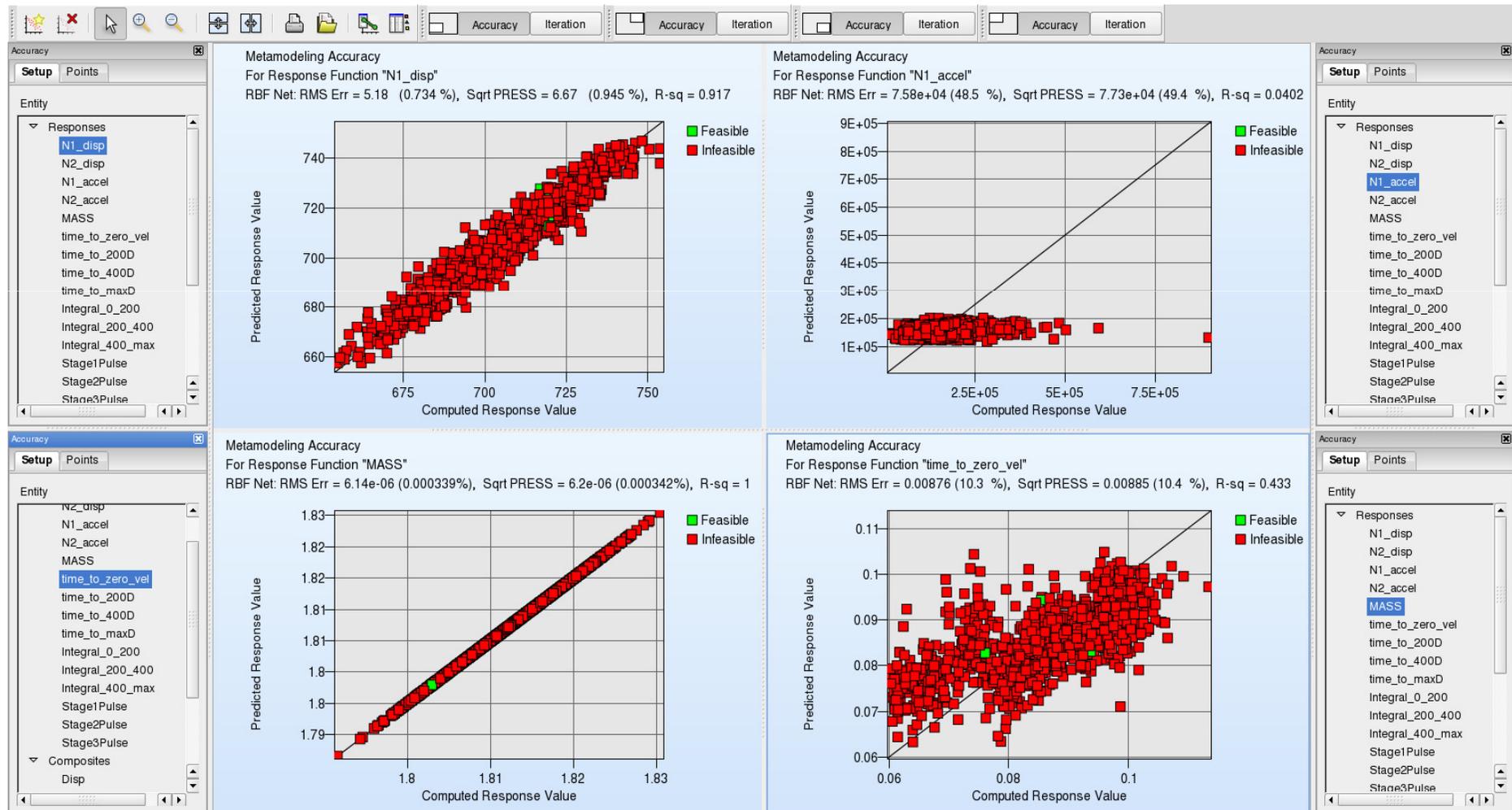
Add a Variable Delete a Variable

# Scatterplot of intrusion: feasibility level



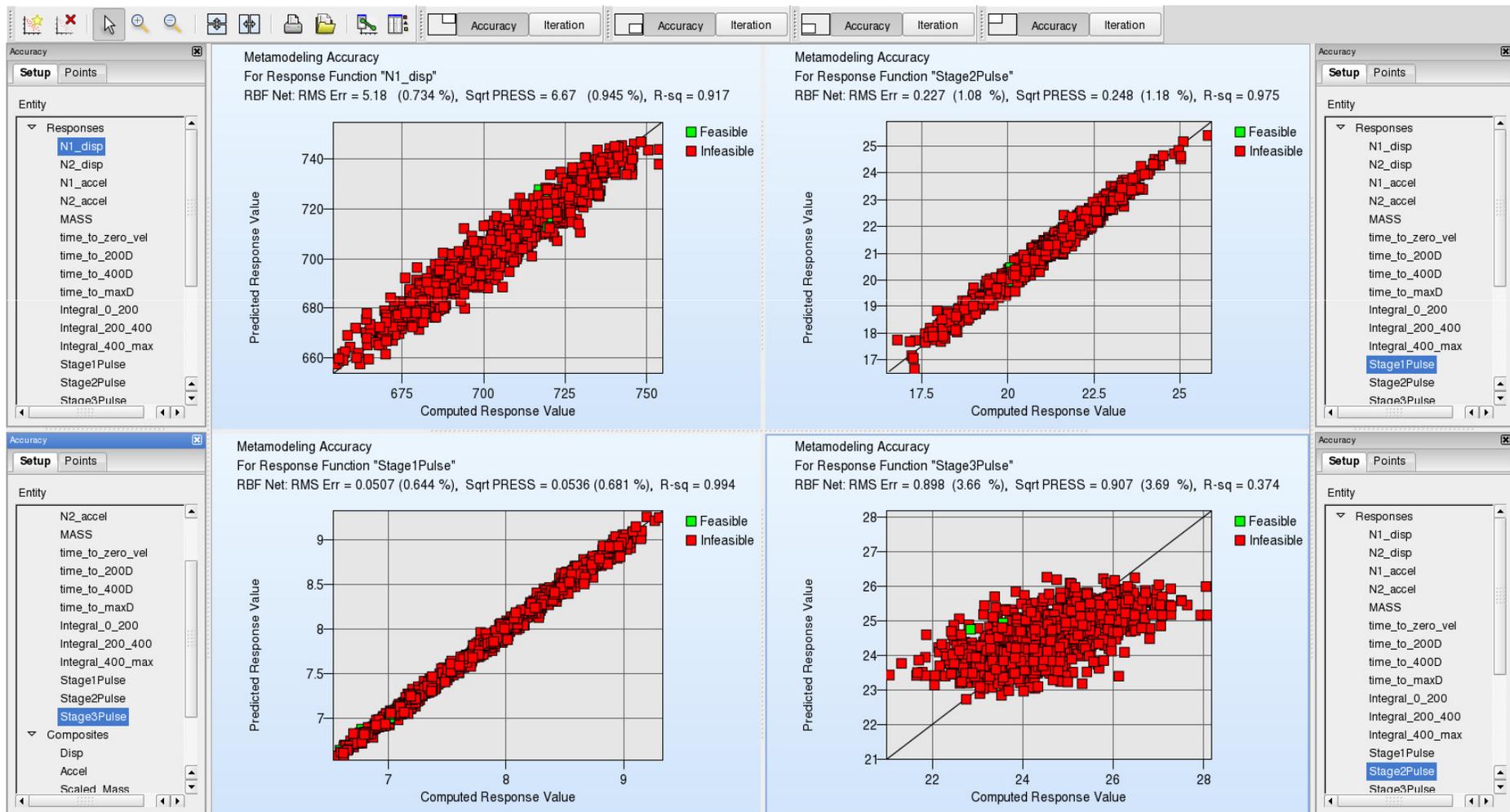
# Metamodel Accuracy

## Objective Functions

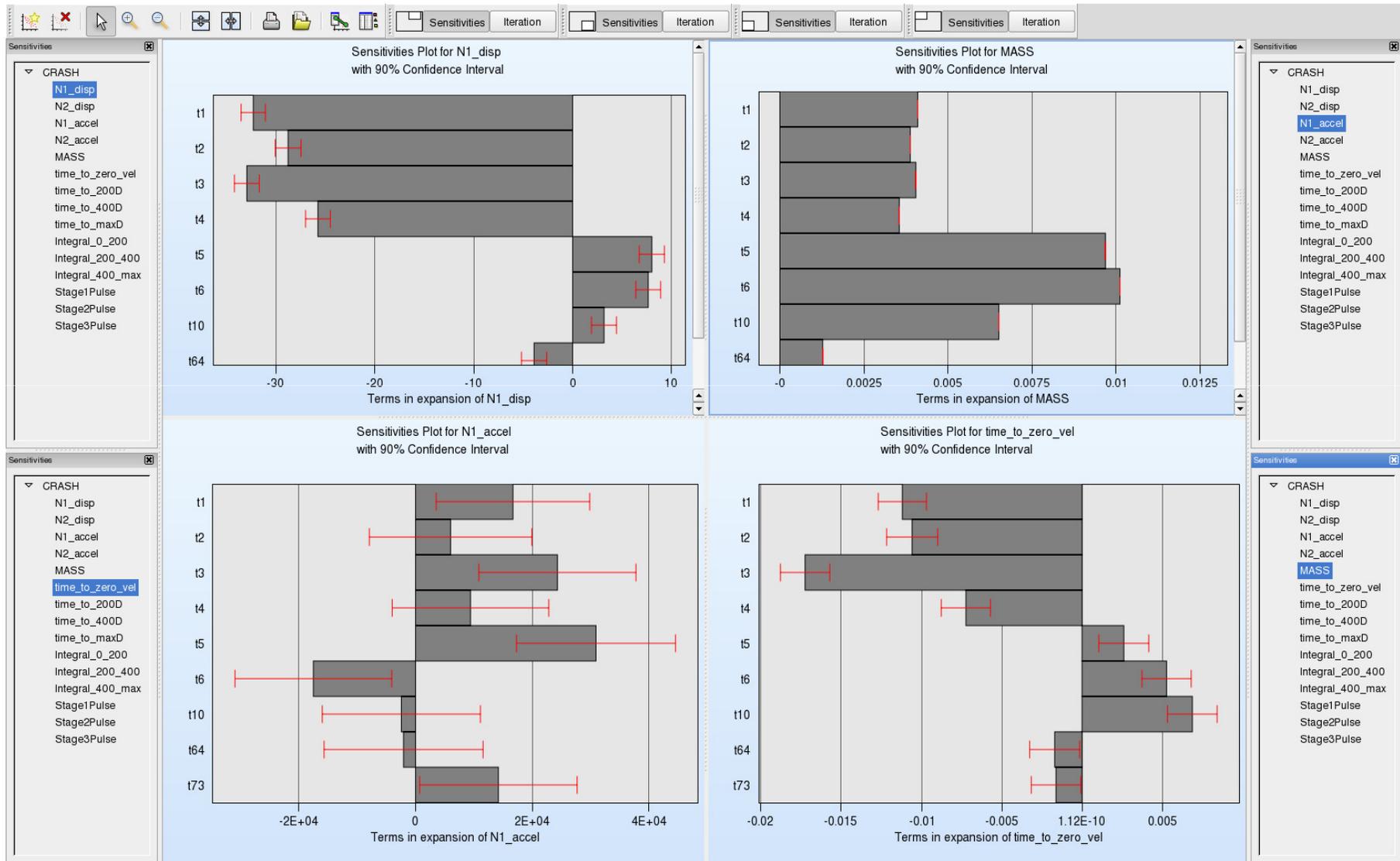


# Metamodel Accuracy

## Constraint Functions



# Sensitivity: Objectives



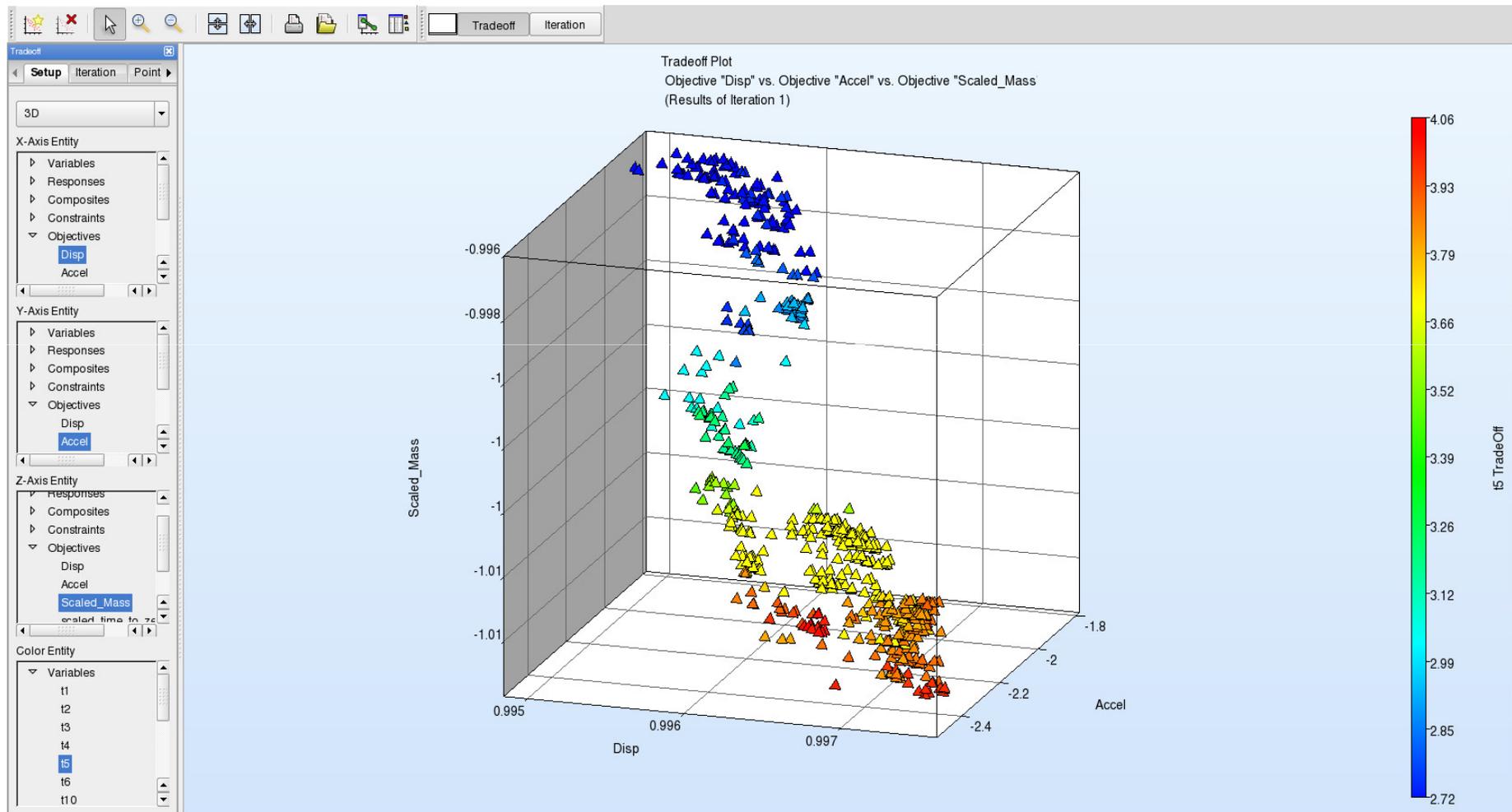
# Pareto Optimal Frontier

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- ◆ A hyper-surface of optimal designs for multiple objectives
- ◆ Visualization is complicated, hence 4 tools are provided
  - ◆ 4D Spatial plot
    - Traditional
  - ◆ Parallel Coordinate plot
    - Pans and zooms in hyperspace
  - ◆ Hyper-Radial Visualization
    - Weighting of objectives
  - ◆ Self-Organizing Maps (Ver. 4.1)
    - Continuous mapping of objective space
    - "Hole" detection

