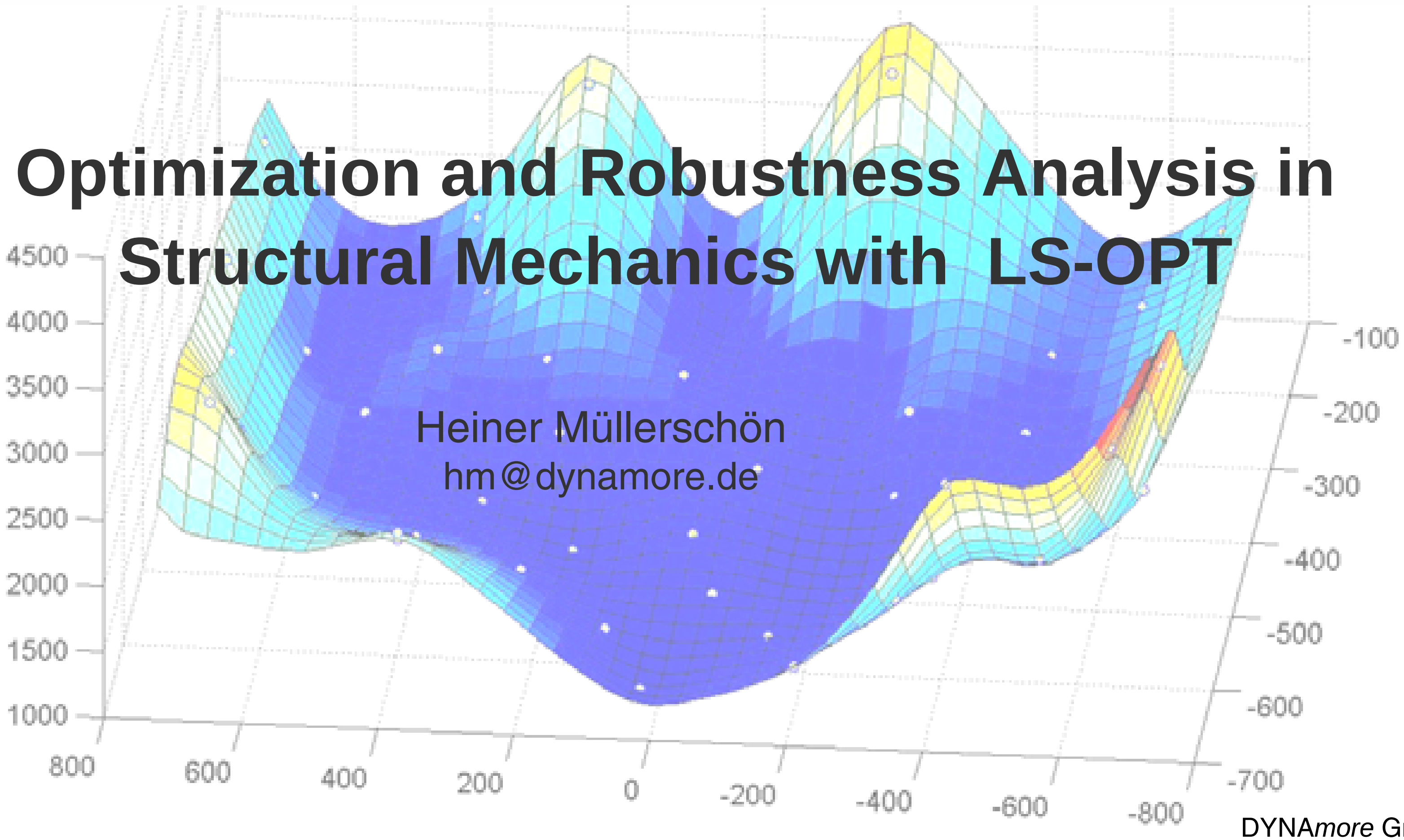
Optimization and Robustness Analysis in Structural Mechanics with LS-OPT



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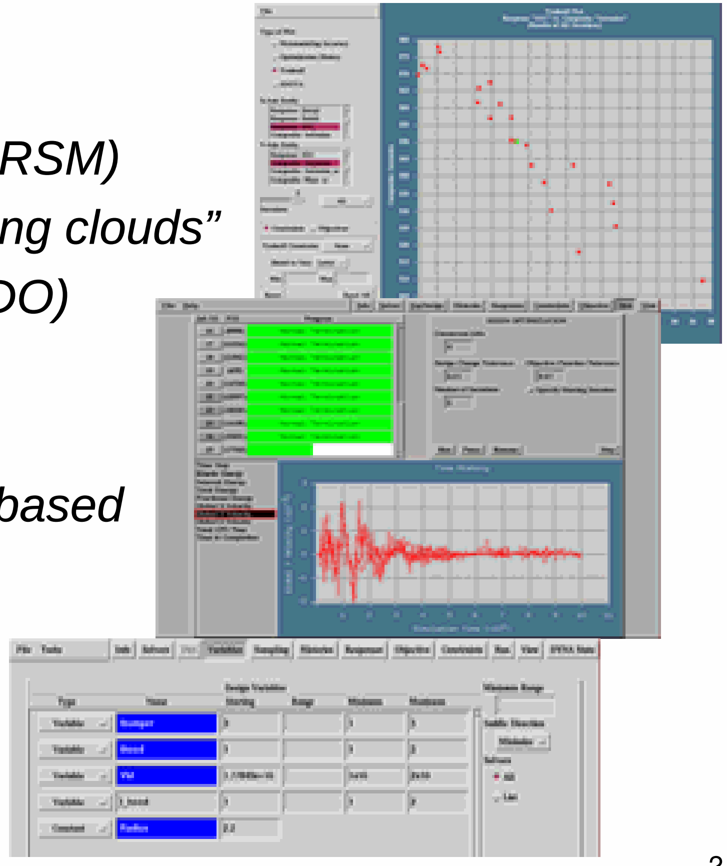
Introduction / Features

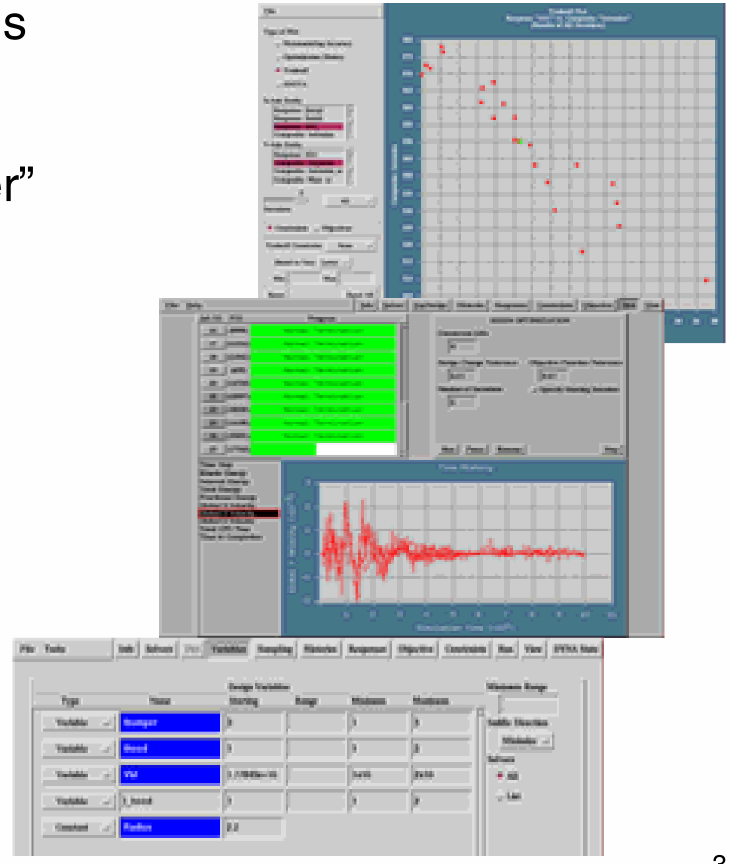
➔ About LS-OPT

- LS-OPT is a product of LSTC (Livermore Software Technology Corporation)
- LS-OPT can be linked to any simulation code – stand alone optimization software
- Methodologies/Features:
  - *Successive Response Surface Method (SRSM)*
  - *Search Based optimization (SRS) – “moving clouds”*
  - *Reliability based design optimization (RBDO)*
  - *Multidisciplinary optimization (MDO)*
  - *Multi-Objective optimization (Pareto)*
  - *numerical/analytical sensitivities gradient based*
  - *Analysis of Variance (ANOVA)*
  - *Stochastic/Probabilistic Analysis*
  - *Monte Carlo Analysis using Metamodels*
  - *….*



➔ About LS-OPT

- LS-OPT provides a graphical user interface (GUI) – interaction with LS-PrePost
- Job Distribution - Interface to Queuing Systems
  - *PBS, LSF, LoadLeveler, AQS*
- LS-OPT might be used as a “Process Manager”
- Shape Optimization
  - *Interface to HyperMorph, DEP-Morpher*
  - *User-defined interface to any Pre-Processor*



- Introduction/Features
- Methods – Optimization
- Methods - Robustness
- Example I - Optimization
- Example II - Optimization
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- Outlook Version 3.0/3.1

➔ Design Variables

- Imported Variables
  - *Variables in Keyword file automatically imported into GUI*
  - *LS-DYNA *PARAMETER keyword support*
    Parameter definitions automatically imported into GUI
  - *Include files recursively parsed for parameters/variables*

➔ Design Variables

- Type of Variables
  - *`Variable` – standard design variable*
  - *`Constant` – fixed variable*
  - *`Dependent variable`:*

Ex.: variable ‘Youngs_modulus’ 2.0e08
variable ‘Poisson_ratio’ 0.42
dependent ‘Shear Modulus’ {Youngs_modulus/(2(1+Poisson_ratio))}*

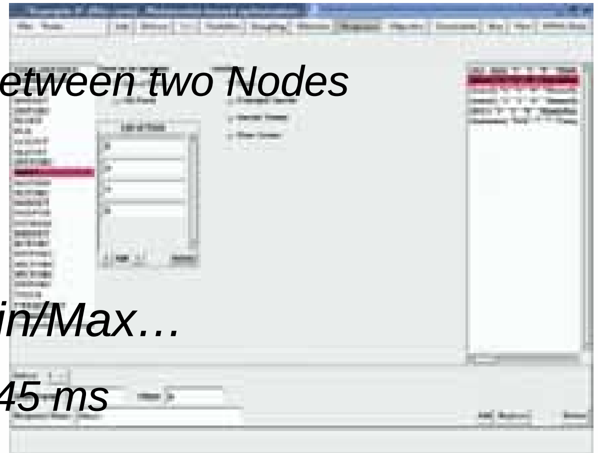
  - *`Noise variable` – stochastic analysis*

Introduction / Features

➔ Evaluation of Results (responses)

- Definition of History Responses

  Ex.: u12(t)=u1(t) - u2(t) -> Relative Displacement between two Nodes



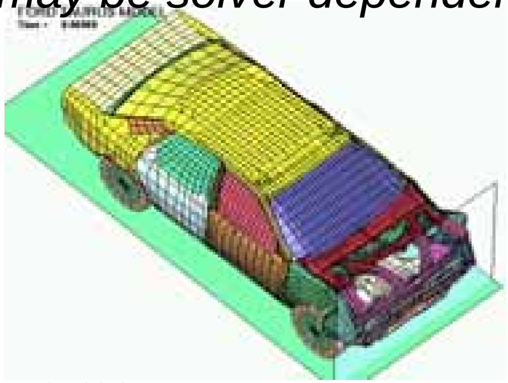
- Mathematical Expressions
  - *All C language type expressions...*
  - *Integrals, Derivatives, Lookup Functions, Min/Max…*

  Ex.: Max(u12(t),5,45) -> Maximum between 5 and 45 ms

- Comfortable extraction of LS-DYNA results within the GUI
  - *LS-DYNA ASCII and binary (d3plot, binout) databases*
  - *Mass, FLD, Injury Coefficients (HIC, CSI), Thickness, Frequency…*

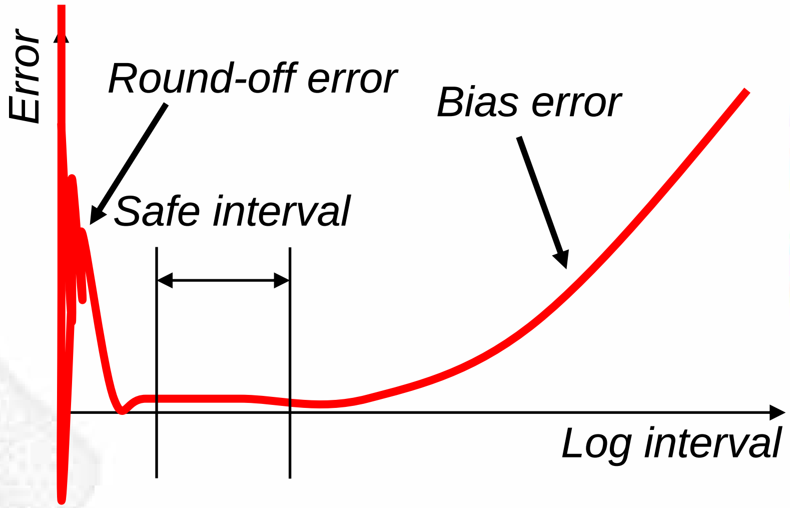
➔ Multidisciplinary Optimization

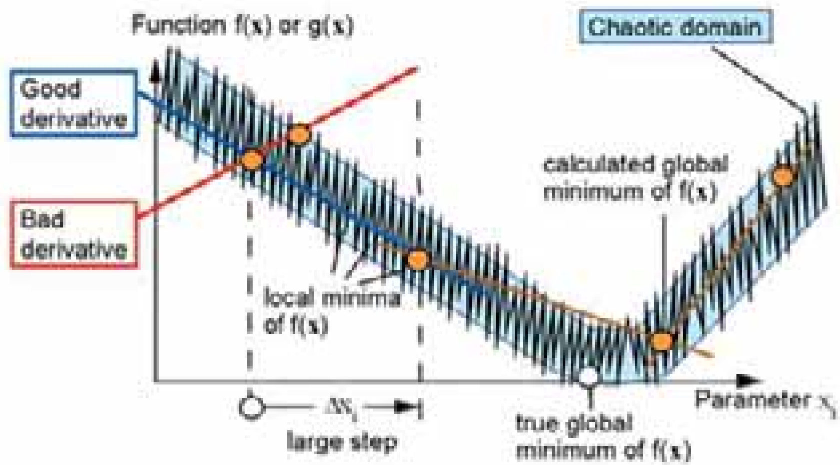
- Sharing of Variables
  - *Each discipline is defined by own variable subset*
- Mode Tracking (Eigenvalue analysis)
  - *Mode shape is tracked according to selected mode*
- Discipline-Specific Sampling/Response Surface
  - *Crash: RSM (Response Surface Method - usually D-Optimal DOE)*
  - *Vibration: DSA (Design Sensitivity Analysis – numerical/analytical)*
- Discipline-Specific Job Distribution
  - *Memory requirements may be solver dependent*



➔ Why Response Surface Methodology?