# Pareto Optimal Frontier

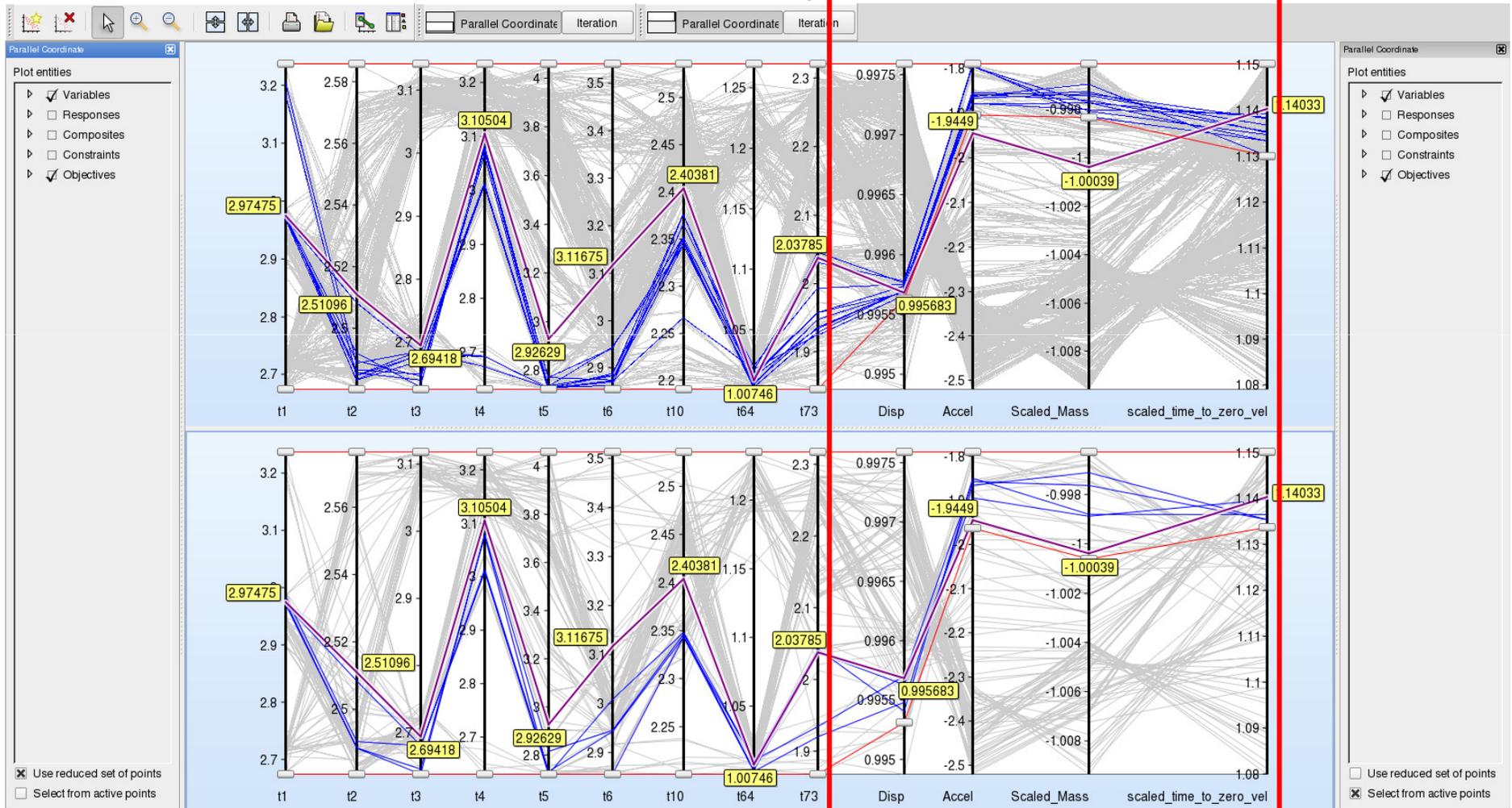
Spatial plot:  $t_5$  in color



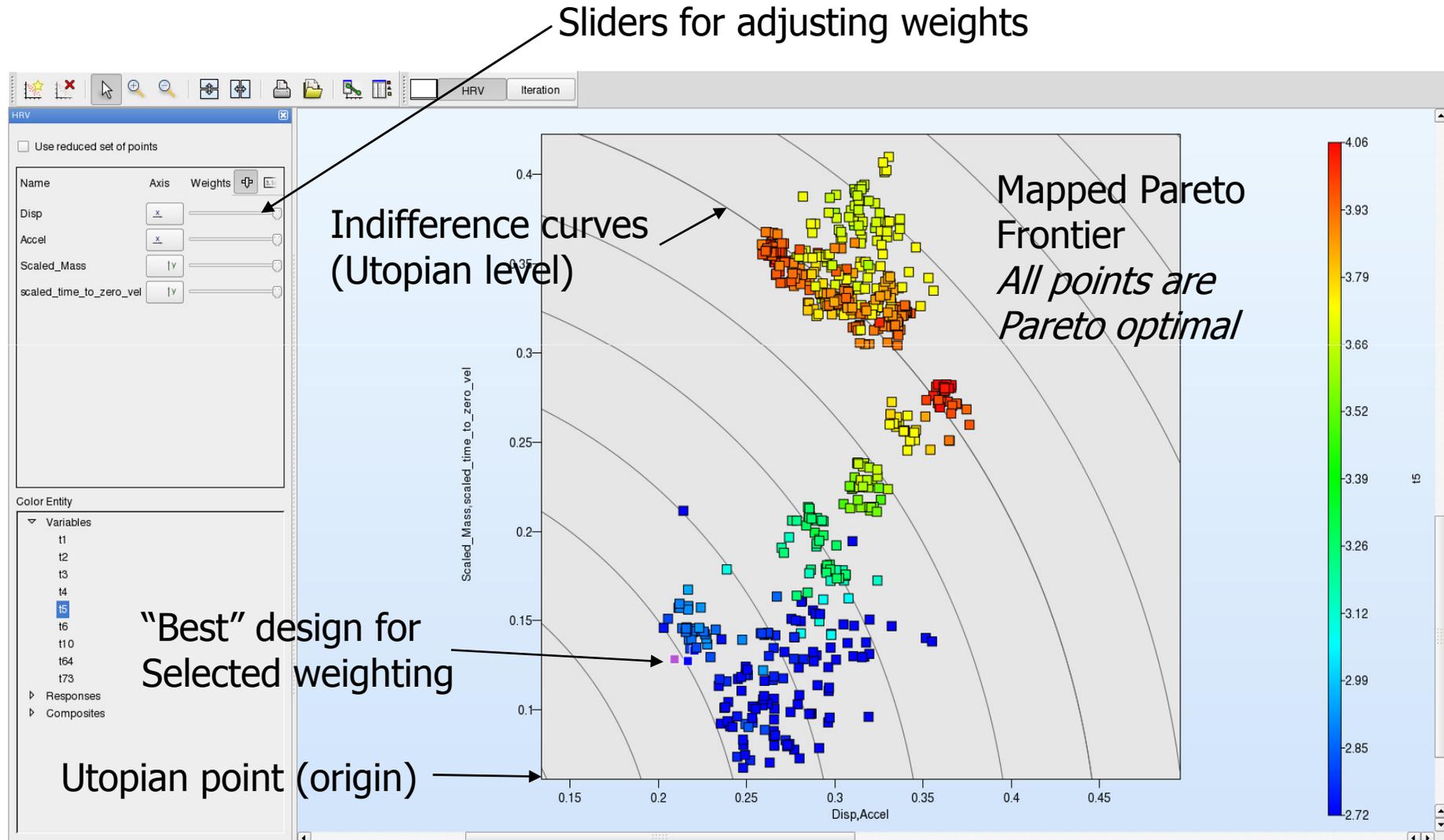
# Pareto Optimal Frontier

## Parallel Coordinate Plot: Variables and Objectives (Full/Reduced databases)

Objectives



# Pareto Optimal Frontier Hyper Radial Visualization (variable $t5$ in color)

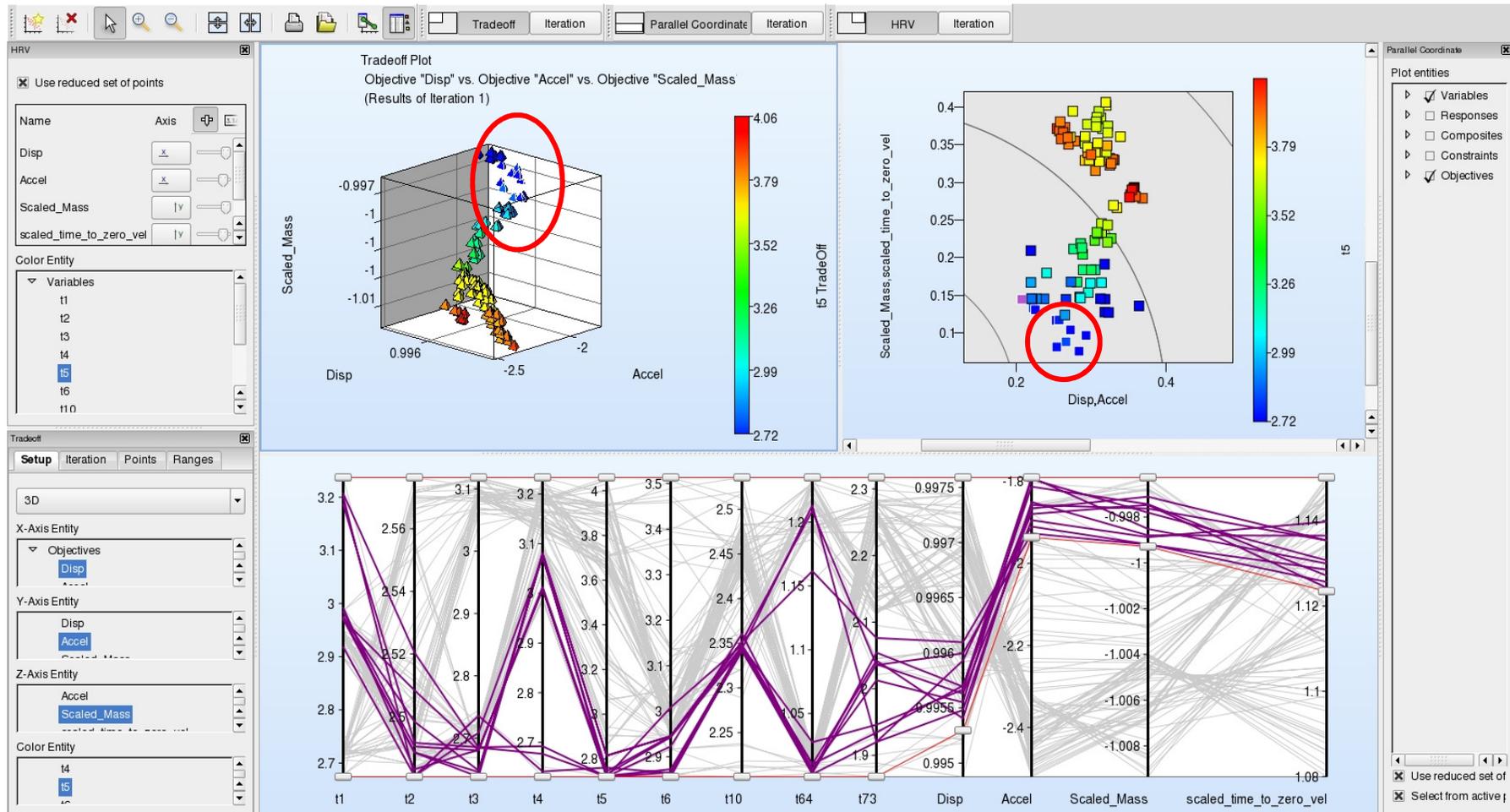


# Hyper Radial Visualization

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- ◆ Hyper Radial Visualization (HRV) maps any number of objectives to 2D
- ◆ Objectives are placed in X and Y groups
- ◆ Grouping does not matter as “best” point (closest to Utopian point) is always the same
- ◆ Points on the same contour have the same “value”
- ◆ Objectives can be weighted by moving sliders

# Cross-display of selected points



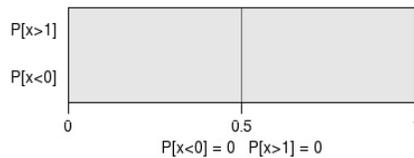
# Spreadsheet of selected points

Point selection													
Point ID	Variables										N1_disp	N2_disp	N1_a
	t1	t2	t3	t4	t5	t6	t10	t64	t73				
t1.61	2.97461	2.48845	2.63813	3.0794	2.81527	2.94545	2.34648	1.00323	2.03686	717.13	718.566	138	
t1.71													
t1.78	t1.314	2.97028	2.50838	2.68088	3.01328	2.73141	2.94295	2.34327	1.01036	1.93423	717.33	718.472	135
t1.80													
t1.83													
t1.99	t1.339	2.97033	2.48855	2.6456	3.07694	2.72019	2.85593	2.34345	1.00244	1.92001	717.046	718.437	135
t1.113													
t1.118	t1.360	2.97461	2.49834	2.64825	3.08183	2.81396	2.94505	2.35213	1.20886	2.0356	718.167	718.057	140
t1.128													
t1.137	t1.381	2.98462	2.4904	2.68054	3.00873	2.72048	3.00838	2.34825	1.01035	2.04238	716.999	718.375	135
t1.144													
t1.151	t1.388	3.2071	2.52048	2.68494	2.6768	2.72071	2.92279	2.36076	1.00453	2.05429	717.589	718.2	132
t1.156													
t1.161	t1.395	3.18645	2.49159	2.68559	2.69227	2.72118	2.86564	2.34113	1.00694	2.01281	717.287	718.296	132
t1.172													
t1.180	t1.510	3.20129	2.48092	2.73607	2.64129	2.76148	2.86426	2.3466	1.02748	1.94592	717.561	718.189	133