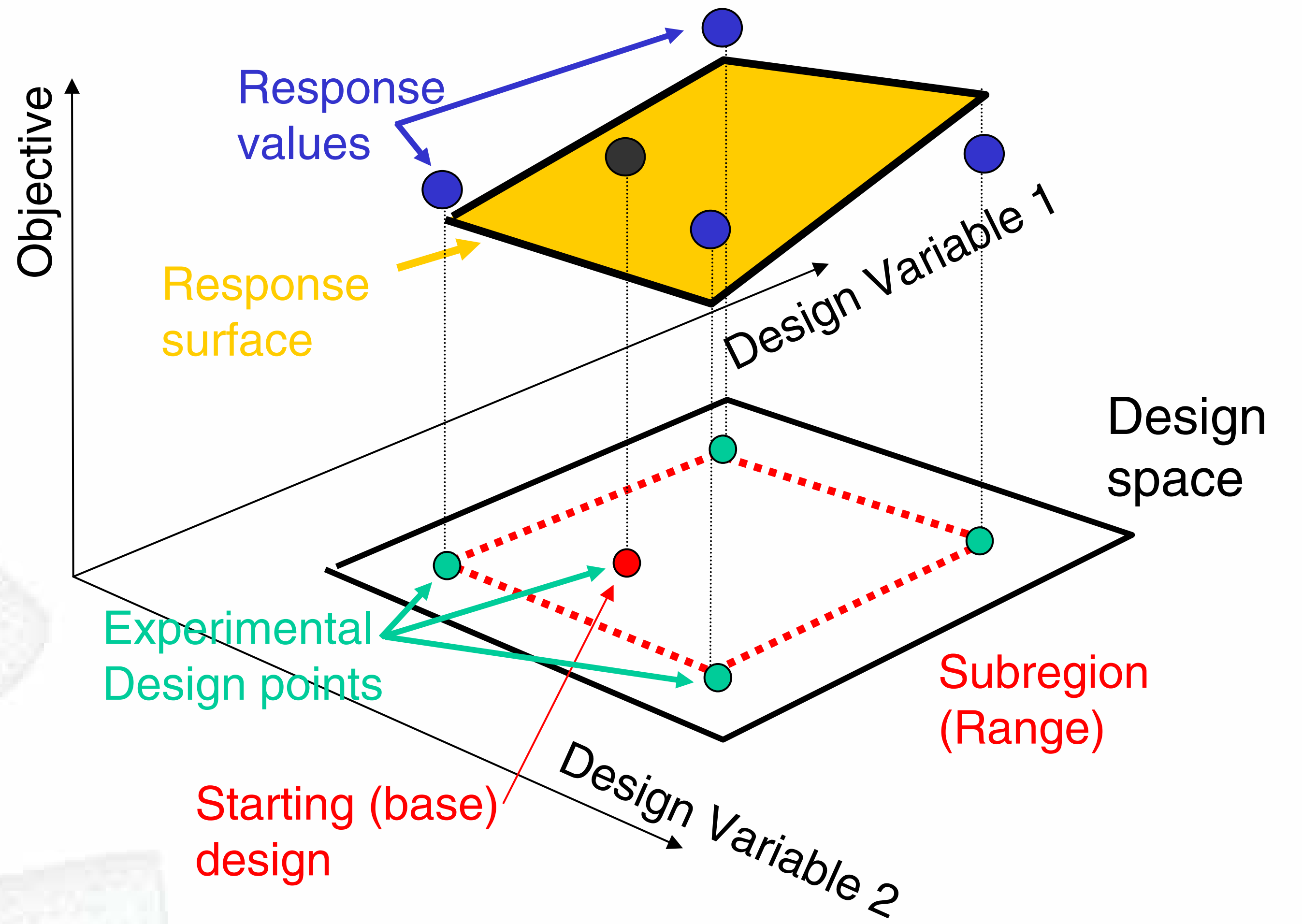
- Gradient based methods
  - *Local Sensitivities may lead to local optimums (highly nonlinear problems)*
  - *Difficulties by the Computation of Numerical Gradients*



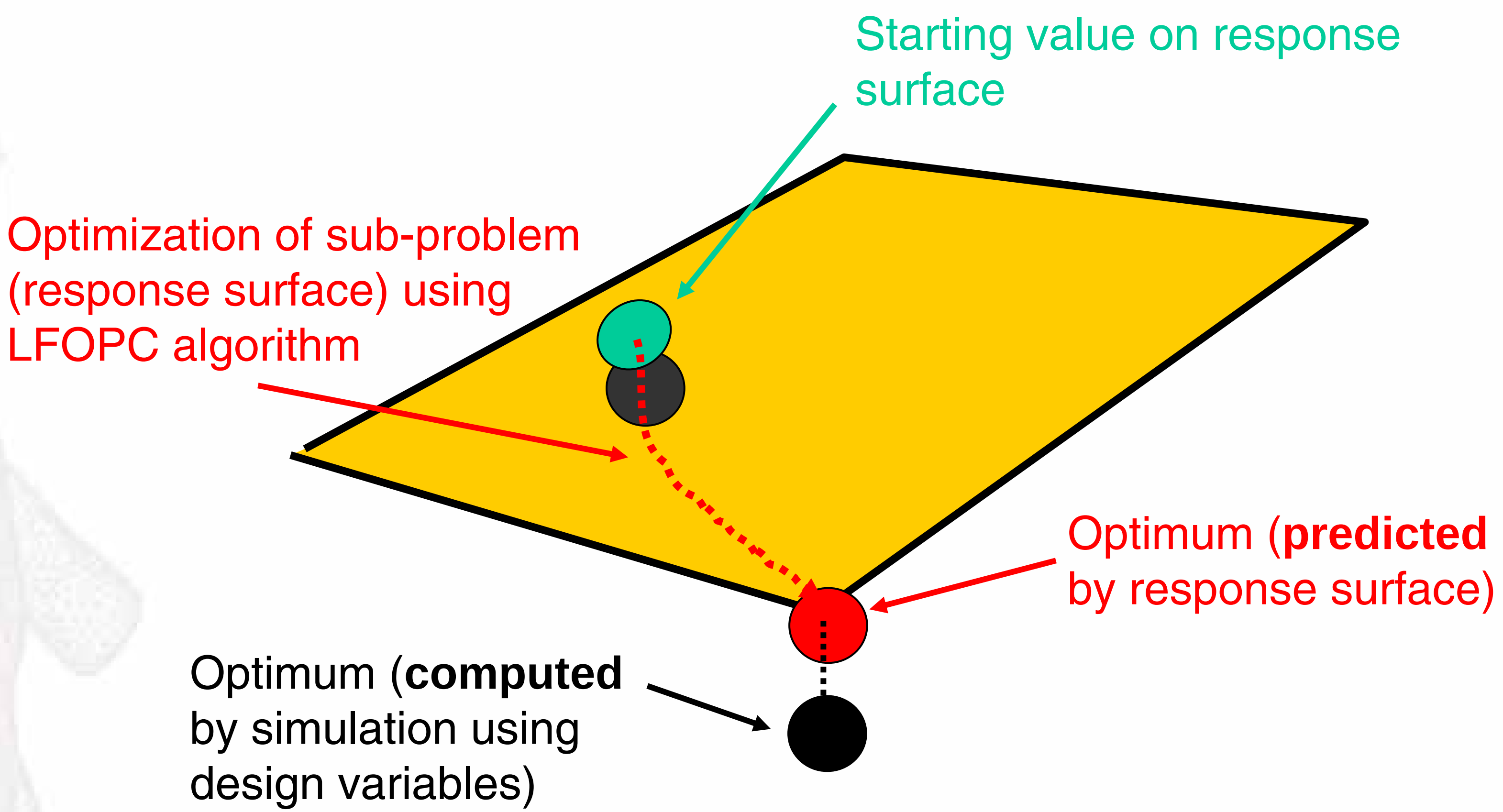


- Response Surfaces
  - *Local minima caused by noisy response as well as the step-size dilemma for numerical gradients are avoided*

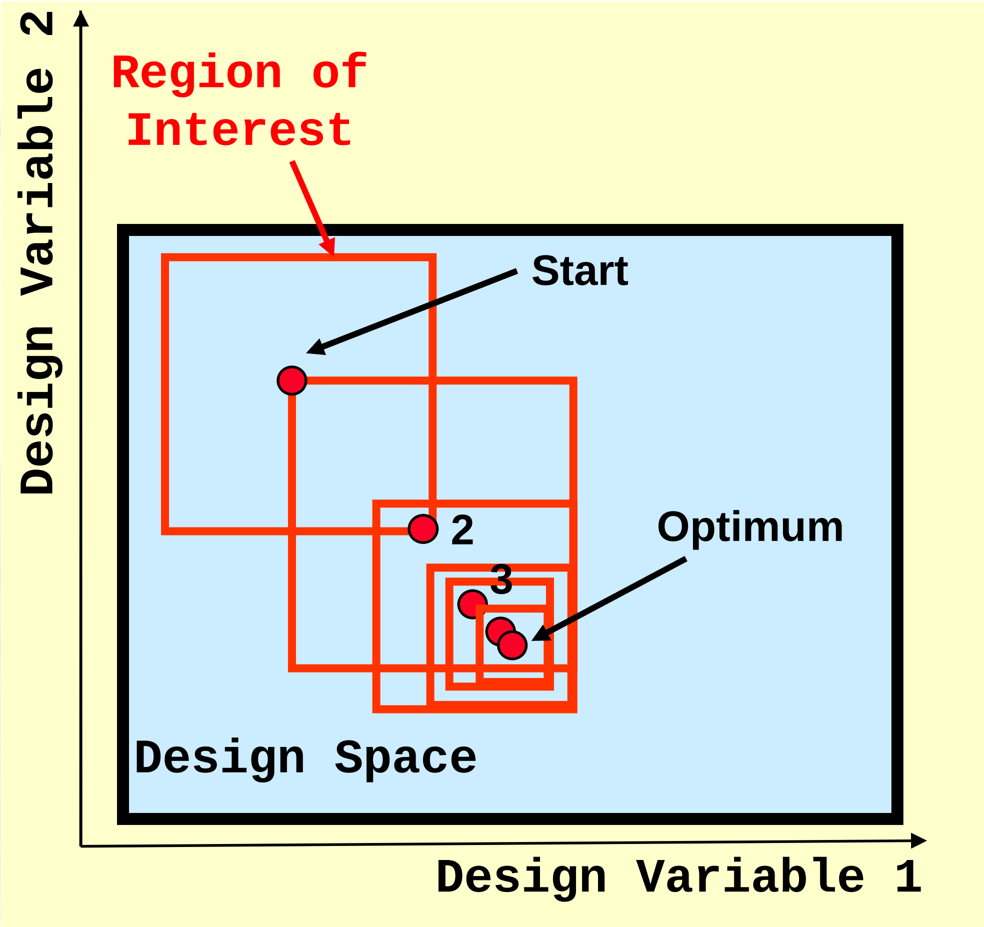
➔ Optimization Process - Response Surface Methodology



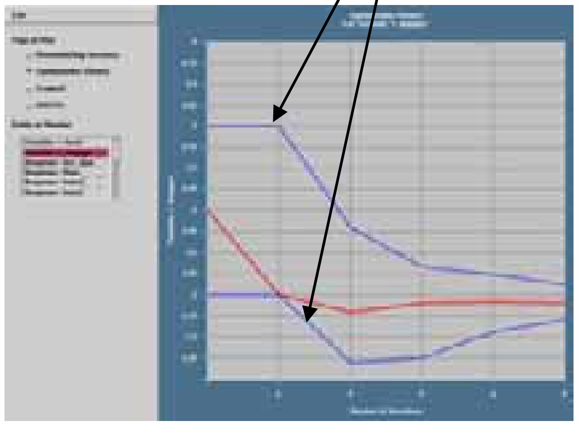
➔ Find an Optimum on the Response Surface (one iteration)

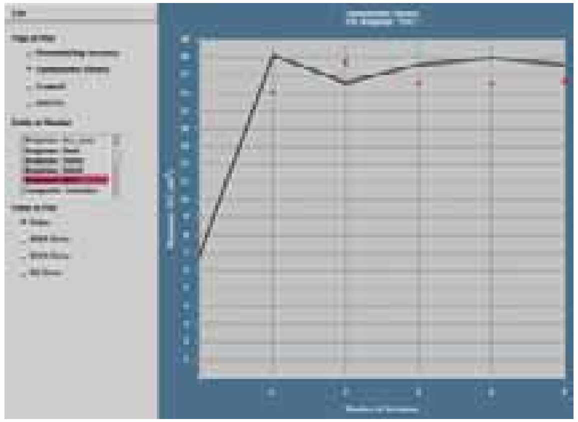


➔ Successive Response Surface Methodology



Bounds of Region of Interest



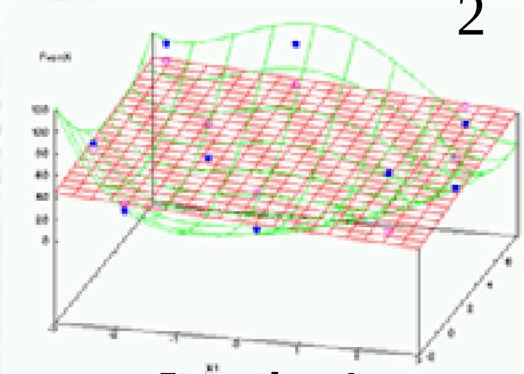


Methods - Optimization

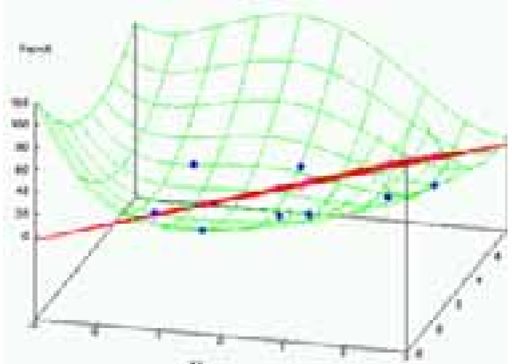
➔ Successive Response Surface Methodology

- Example - 4th order polynomial

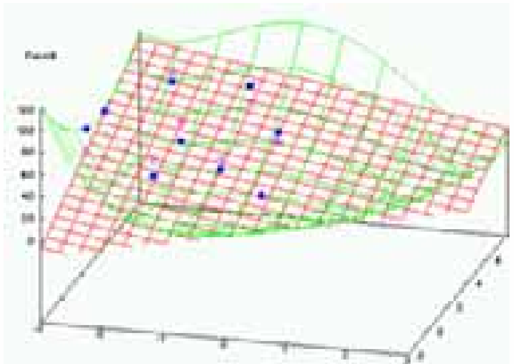
$$g(\mathbf{x}) = 4 + \frac{9}{2}x_1 - 4x_2 + x_1^2 + 2x_2^2 - 2x_1x_2 + x_1^4 - 2x_1^2x_2$$



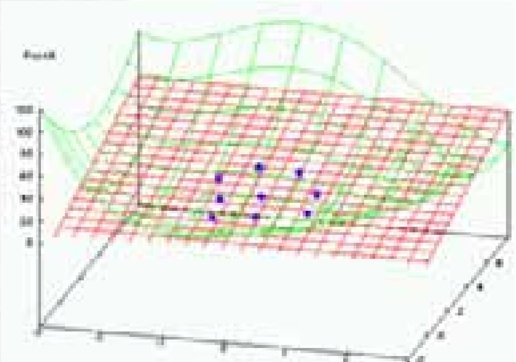
Iteration 1



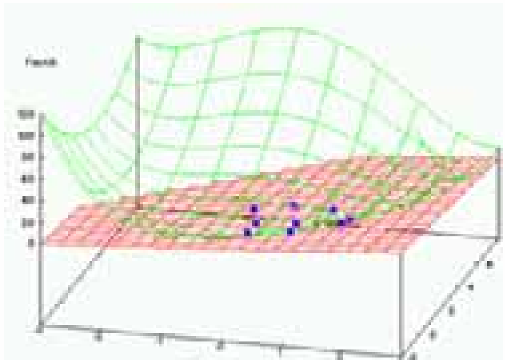
Iteration 2



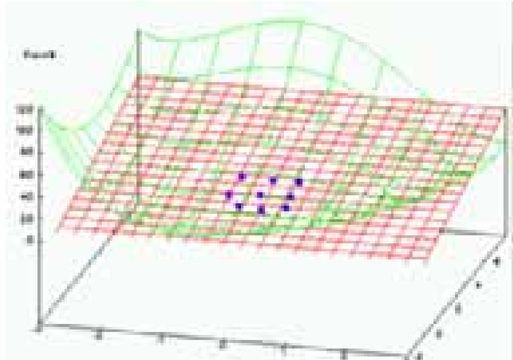
Iteration 3



Iteration 4



Iteration 5



Iteration 6

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➔ Successive Response Surface Methodology

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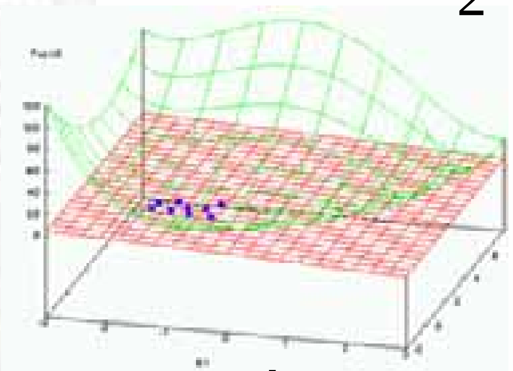
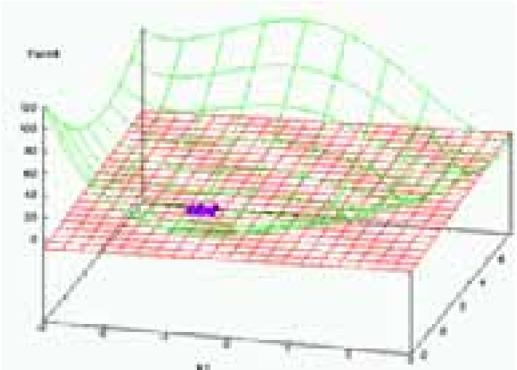
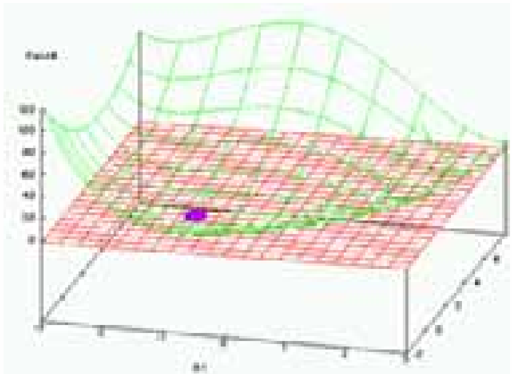
$$g(\mathbf{x}) = 4 + \frac{9}{2}x_1 - 4x_2 + x_1^2 + 2x_2^2 - 2x_1x_2 + x_1^4 - 2x_1^2x_2$$