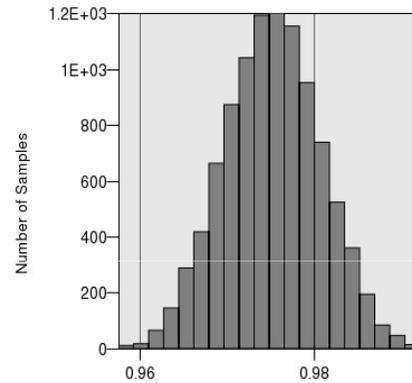
# Probability distributions of constraint values

## Starting Design

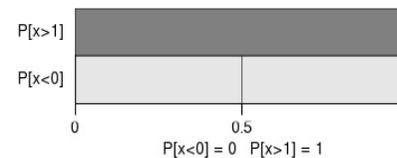
Composite: Disp  
 10000 samples: Mean = 0.975 Standard Deviation = 0.00552  
 95% confidence interval in red



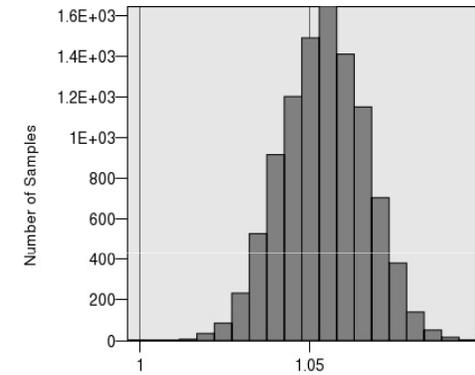
Composite: Disp  
 10000 samples: Mean = 0.975 Standard Deviation = 0.00551



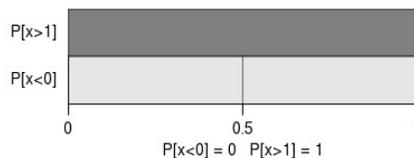
Composite: scaled\_stage2\_pulse  
 10000 samples: Mean = 1.05 Standard Deviation = 0.0123  
 95% confidence interval in red



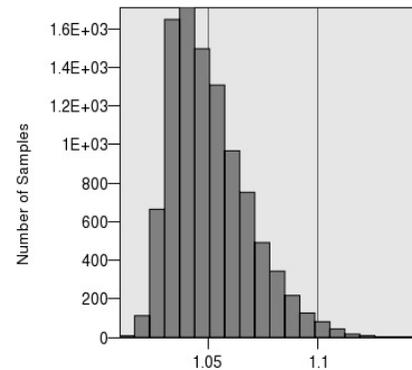
Composite: scaled\_stage2\_pulse  
 10000 samples: Mean = 1.05 Standard Deviation = 0.0123



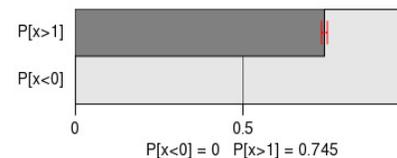
Composite: scaled\_stage1\_pulse  
 10000 samples: Mean = 1.05 Standard Deviation = 0.0178  
 95% confidence interval in red



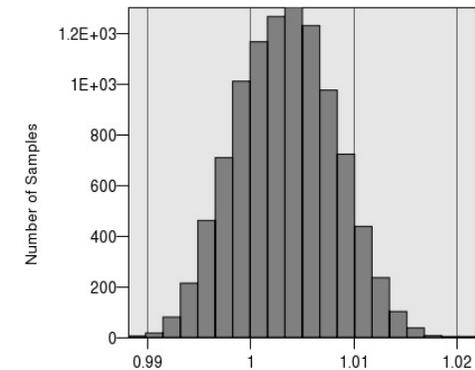
Composite: scaled\_stage1\_pulse  
 10000 samples: Mean = 1.05 Standard Deviation = 0.0178



Composite: scaled\_stage3\_pulse  
 10000 samples: Mean = 1 Standard Deviation = 0.00476  
 95% confidence interval in red



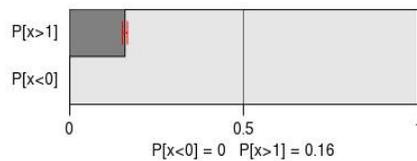
Composite: scaled\_stage3\_pulse  
 10000 samples: Mean = 1 Standard Deviation = 0.00475



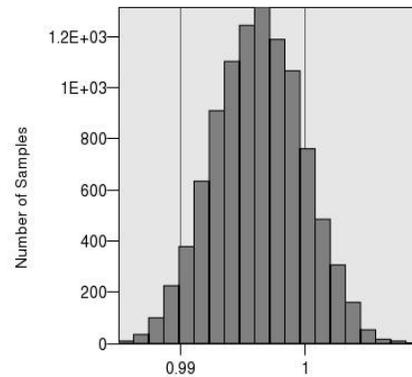
# Probability distributions of constraint values

## Optimal Design (equal weights)

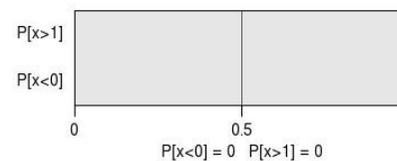
Composite: Disp  
10000 samples: Mean = 0.996 Standard Deviation = 0.00365  
95% confidence interval in red



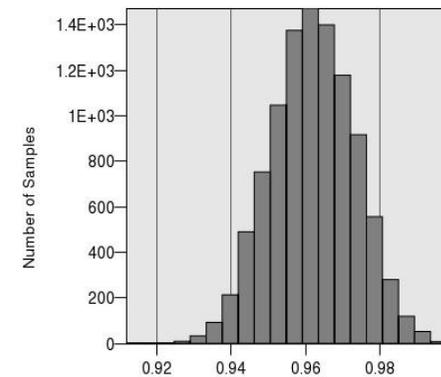
Composite: Disp  
10000 samples: Mean = 0.996 Standard Deviation = 0.00359



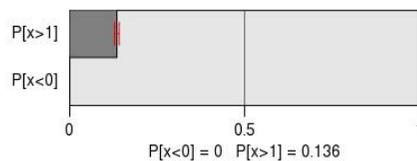
Composite: scaled\_stage2\_pulse  
10000 samples: Mean = 0.962 Standard Deviation = 0.0113  
95% confidence interval in red



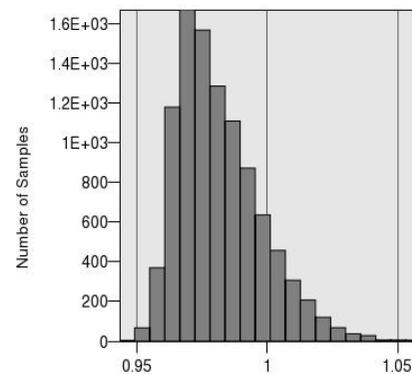
Composite: scaled\_stage2\_pulse  
10000 samples: Mean = 0.962 Standard Deviation = 0.0112



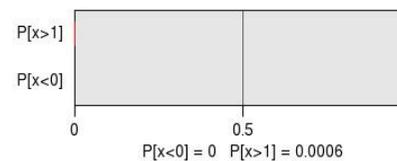
Composite: scaled\_stage1\_pulse  
10000 samples: Mean = 0.982 Standard Deviation = 0.0159  
95% confidence interval in red



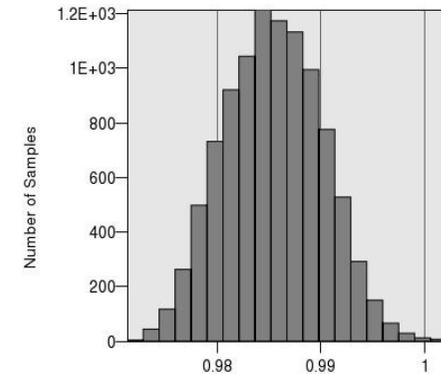
Composite: scaled\_stage1\_pulse  
10000 samples: Mean = 0.982 Standard Deviation = 0.016



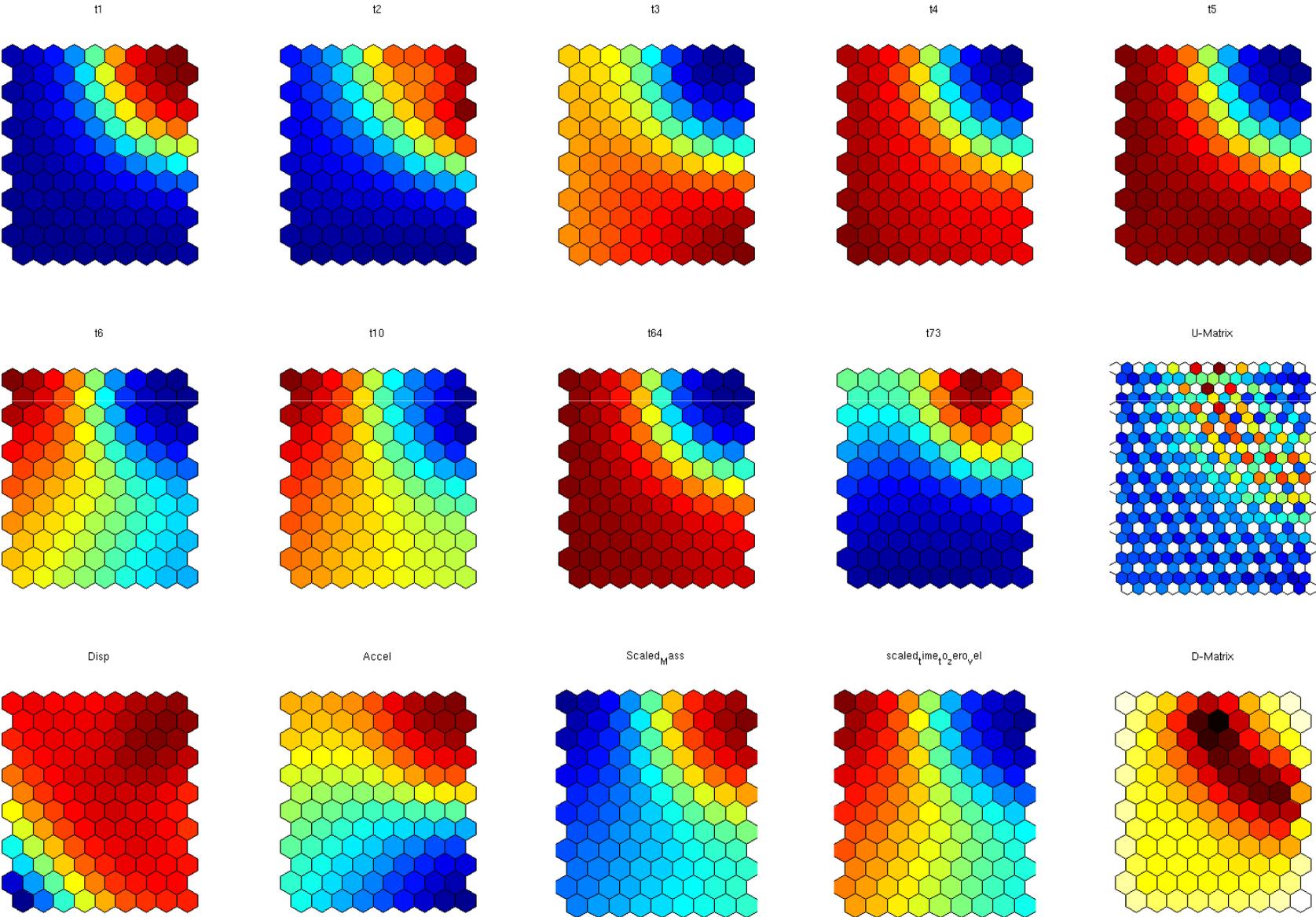
Composite: scaled\_stage3\_pulse  
10000 samples: Mean = 0.985 Standard Deviation = 0.00475  
95% confidence interval in red



Composite: scaled\_stage3\_pulse  
10000 samples: Mean = 0.985 Standard Deviation = 0.00473



# Self-Organizing Maps



# Self-Organizing Maps

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- ◆ In prototype stage (*D-SPEX* by *DYNAmore* GmbH shown)
- ◆ Released in Version 4.1, Fall 2009

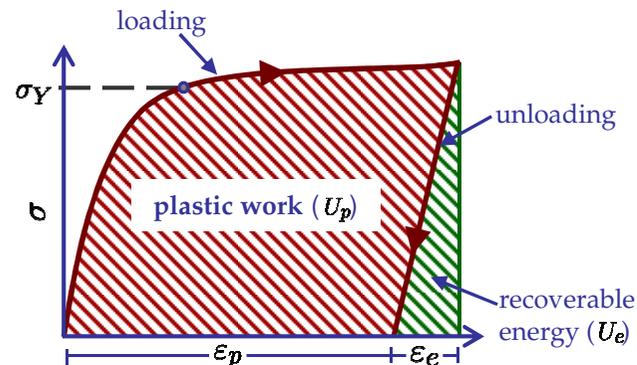
# Hybrid Cellular Automata (HCA) algorithm

- ◆ In traditional elastic-static problems, material is distributed based on the strain energy ( $U^e$ ) generated during loading