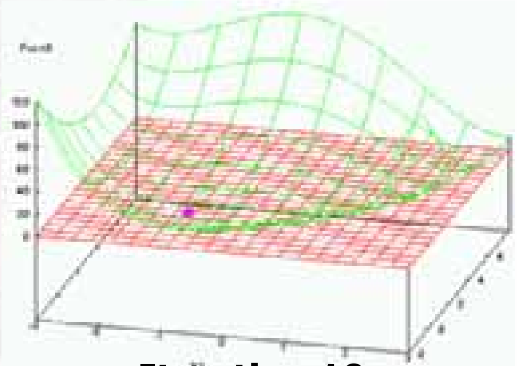
Iteration 7



Iteration 8



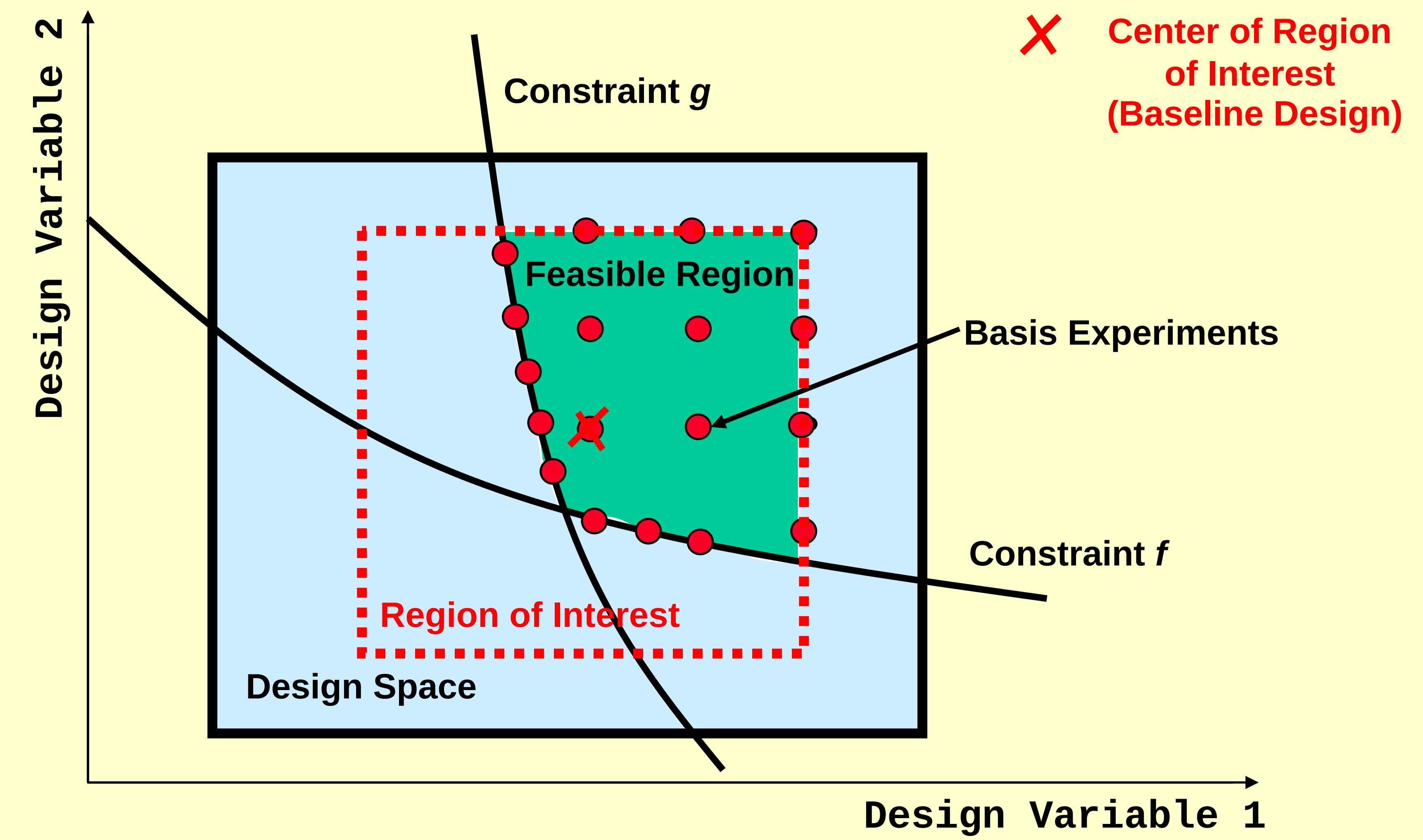
Iteration 9



Iteration 10

Methods - Optimization

➔ Feasible Experimental Design

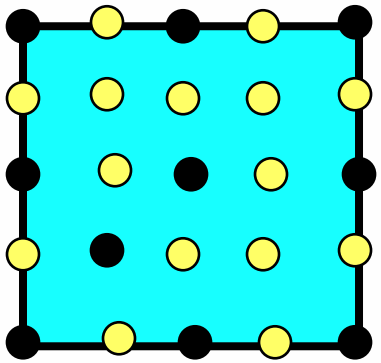


DYNA MORE

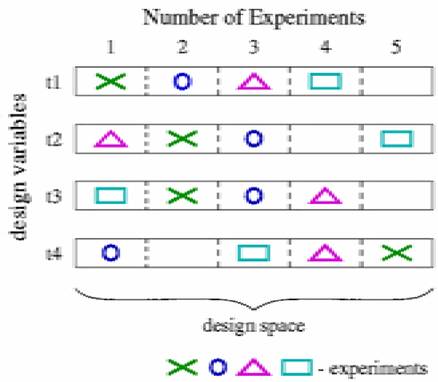
➔ Design of Experiments (DOE) - Sampling Point Selection

- Koshal, Central Composite, Full Factorial
- D-Optimality Criterion - Gives maximal confidence in the model

$$\max \left| X^T X \right|$$

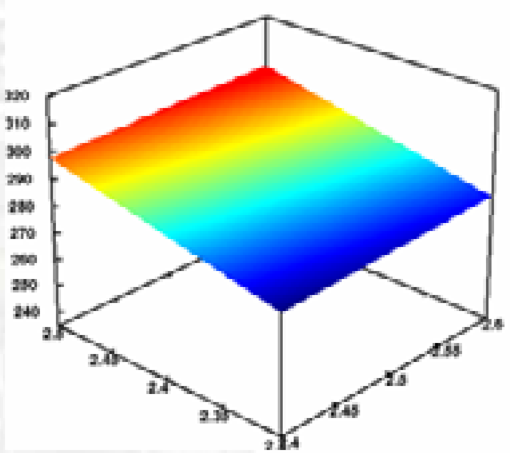


- Monte Carlo Sampling
- Latin Hypercube Sampling (stratified Monte Carlo)
- Space Filling Designs

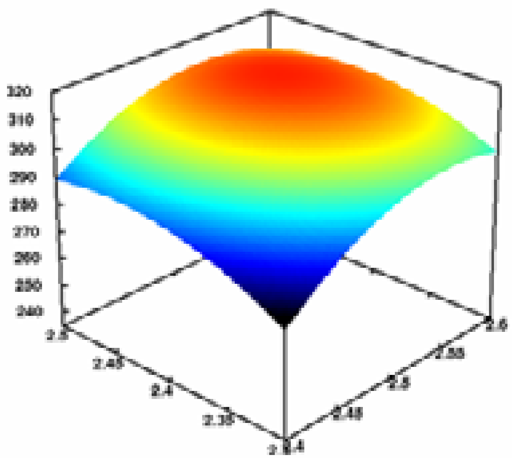


→ Response Surfaces (Meta Models)

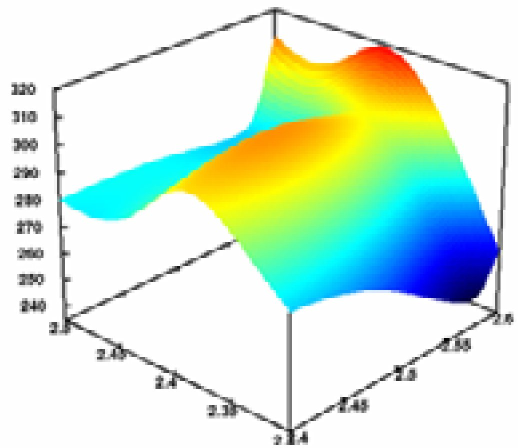
- Linear, Quadratic and Mixed polynomial based
- Neural Network and Kriging for Nonlinear Regression



linear polynomial



quadratic polynomial

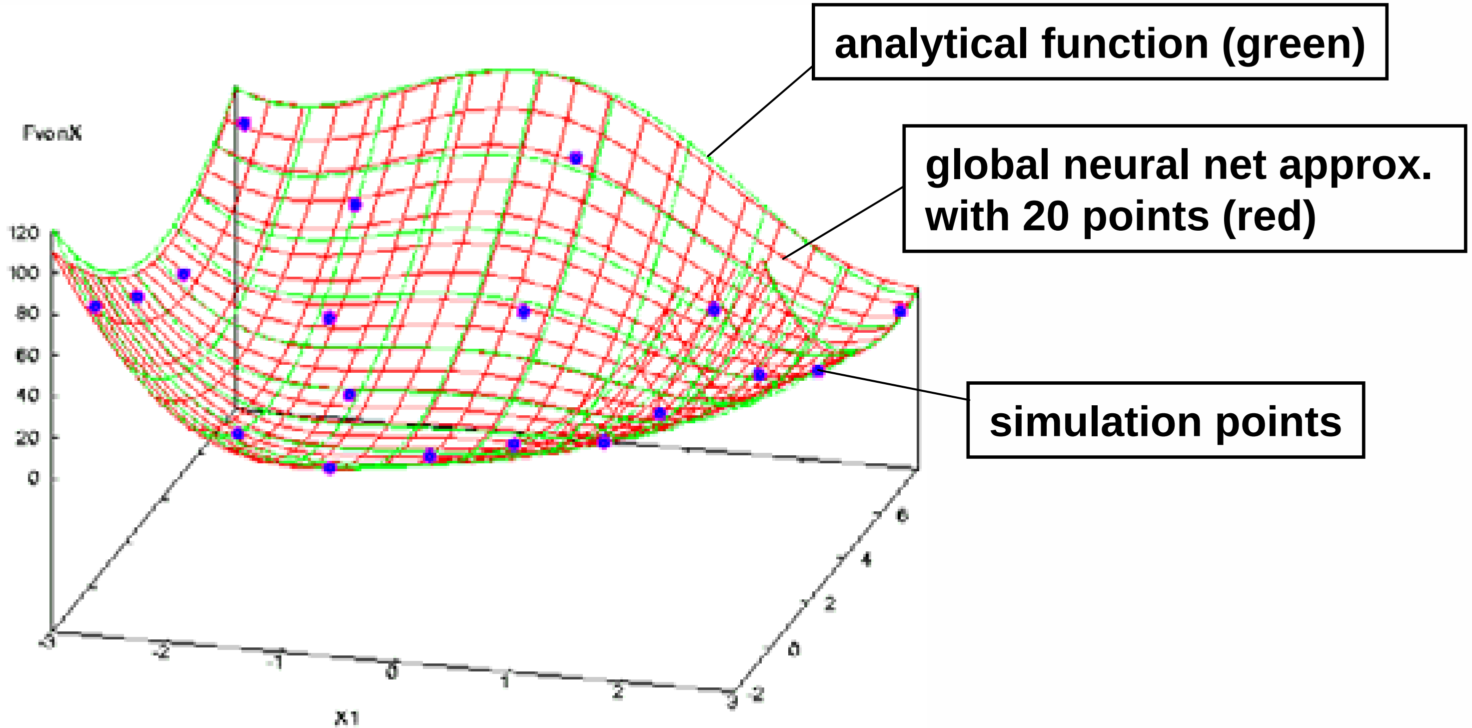


neural network

➔ Neural Network Regression

- Example - 4th order polynomial

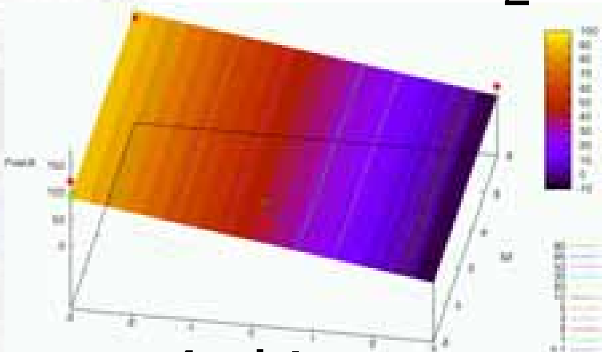
$$g(\mathbf{x}) = 4 + \frac{9}{2}x_1 - 4x_2 + x_1^2 + 2x_2^2 - 2x_1x_2 + x_1^4 - 2x_1^2x_2$$



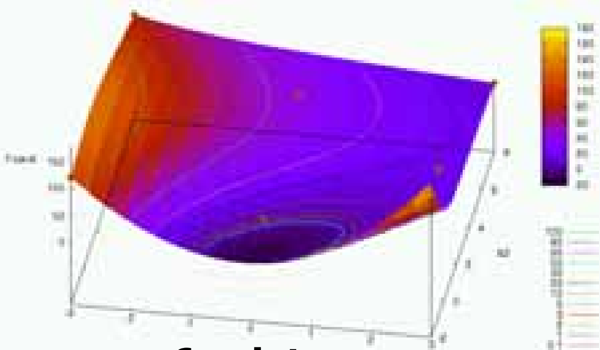
➔ Successive Scheme with Neural Network

- Example - 4th order polynomial

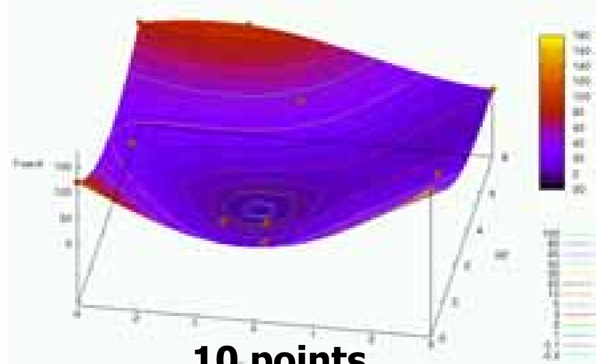
$$g(\mathbf{x}) = 4 + \frac{9}{2}x_1 - 4x_2 + x_1^2 + 2x_2^2 - 2x_1x_2 + x_1^4 - 2x_1^2x_2$$