target ( $S$ )  $\rightarrow$  strain energy density

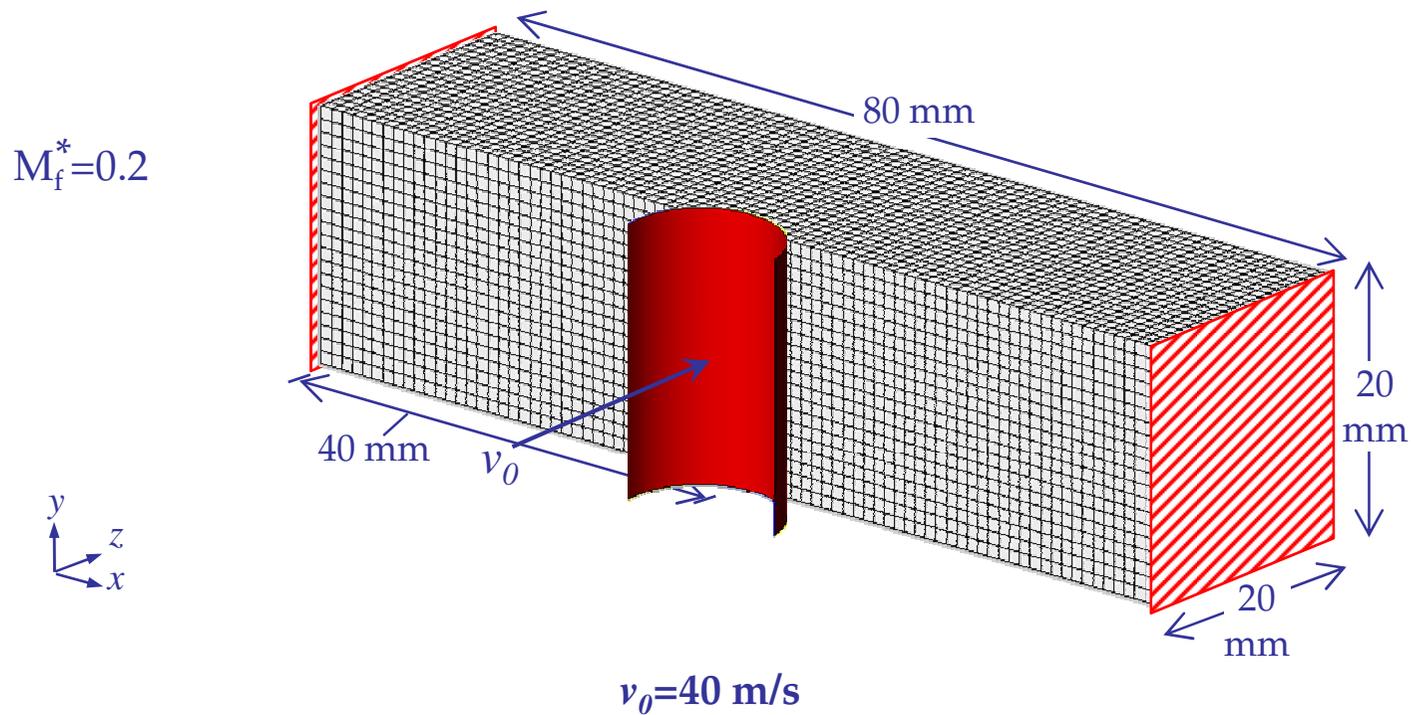
- ◆ For elastic-plastic problems, every finite element must contribute to absorb internal energy ( $U$ ) which includes both elastic strain energy and plastic work during loading.

target ( $S$ )  $\rightarrow$  internal energy density



# Example problem: short beam

Courtesy  
Neal Patel



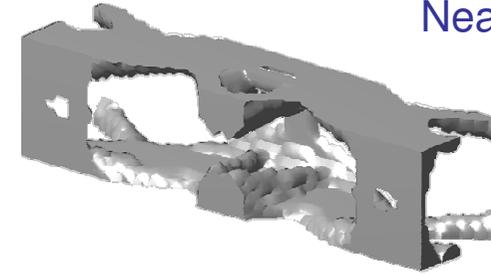
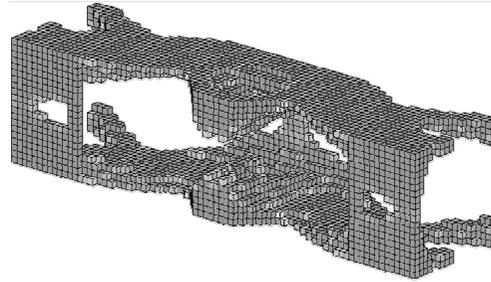
$80 \times 20 \times 20$  elements\*

\*~7 minutes/FEA (DYNA) evaluation

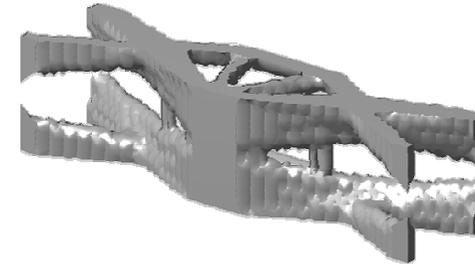
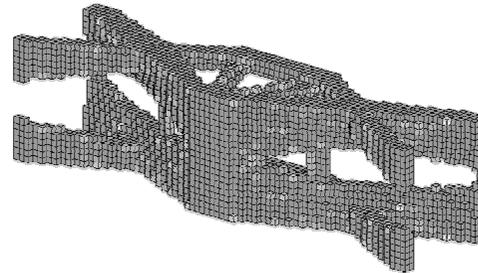
# Effects of model simplifications

$M_f^* = 0.2$

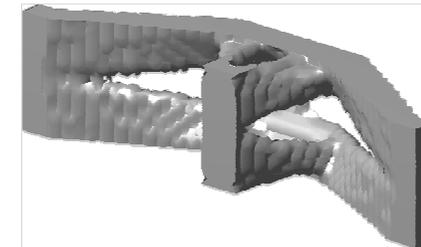
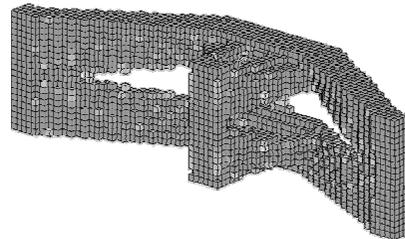
Nonlinear-dynamic