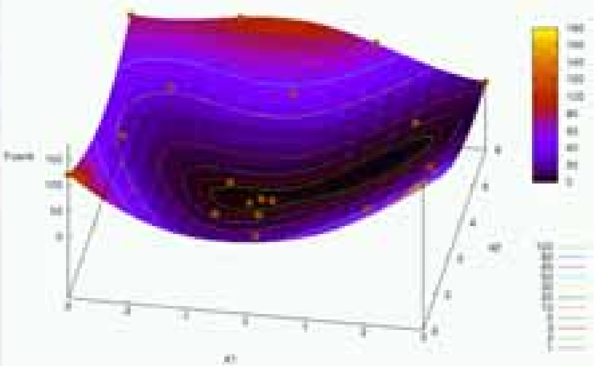
4 points



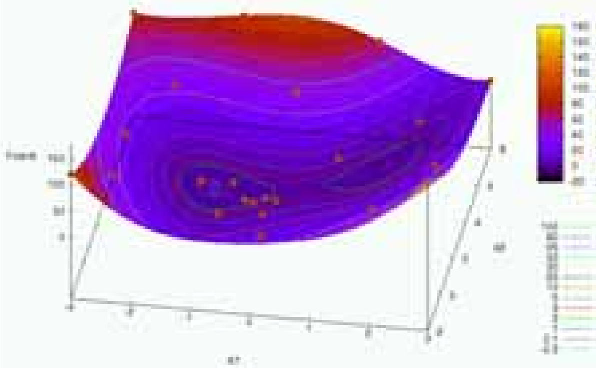
6 points



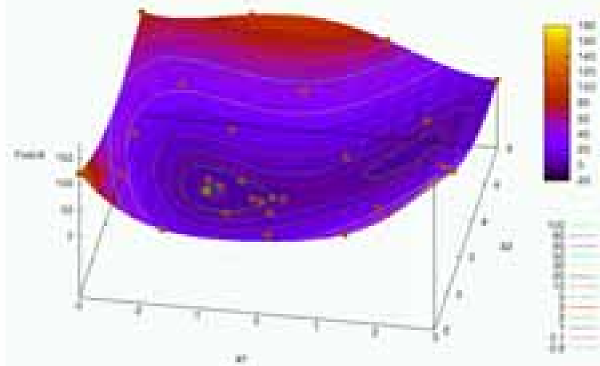
10 points



18 points



22 points

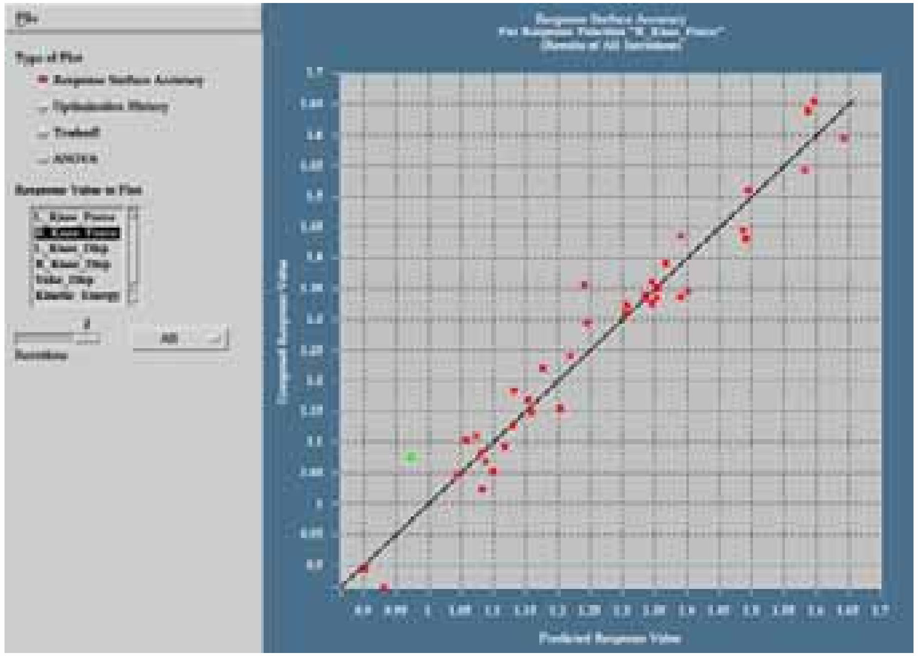


30 points

Methods - Optimization

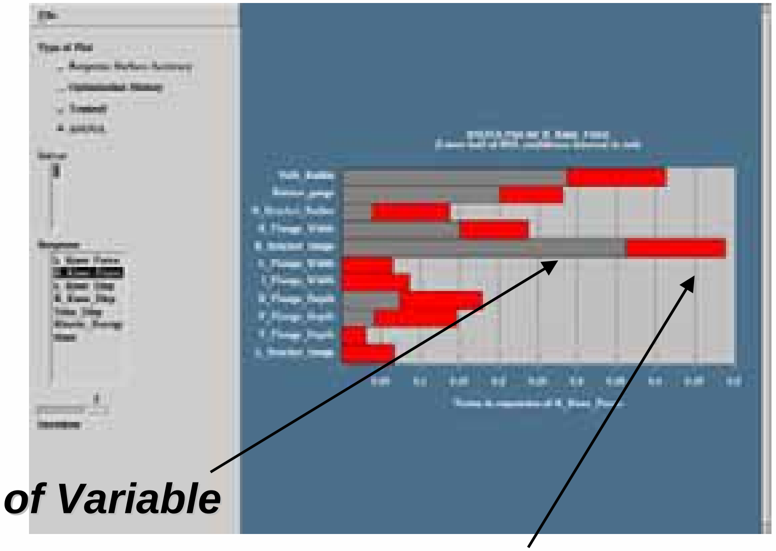
➔ Error Analysis

- Meta Model Accuracy
- Error Analysis
  - *RMS*
  - *Average error*
  - *Maximum error*
  - *PRESS (Prediction Error)*
  - *R2 indicator*



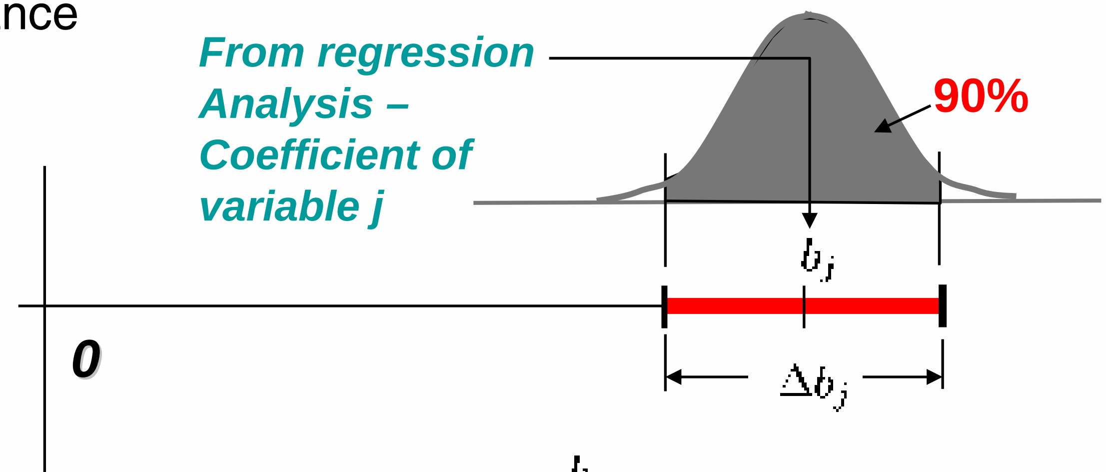
→ Response Surface Based Variable Screening using ANOVA

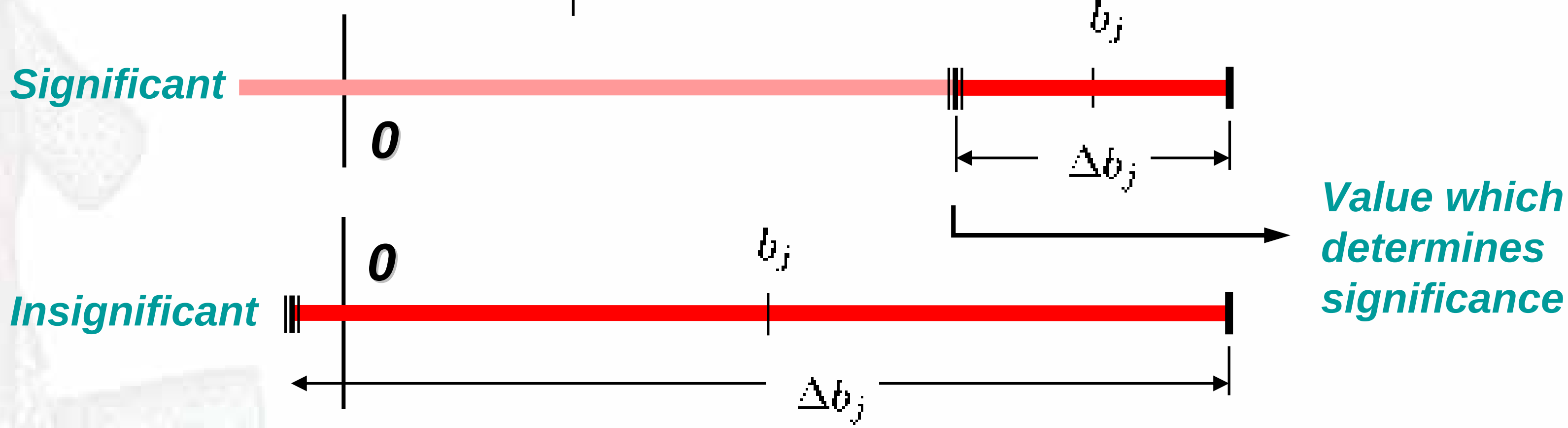
- Variable Screening
  - *ANOVA – Analysis of Variance*
  - *Removal of unimportant variables*
  - *Confidence levels of each variable*



➔ Response Surface Based Variable Screening

- Δb_j depends on the variance of the simulation points
- Use a 90% confidence level and determine the lower bound
- Variables are ranked according to lower bound





➔ Multi-Objective Optimization

- Simple Example: Cantilever Beam

Design Objective

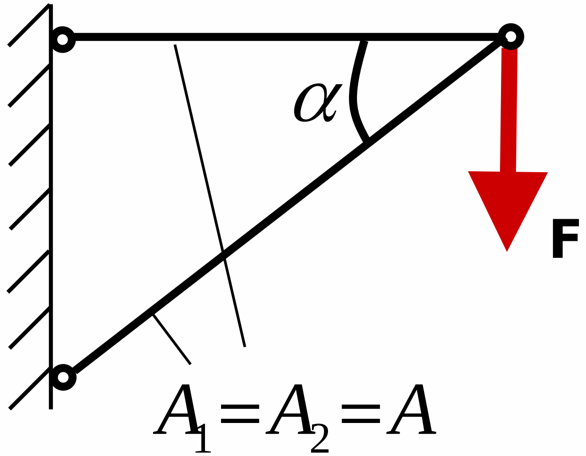
- Minimize truss volume (mass)
- Minimize maxStress

Design variables

- Cross section area A
- Angel α

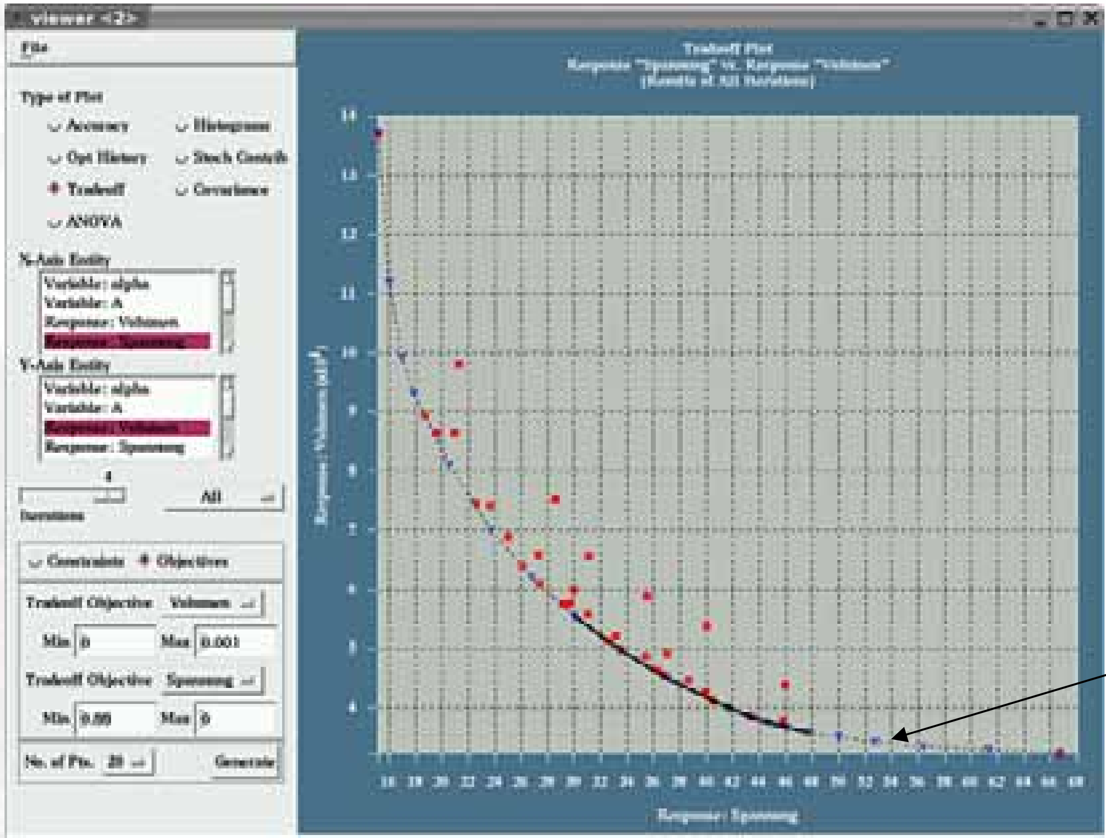
Design space

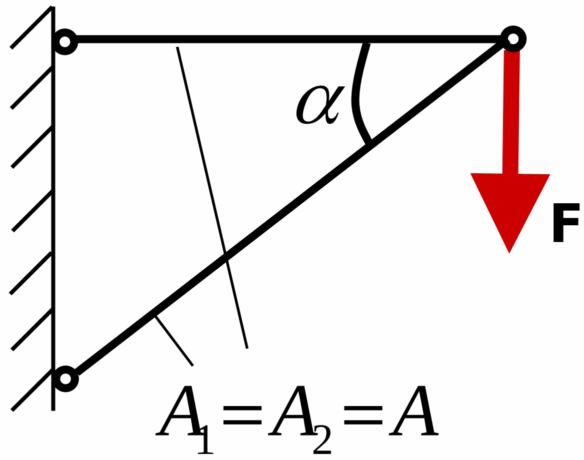
- $A \in [10mm^2; 100mm^2]$
- $\alpha \in [5^\circ; 85^\circ]$



➔ Multi-Objective Optimization - Volume vs. Stress

- Trade-Off Study using Neural Network Response Surface





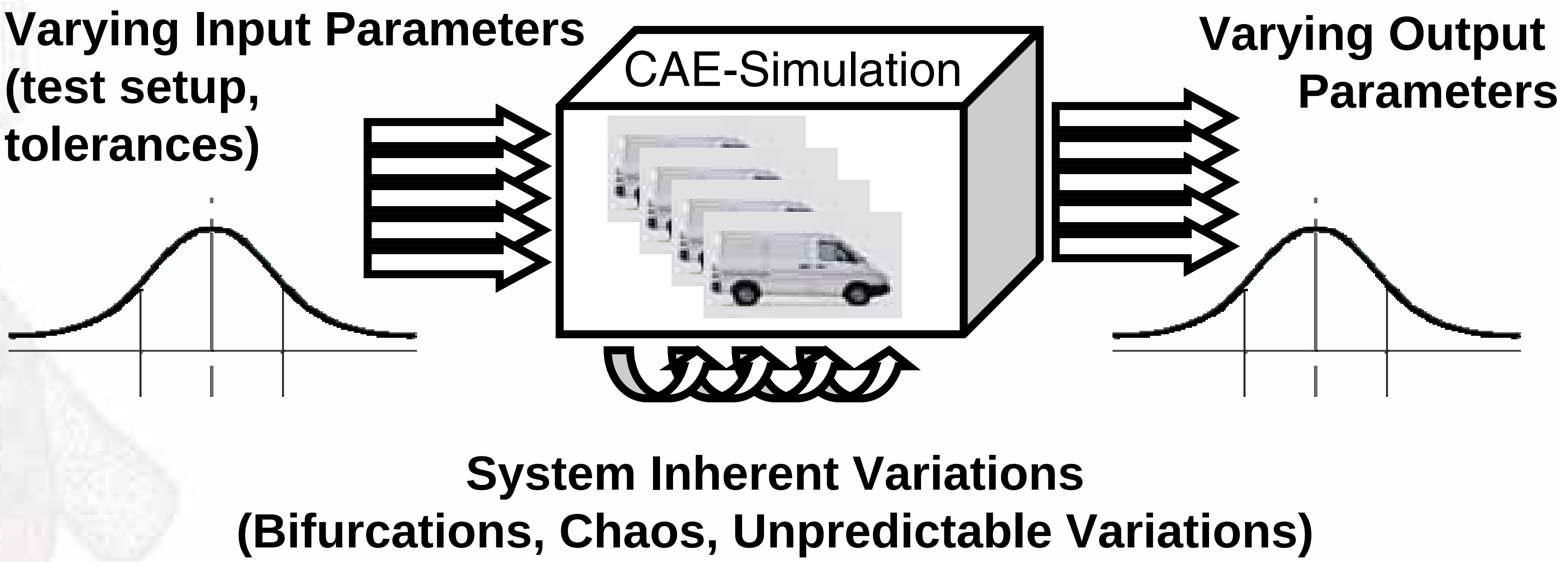
PARETO-line

Methods - Optimization

➔ Overview – Optimization Methodologies for highly nonlinear Applications

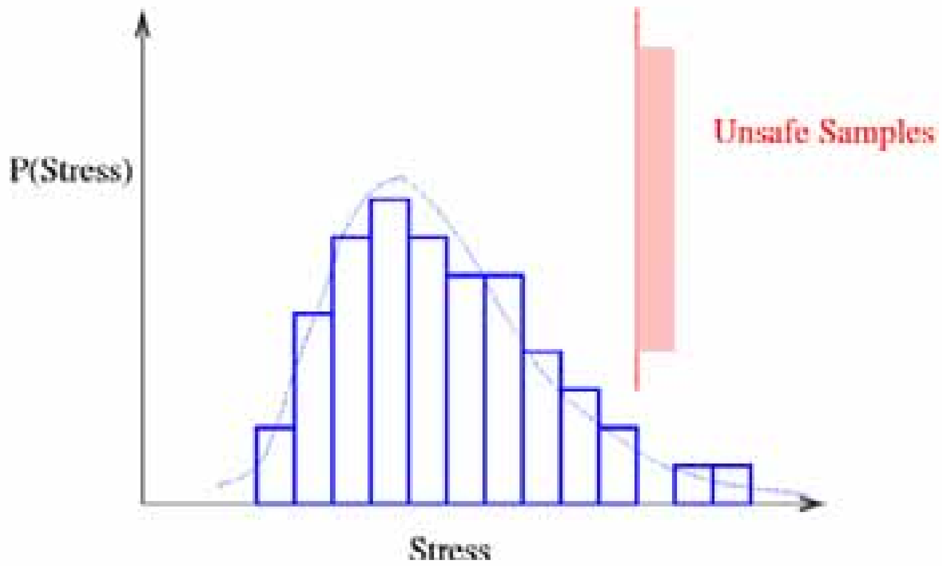
	Gradient based methods	*Random Search*	*Evolutionary Algorithms*	*RSM / SRSM*
	▪ accuracy of solution ▪ number of solver calls	▪ very robust, can not diverge ▪ easy to apply	▪ good for problems with many local minimas	▪ very effective, particularly SRSM ▪ trade-off studies on RS ▪ filter out noise, smoothing of results
	▪ can diverge ▪ can stuck in local minimas ▪ step-size dilemma for numerical gradients	▪ bad convergence, not effective ▪ Chooses best observation – may not be representative of a good (robust) design	▪ many solver calls, only suitable for fast solver runs ▪ Chooses best observation – may not be representative of a good (robust) design	▪ approximation error, verification run may be infeasible

➔ Stochastic/Probabilistic Analysis



➔ Stochastic/Probabilistic Analysis

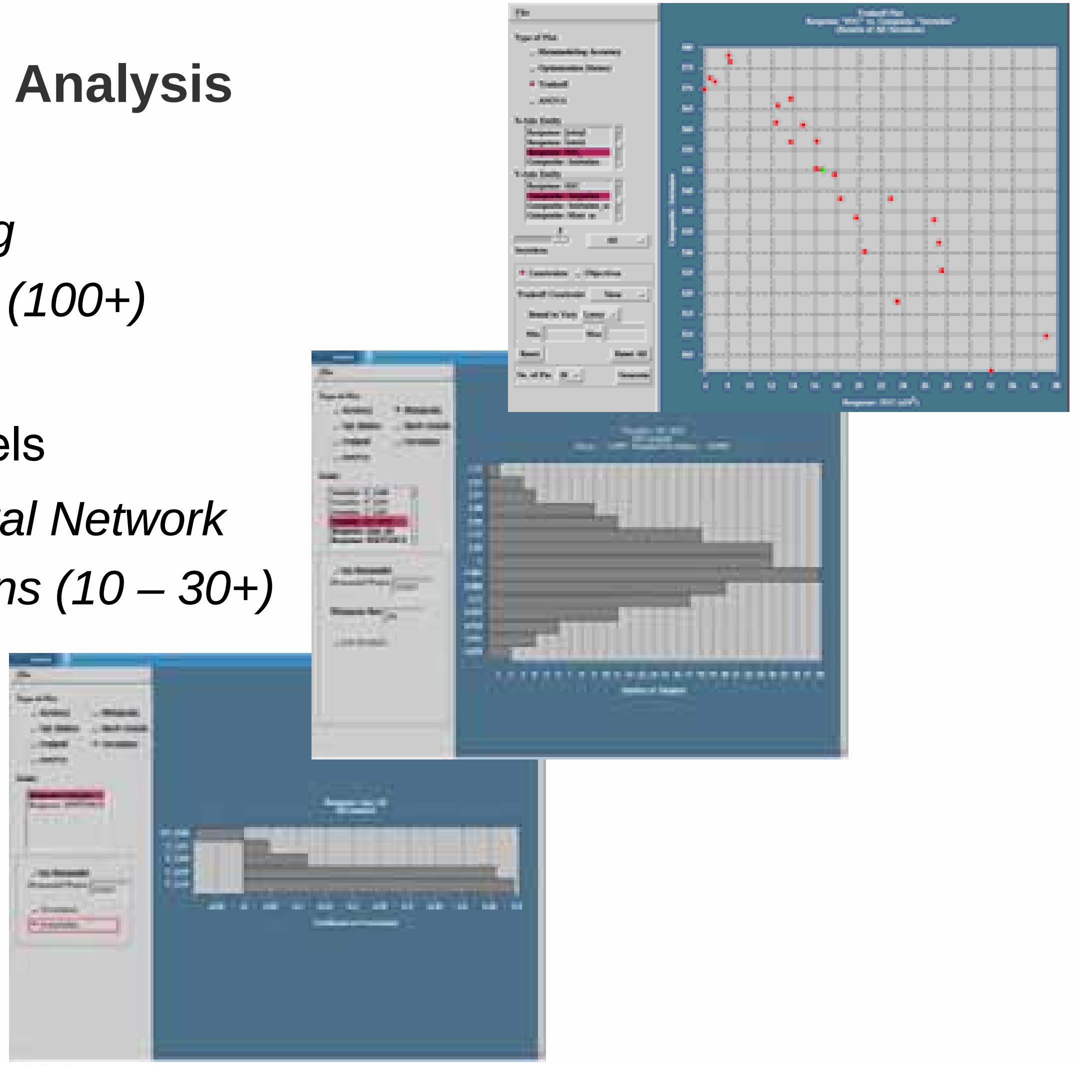
- Statistical Distributions
  - *Beta*
  - *Binomial*
  - *Lognormal*
  - *Normal*
  - *Uniform*
  - *User defined*
  - *Weibull*
- Response Variability
  - *Response distribution,*
  - *Mean, Standard deviation*
  - *Probability of Failure*



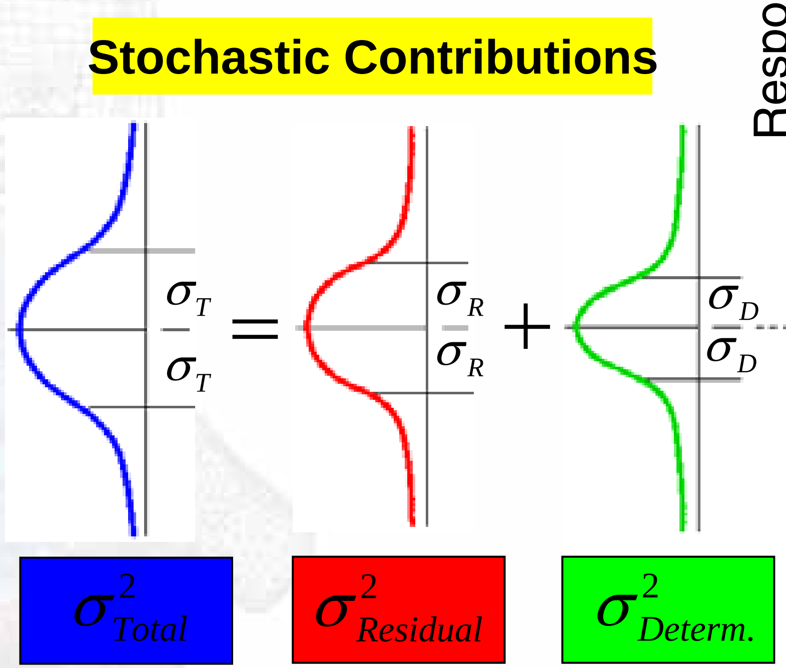
Methods – Robustness

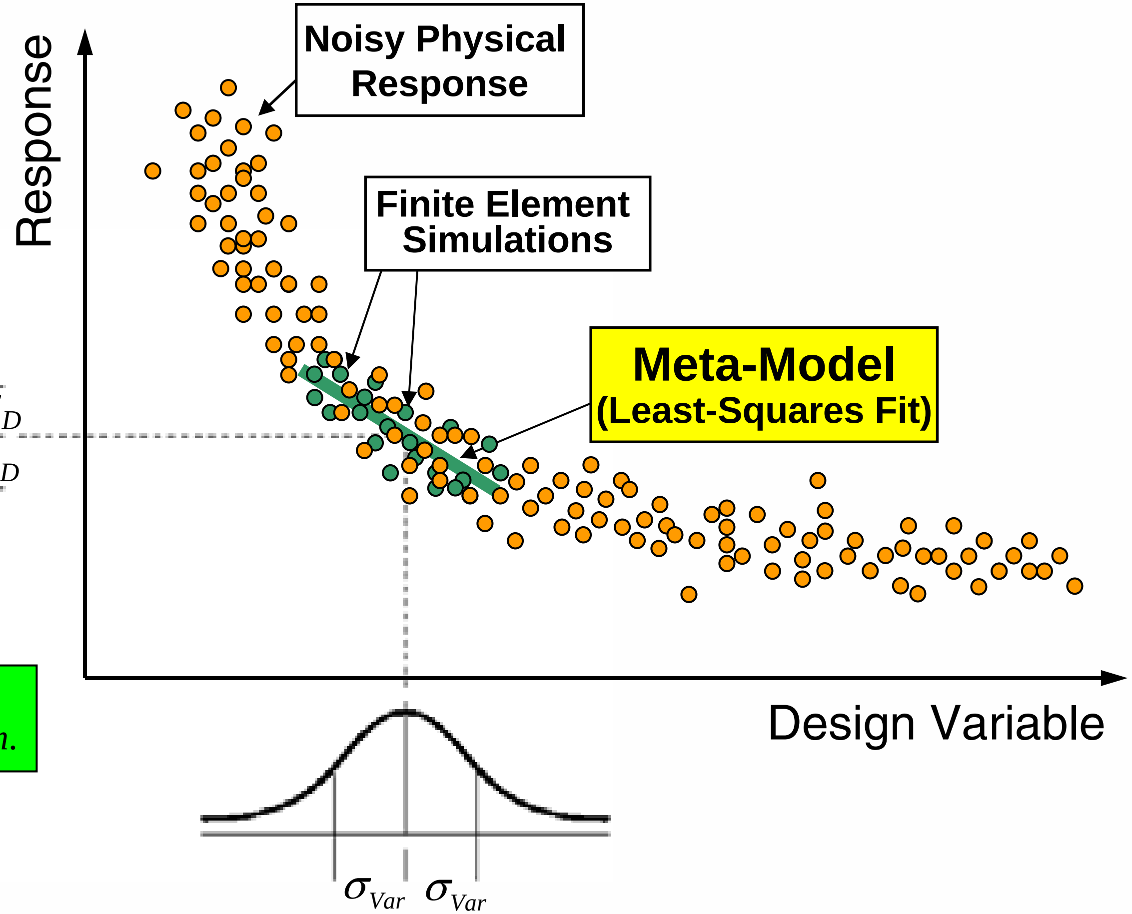
➔ Stochastic/Probabilistic Analysis

- Monte Carlo
  - *Latin Hypercube sampling*
  - *Large number of FE runs (100+)*
  - *Random process*
- Monte Carlo using Meta-Models
  - *Response Surface / Neural Network*
  - *Medium number of FE runs (10 – 30+)*
  - *Identify design variable contributions clearly*
- Outlier investigation
  - *Unexpected events*