Linear-static



Nonlinear-static

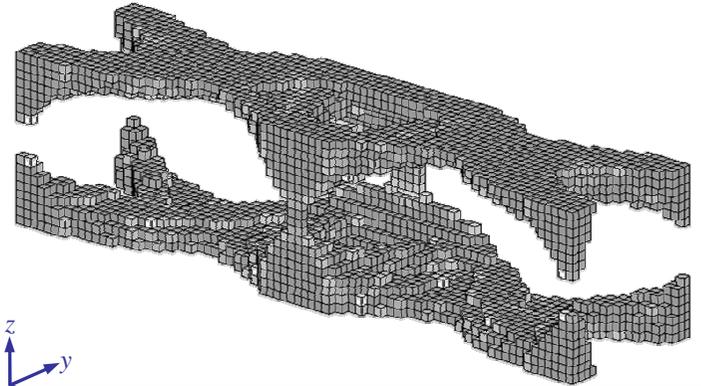


Courtesy  
Neal Patel

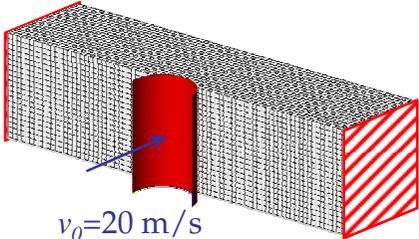
# Short beam: extrusion results

$M_f^* = 0.2$

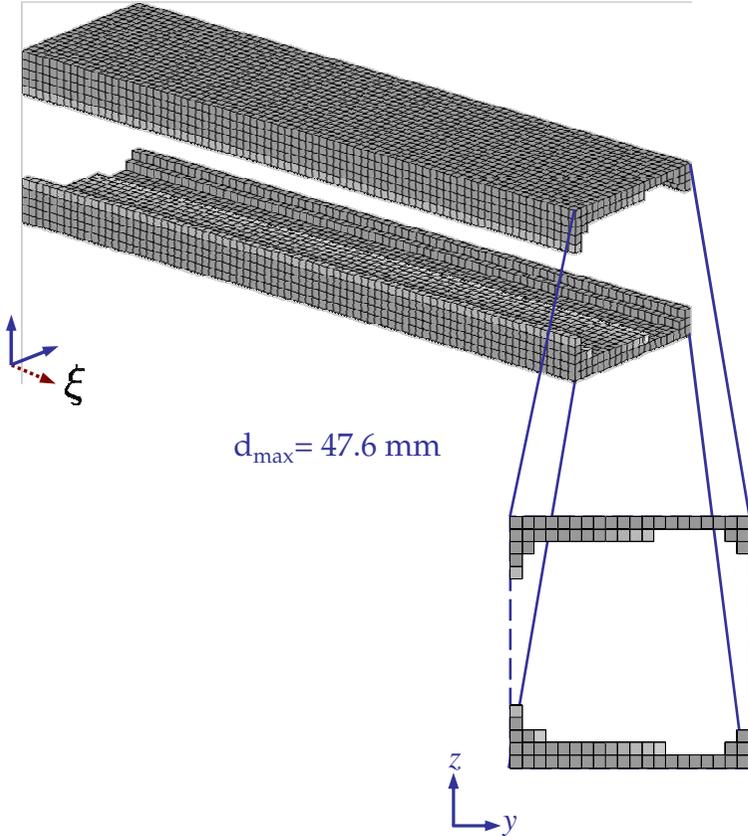
**Conventional topology**  
(no extrusion)



$d_{\max} = 40.1 \text{ mm}$



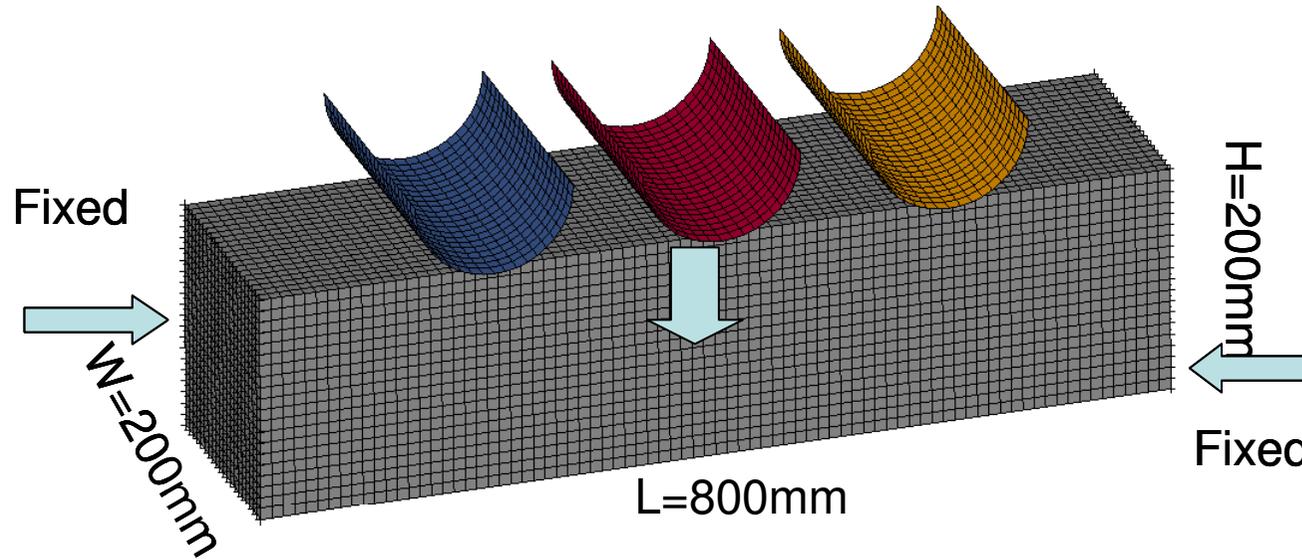
**Extruded topology**



$d_{\max} = 47.6 \text{ mm}$

Courtesy  
Neal Patel

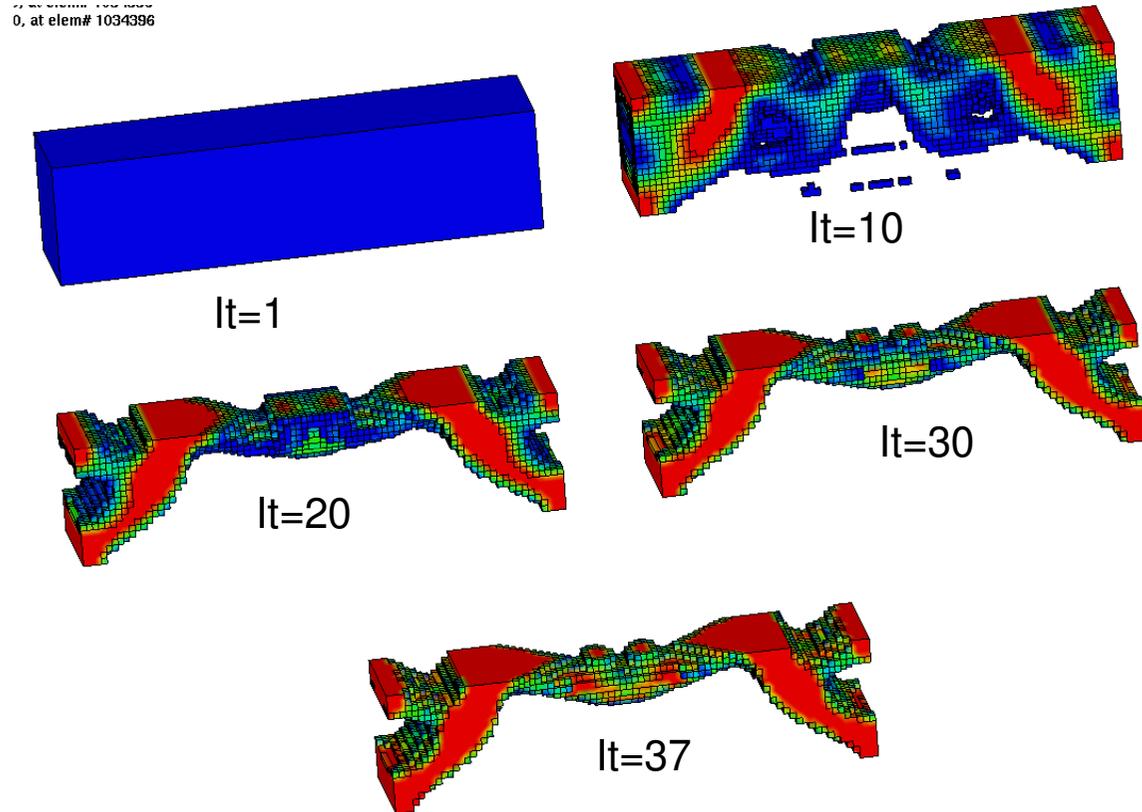
# Problem Definition



- ◆ Three poles hit the fixed-fixed beam with an initial velocity of 40m/s, one at a time (three load cases)
- ◆ Get the optimal structure with 30% mass, equal importance of each load case
- ◆ Mesh size – 10mm<sup>3</sup>, **Material:** Bi-linear Aluminum
- ◆ MPP LS-DYNA simulations with 8 processors per case

# Final Results

- ◆ 37 iterations to obtain optimal topology
- ◆ The initial shape was evolved within 20 iterations
- ◆ Tabular structure with two legs was evolved as optima
- ◆ Uniform distribution of material



# Estimated beta release

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- ◆ Version 4.0: April, 2009
- ◆ Version 4.1: September, 2009
- ◆ Topology Optimization, April, 2009