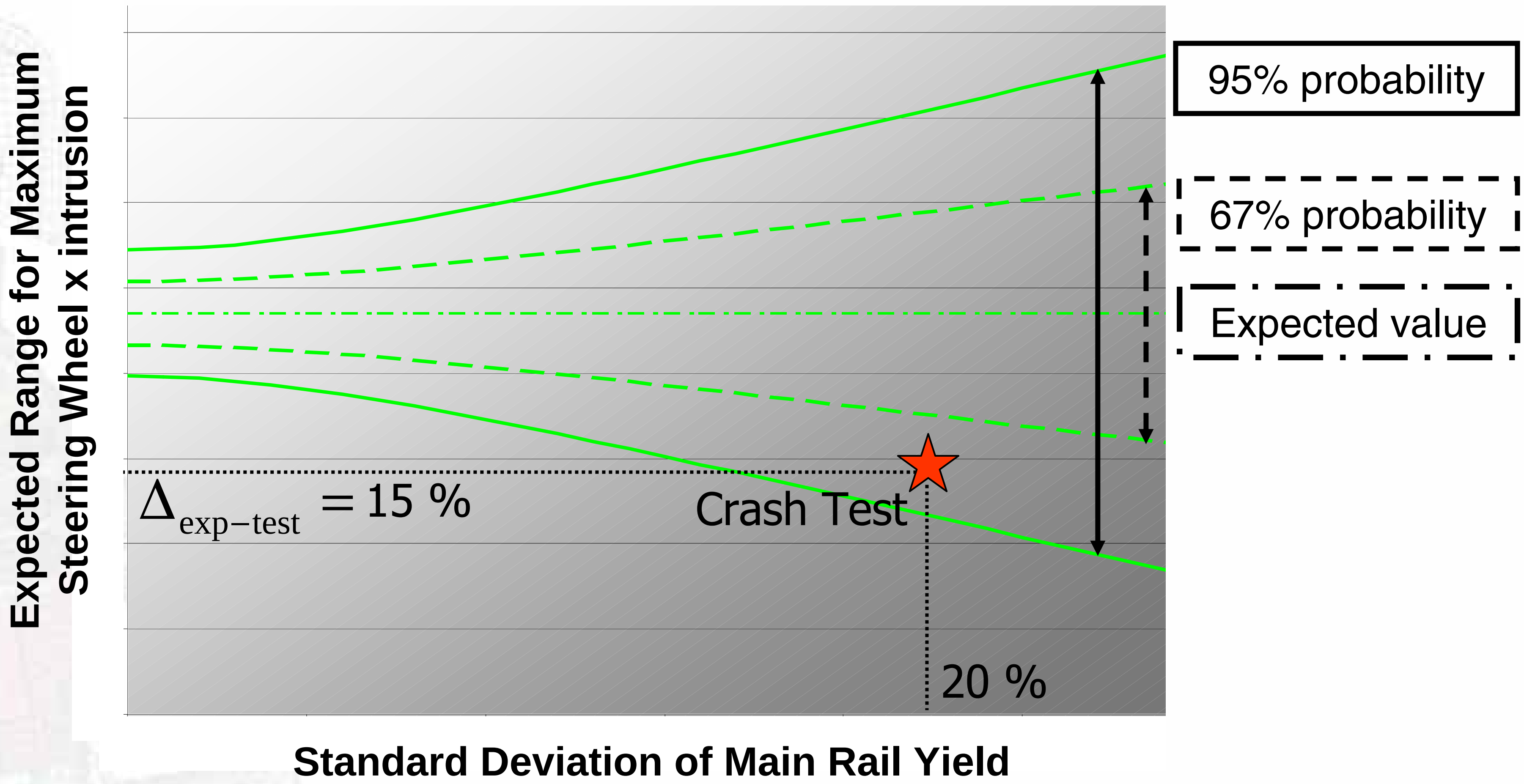


➔ Meta-Modeling and Stochastic Contributions



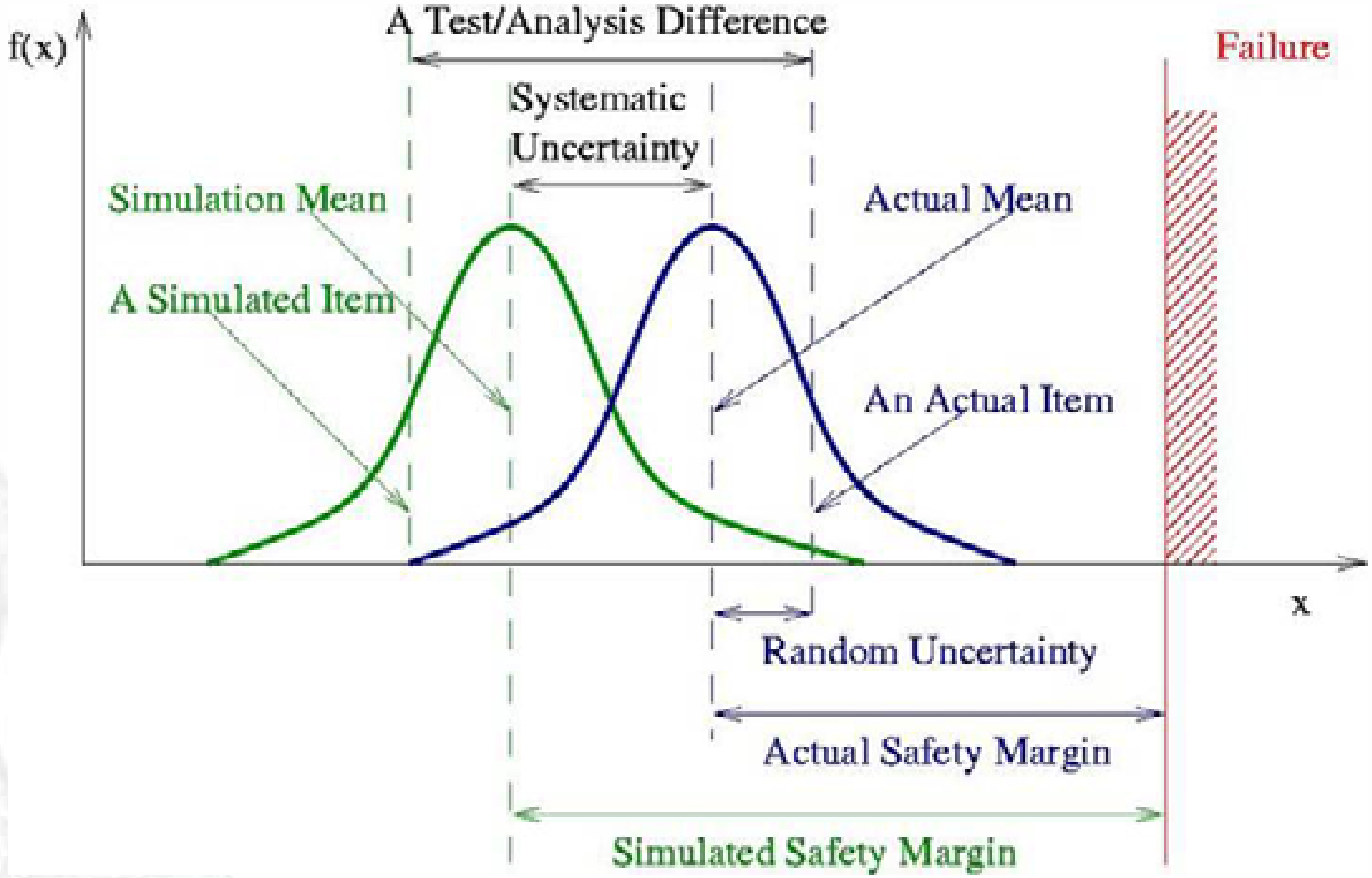


➔ Test vs. Analysis – Example Front Crash



Methods – Robustness

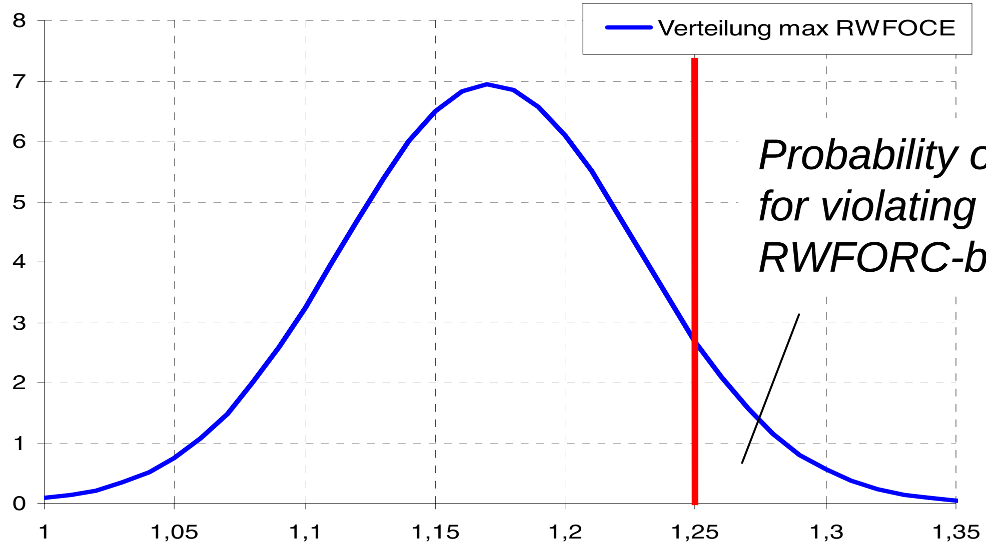
➔ Test vs. Analysis



Methods – Robustness

➔ Reliability Analysis

- Probability of failure
- Evaluation of confidence interval
- Prediction error (confidence interval) depends
  - *on the number of runs*
  - *on the probability of event*
  - ***not** on the dimension of the problem (number of design variables)*



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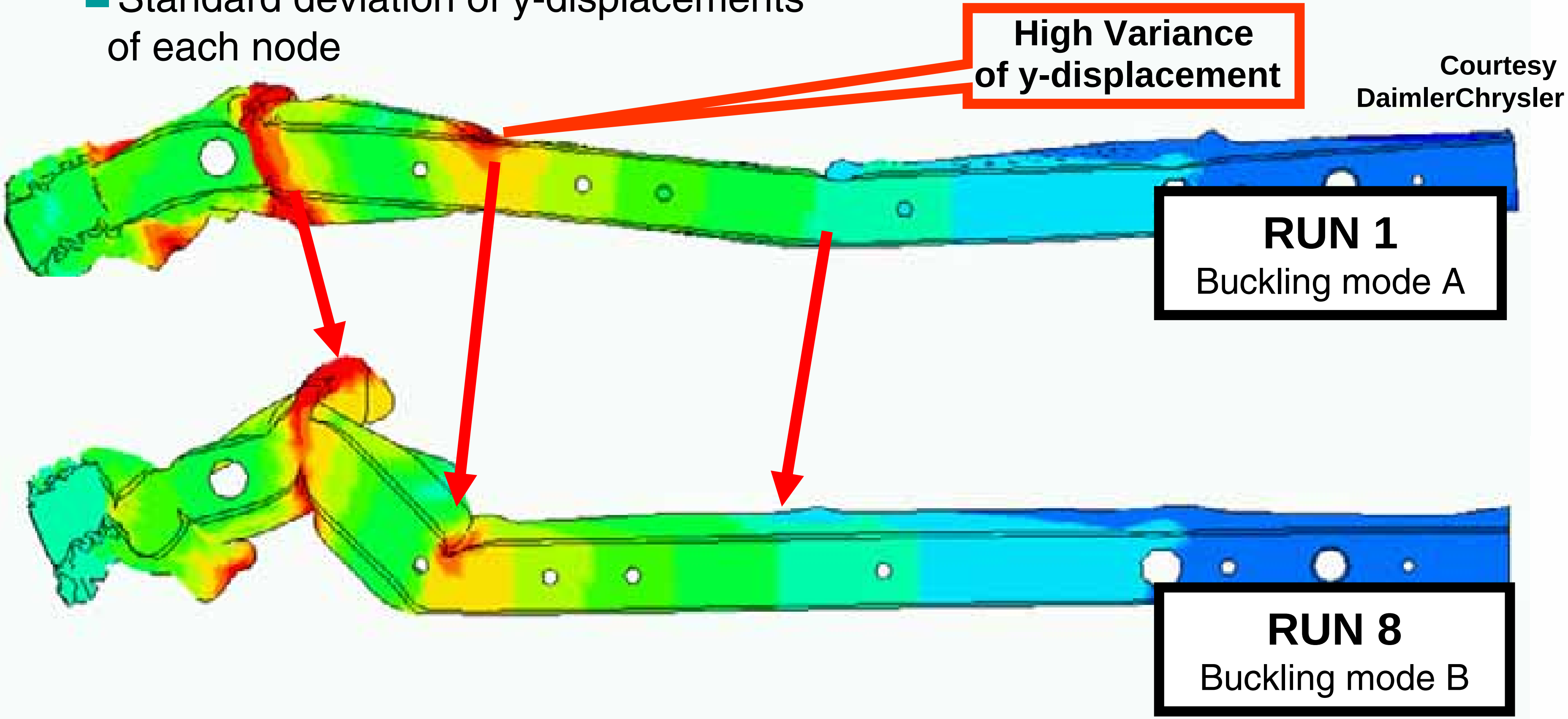
➔ Buckling Analysis - Fringe Components of Displ/Velo/Accl-Variance (40 runs)

- Standard deviation of y-displacements of each node



➔ Parameter Identification of Plastic Material

- Material properties: nonlinear visco-elastic behaviour
- LS-DYNA hyperelastic/viscoelastic formulation - *MAT_OGDEN_RUBBER (#77)
- Hyperelasticity

$$W = \sum_{i=1}^{3} \sum_{j=1}^{n} \frac{\mu_j}{\alpha_j}\left(\lambda_i^{\alpha_j} - 1\right) + \frac{1}{2} K (J-1)^2$$

- Prony series representing the viscos-elastic part (Maxwell elements):

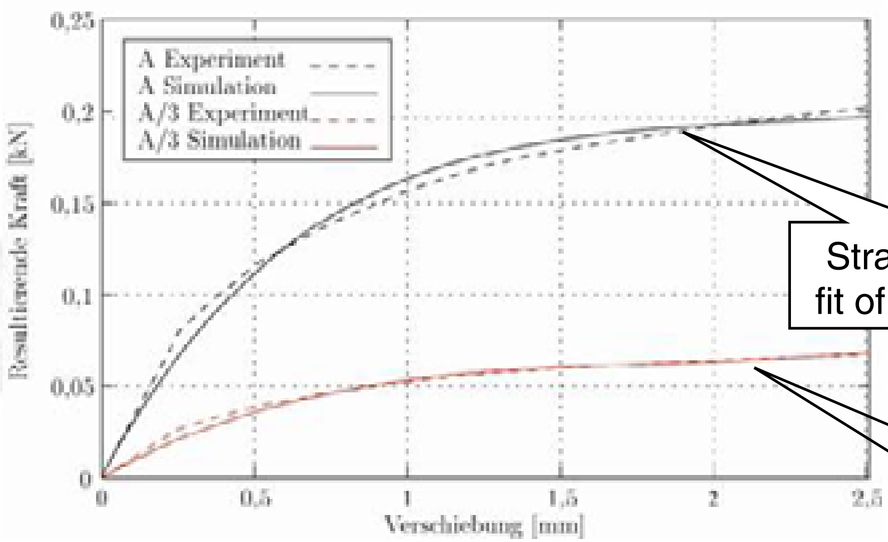
$$g(t) = \sum_{m=1}^{N} G_m e^{-\beta_m t} \quad ; \; \text{N=1, 2, 3, 4, 5, 6} \quad ; \; \sigma_{ij} = \int_0^t g_{ijkl}(t-\tau) \frac{\partial \varepsilon_{kl}}{\partial \tau} d\tau$$

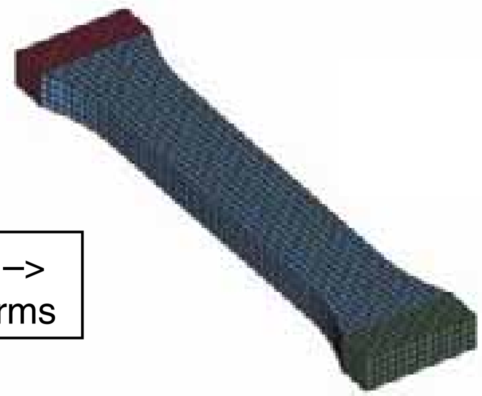
Example I - Optimization

➔ Parameter Identification of Plastic Material

- Minimize the distance between experimental curve and simulation curve
- Least-Squares Objective Function

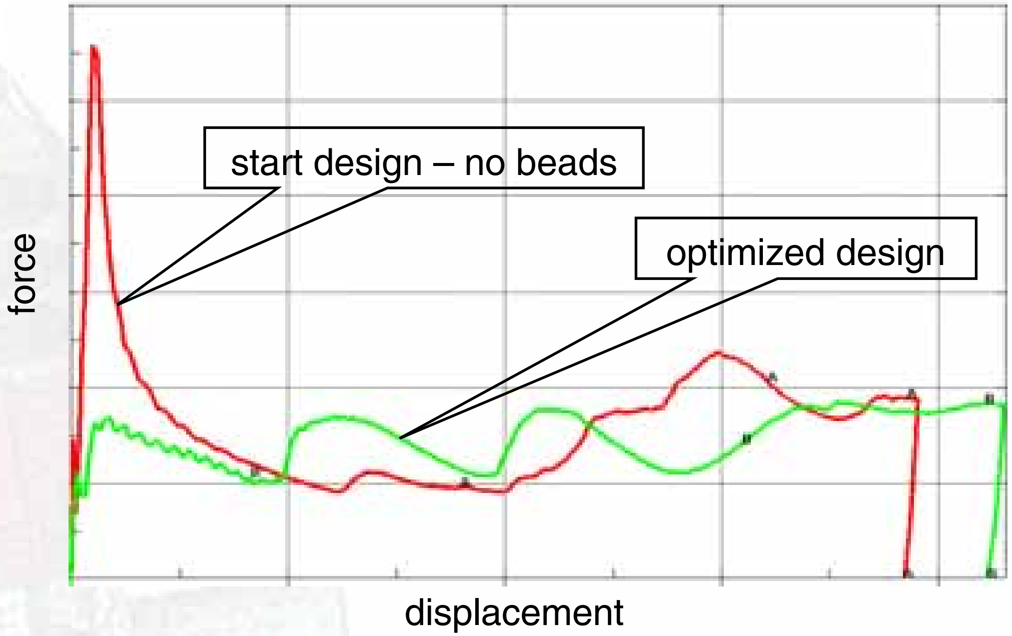
$$F(\mathbf{x}) = \sum_{p=1}^{P} \{[y(\mathbf{x}) - f(\mathbf{x})]^2\} \rightarrow \min F(\mathbf{x})$$

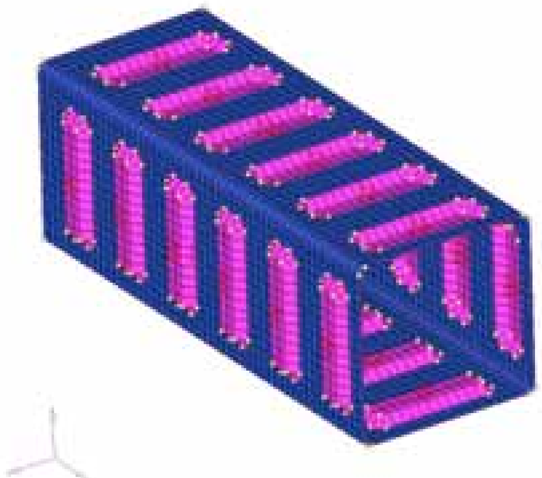




➔ Shape Optimization of a Crash Box

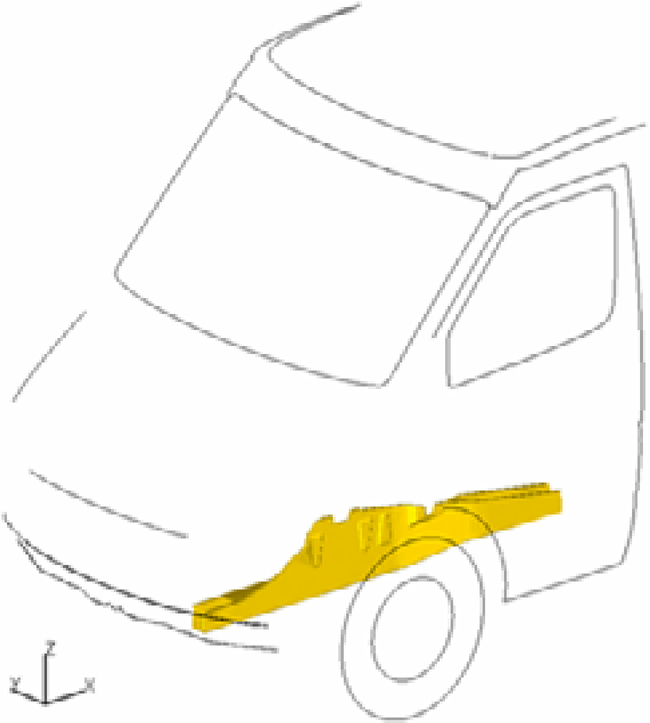
- Scope of optimization:
  - *minimize the maximum crash force*
  - *steady-going force progression*
- Shape variation by using Hypermorph and LS-OPT (20 design variables)

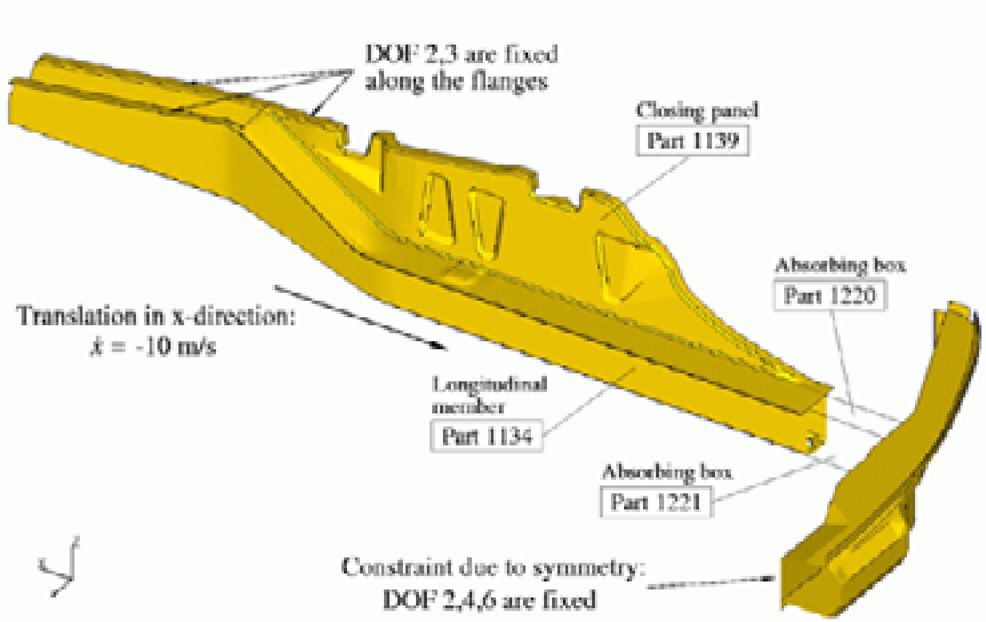




➔ Optimization of a Van Component Model

- Scope of optimization: Assembly of a vehicle body for a commercial van

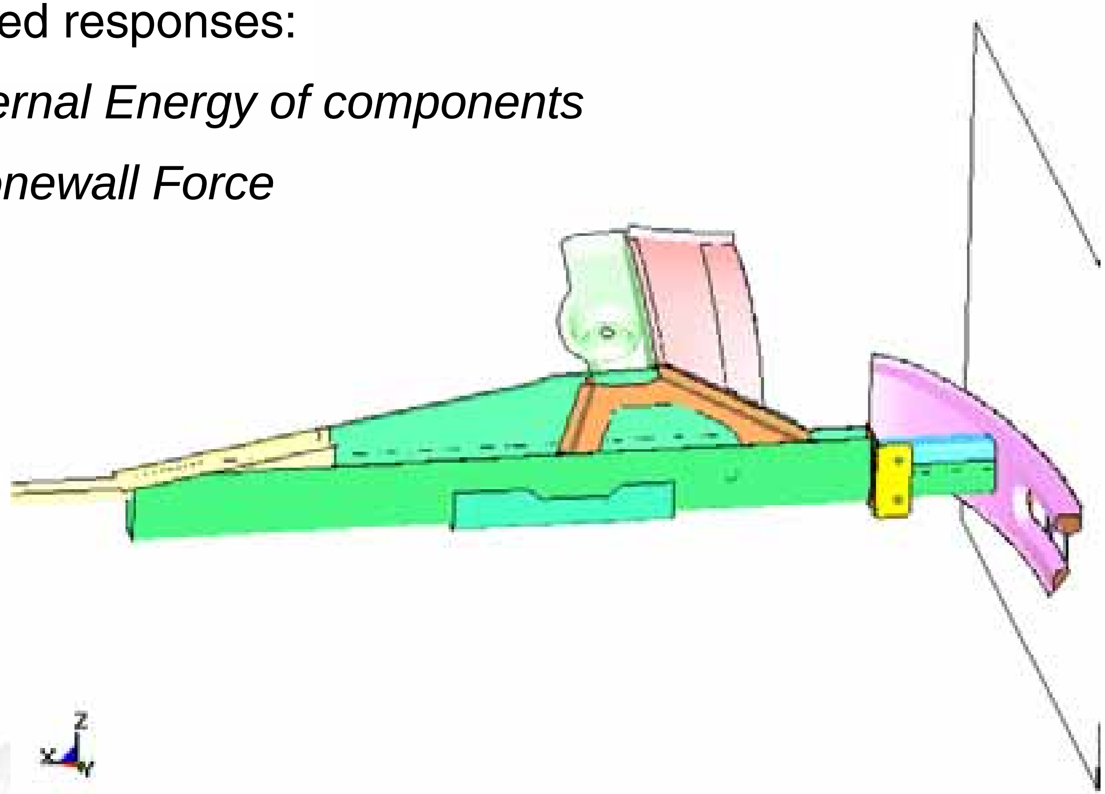




Courtesy DaimlerChrysler

➔ Optimization of a Van Component Model

- Load is applied displacement driven by a constant velocity of the stonewall in x-direction
- Monitored responses:
  - *Internal Energy of components*
  - *Stonewall Force*



Courtesy DaimlerChrysler

→ Optimization Problem

- Objective
  - *Maximize the ratio of the maximum value of the internal energy and the mass of the considered components*

→ $$E_M = \frac{E_{\max}}{M}$$

- Constraint
  - *Upper Bound for the stonewall force*

→ *maxRWFORC < 1.25*

- Design Variables
  - *Sheet thicknesses of 15 parts*
  - *Beads defined by 5 design variables*

Example III – Optimization

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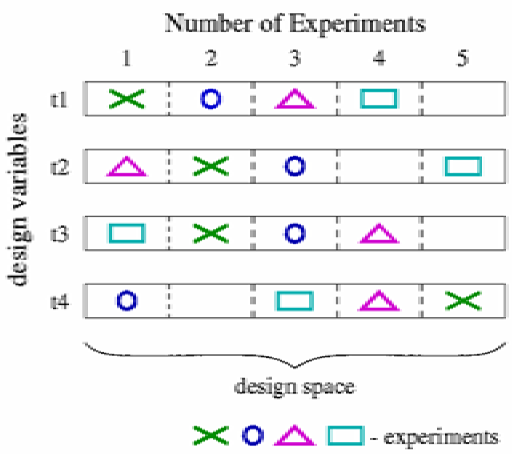
➔ First Stage

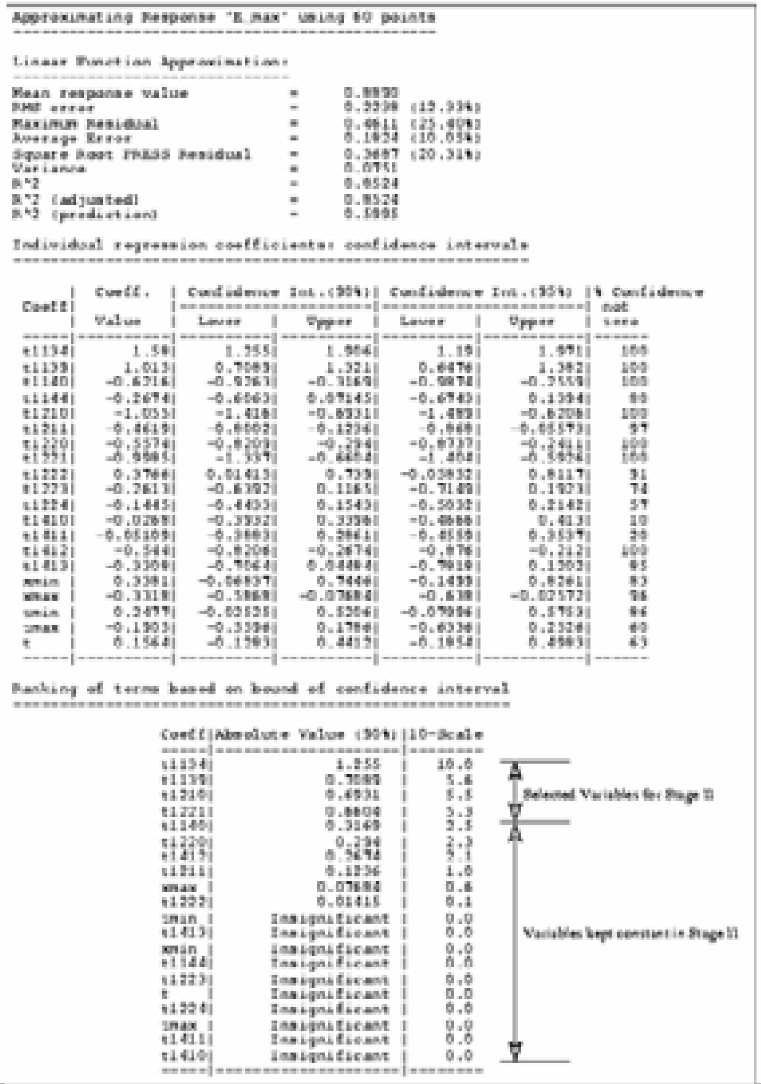
- Latin Hypercube Sampling with 20 variables



- Random search based design improvement (3 iterations) with in total 150 runs

➔ ***22 % design improvement***

- Performing ANOVA analysis in order to reduce the number of design variables



Approximating Response 'E_max' using 60 points

Linear Function Approximation:

Mean response value	=	0.8830
RMS error	=	0.3338 (15.33%)
Maximum Residual	=	0.4611 (21.40%)
Average Error	=	0.1824 (10.05%)
Square Root PRESS Residual	=	0.3687 (20.31%)
Variance	=	0.0751
R^2	=	0.8524
R^2 (adjusted)	=	0.8524
R^2 (prediction)	=	0.3888

Individual regression coefficients: confidence intervals

Coeff	Coeff. Value	Confidence Int. (90%) Lower	Confidence Int. (90%) Upper	Confidence Int. (95%) Lower	Confidence Int. (95%) Upper	% Confidence not zero
t1134	1.58	1.255	1.906	1.15	1.971	100
t1139	1.013	0.7089	1.321	0.6476	1.382	100
t1180	-0.6716	-0.9363	-0.3169	-0.9878	-0.2559	100
t1148	-0.2674	-0.6063	0.07145	-0.6745	0.1394	88
t1210	-1.033	-1.418	-0.8331	-1.489	-0.8206	100
t1211	-0.4615	-0.8002	-0.1236	-0.868	-0.05573	97
t1220	-0.2274	-0.8209	-0.294	-0.8737	-0.2411	100
t1221	-0.9065	-1.359	-0.4404	-1.404	-0.3974	100
t1222	0.3766	0.01413	0.739	-0.03832	0.8117	31
t1223	-0.2613	-0.6392	0.1165	-0.7149	0.1923	74
t1224	-0.1445	-0.4433	0.1543	-0.5032	0.2142	57
t1410	-0.0289	-0.3932	0.3356	-0.4666	0.413	10
t1411	-0.05109	-0.3883	0.2861	-0.4558	0.3537	28
t1412	-0.544	-0.8208	-0.2874	-0.876	-0.212	100
t1413	-0.3308	-0.7064	0.04484	-0.7818	0.1203	85
wmin	0.3381	-0.06837	0.7446	-0.1499	0.8261	93
wmax	-0.3318	-0.5868	-0.07684	-0.638	-0.02572	96
umin	0.2477	-0.03535	0.5306	-0.07986	0.5753	86
umax	-0.1303	-0.3386	0.1786	-0.6336	0.2326	60
t	0.1544	-0.1783	0.4417	-0.1854	0.4983	63

Ranking of terms based on bound of confidence interval

Coeff	Absolute Value (90%)	10-Scale
t1134	1.255	10.0
t1139	0.7089	5.6
t1210	0.4931	5.5
t1221	0.4404	3.3
t1180	0.3169	3.3
t1220	0.294	2.3
t1412	0.2874	2.1
t1211	0.1236	1.0
wmax	0.07684	0.6
t1222	0.01413	0.1
umin	Insignificant	0.0
t1413	Insignificant	0.0
wmin	Insignificant	0.0
t1148	Insignificant	0.0
t1223	Insignificant	0.0
t	Insignificant	0.0
t1224	Insignificant	0.0
umax	Insignificant	0.0
t1411	Insignificant	0.0
t1410	Insignificant	0.0

Selected Variables for Stage II

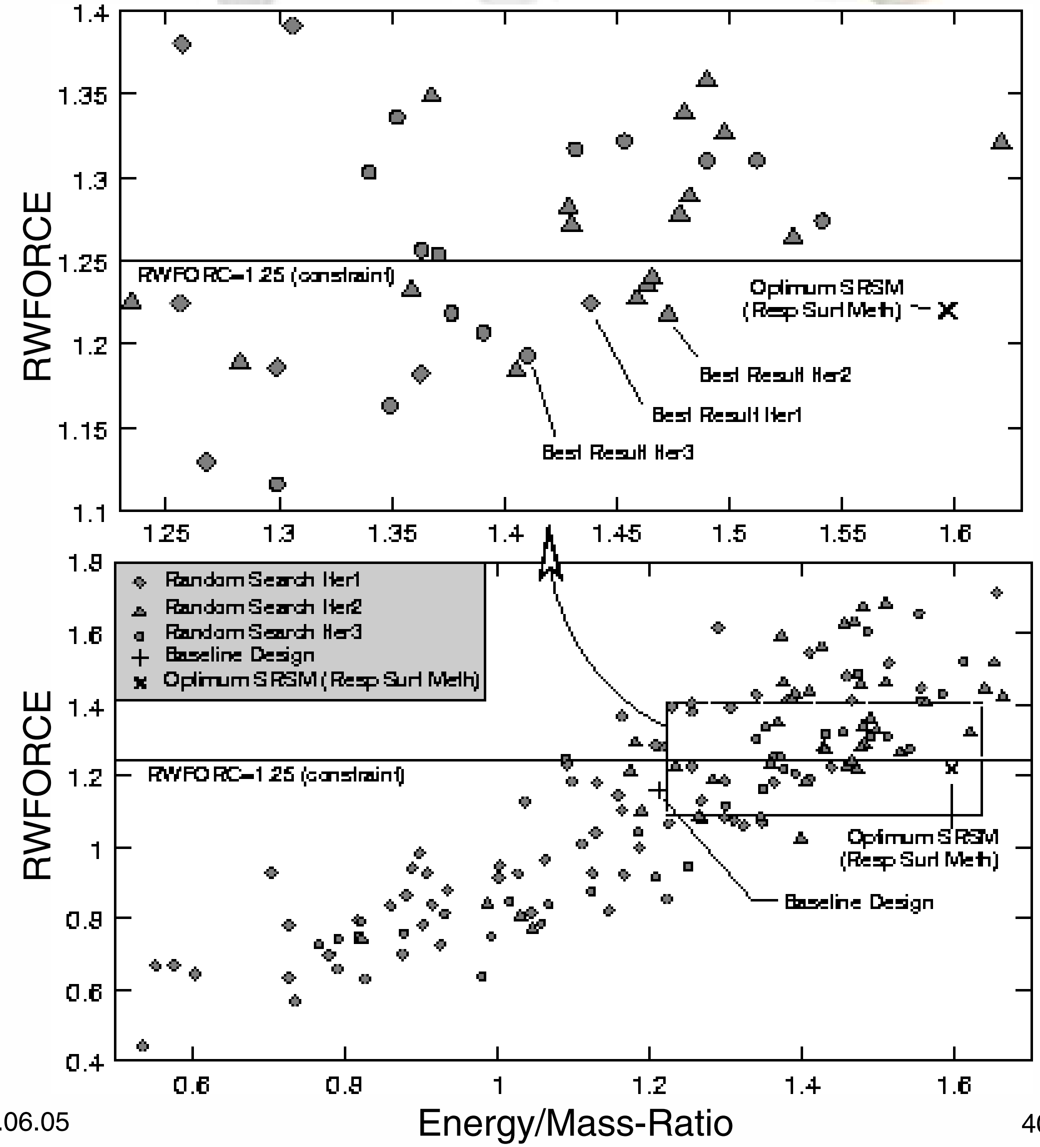
Variables kept constant in Stage II

Example III – Optimization

➔ Second Stage

- Deterministic Optimization using the Successive Response Surface Method (SRSM) with the 4 most significant variables
- Starting values are taken out of the best run of the 150 random simulations (*First Stage*)

➔ ***Additional 10% design improvement***



- Introduction/Features
- Methods – Optimization
- Methods - Robustness
- Example I - Optimization
- Example II - Optimization
- Example III - Optimization
- Example I - Robustness
- Example II - Robustness
- Outlook Version 3.0/3.1

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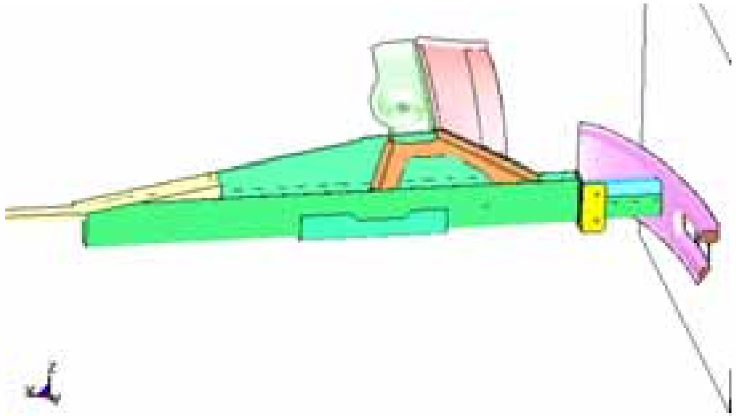
➔ Robustness Investigations – Monte Carlo analysis

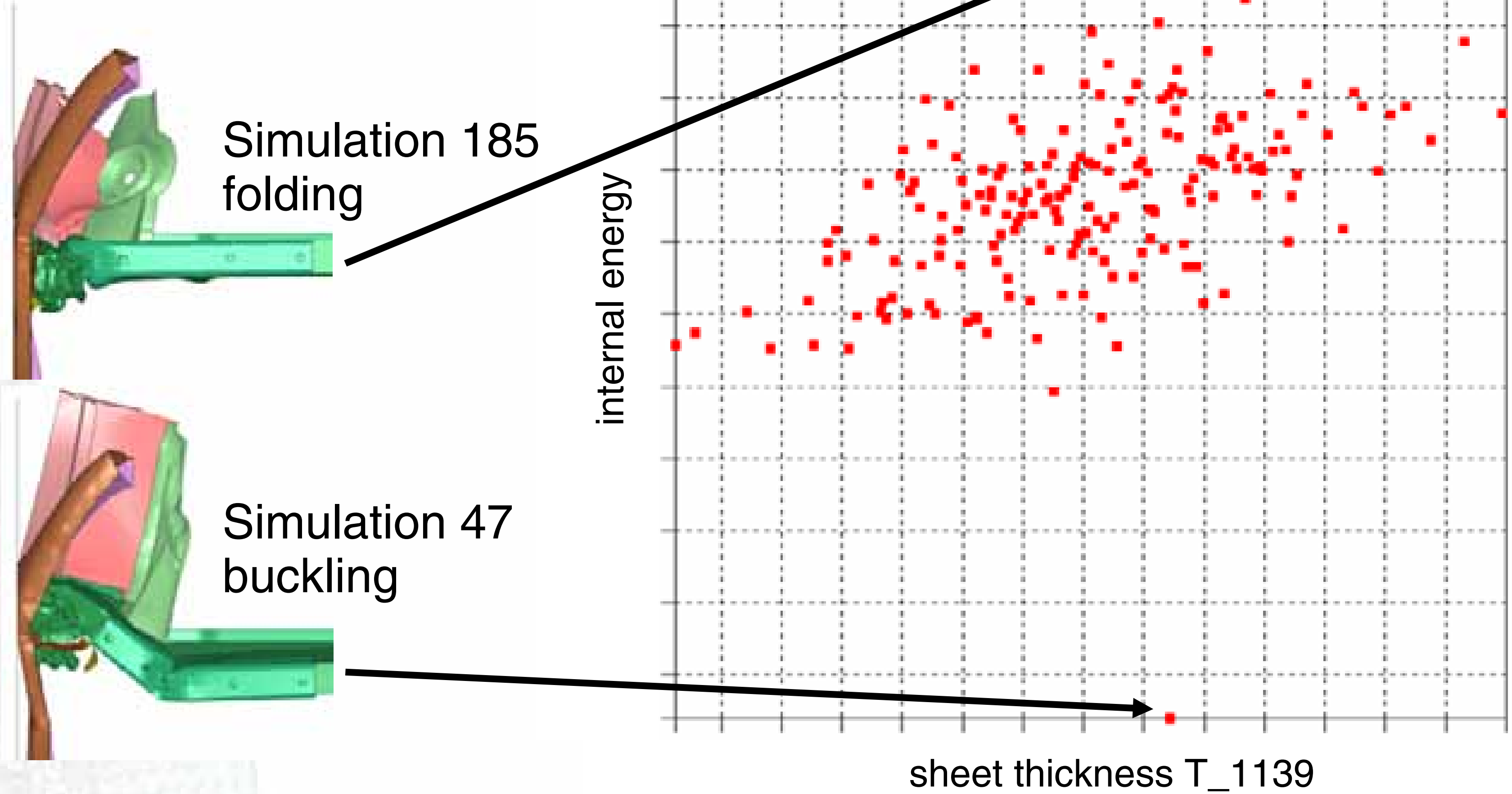
- Variation of sheet thicknesses and yield stress of significant parts in order to consider uncertainties
- Normal distribution is assumed
  - *T_1134 (Longitudinal Member)* *mean = 2.5mm; σ = 0.05mm*
  - *T_1139 (Closing Panel)* *mean = 2.4mm; σ = 0.05mm*
  - *T_1210 (Absorbing Box)* *mean = 0.8mm; σ = 0.05mm*
  - *T_1221 (Absorbing Box)* *mean = 1.0mm; σ = 0.05mm*
  - *SF_1134 (Longitudinal Member)* *mean = 1.0 ; σ = 0.05*
- Monte Carlo analysis using 182 points (Latin Hypercube)



Example I – Robustness

➔ Tradeoff Plot

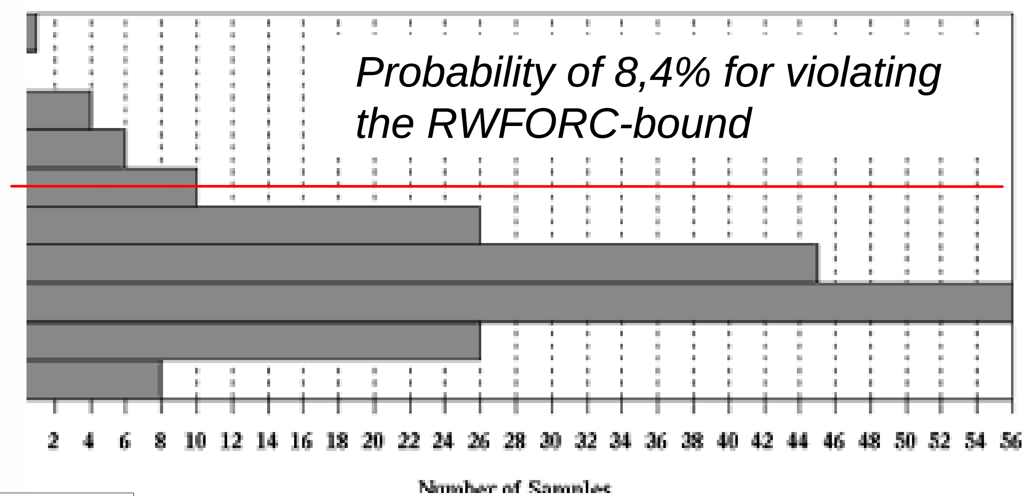
- Monte Carlo Simulation
- Identification of Clustering



Example I – Robustness

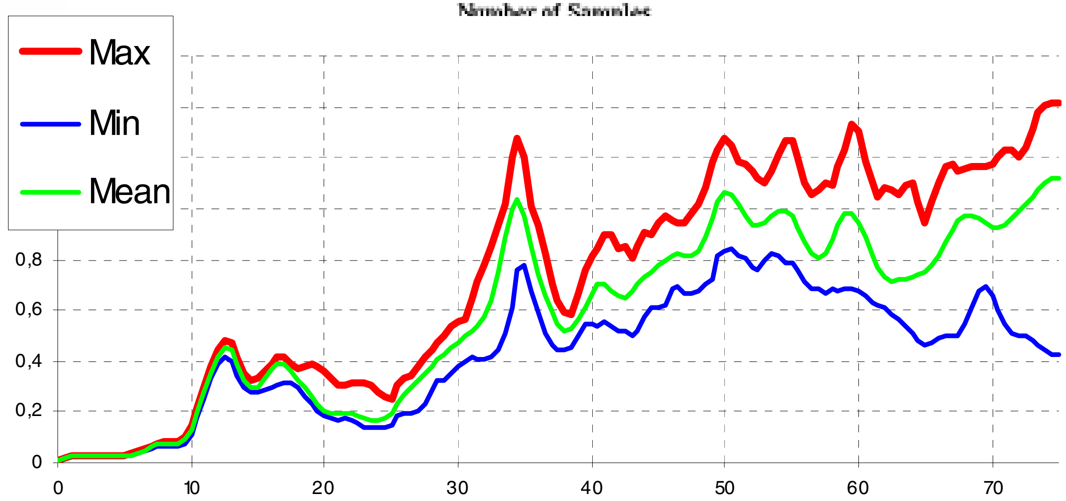
➔ Reliability Analysis

- Histogram of distribution
- Probability of exceeding a constraint-bound

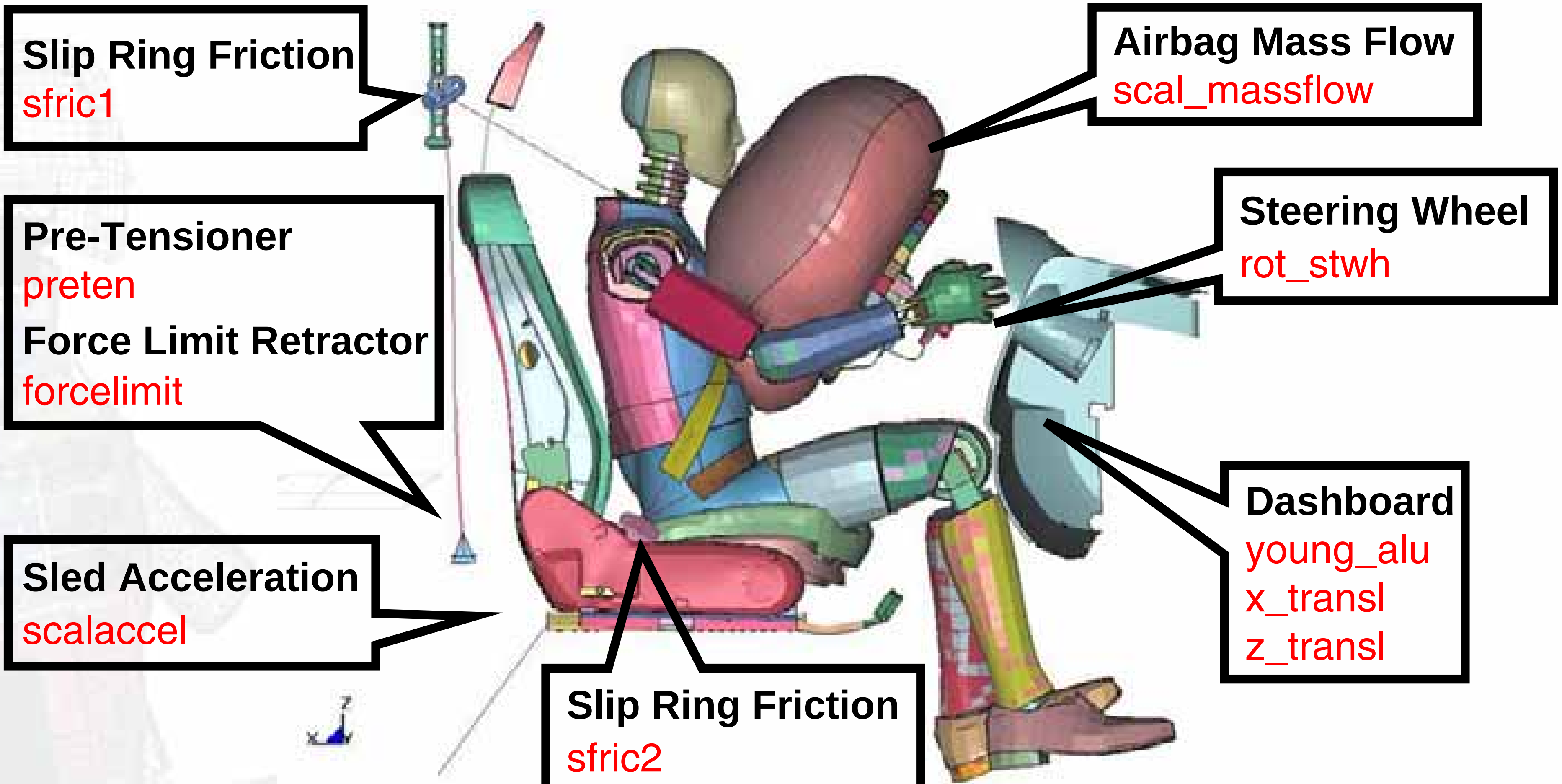


➔ Min-Max Curves

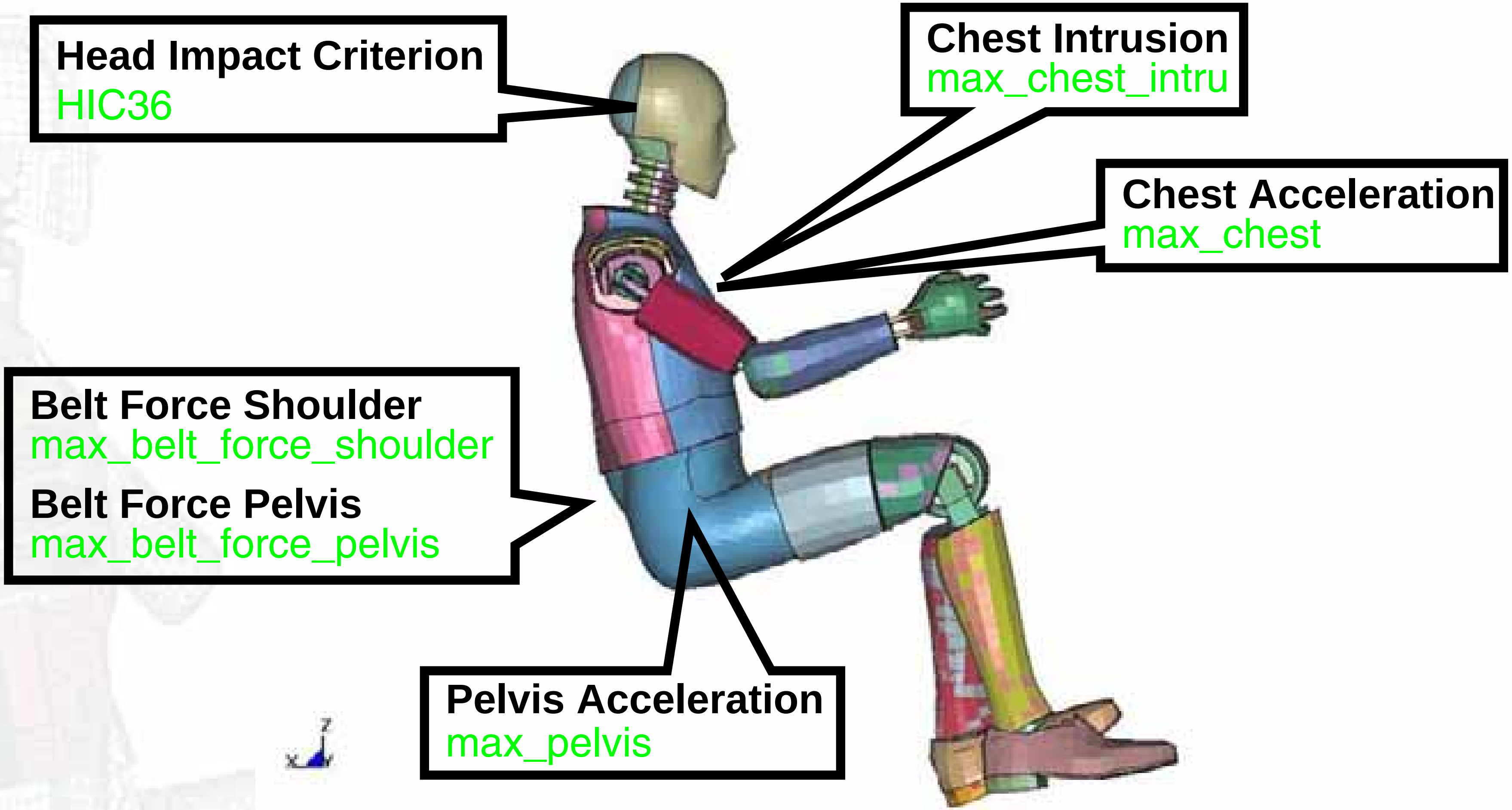
- Plot of minimum, maximum and mean history values
- Gives a confidence interval of history values



➔ Design Variables - Uncertainties in Test Set-Up

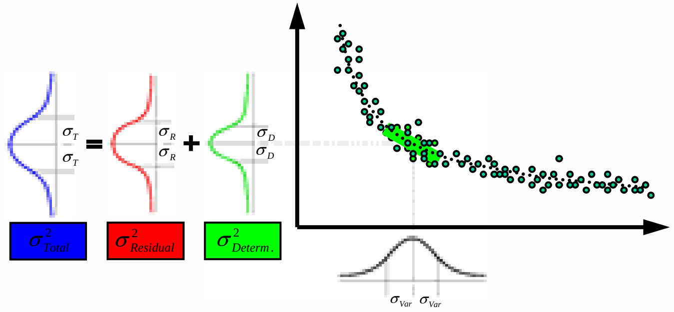


➔ Responses: Standard Dummy Evaluations



➔ Stochastic Contribution - Results of 30 Experiments

Design Variable	Standard Deviation of Design Variable	Standard Deviation Contribution					
		HIC36	max_chest_intru	max_b_f_shoulder	max_bf_pelvis	max_chest	max_pelvis
scalaccel	2,5%	3,1%	1,5%	0,1%	2,3%	1,9%	2,9%
sfric1	25,0%	1,3%	0,6%	4,1%	1,8%	0,7%	0,7%
sfric2	25,0%	0,5%	0,6%	0,1%	3,7%	0,1%	0,1%
preten	4,4%	0,0%	0,5%	0,0%	1,1%	0,3%	0,2%
forcelimit	5,6%	1,3%	0,4%	4,4%	0,6%	1,4%	0,2%
rot_stwh	4,8%	0,5%	0,1%	0,1%	0,0%	0,1%	0,1%
transl_x	50,0%	0,1%	0,1%	0,7%	4,5%	0,5%	0,8%
transl_z	50,0%	1,2%	1,0%	0,3%	1,6%	0,2%	0,9%
scalmassflow	5,0%	1,8%	1,8%	0,6%	2,2%	0,6%	0,9%
young_alu	5,0%	0,3%	0,3%	0,0%	0,5%	0,1%	0,1%
all variables		4,3%	2,8%	6,1%	7,2%	2,6%	3,4%
residuals		4,7%	1,9%	1,8%	6,0%	3,5%	2,3%
Total		**6,4%**	**3,4%**	**6,3%**	**9,4%**	**4,3%**	**4,1%**



Contribution of
variation of design variables to variation of results

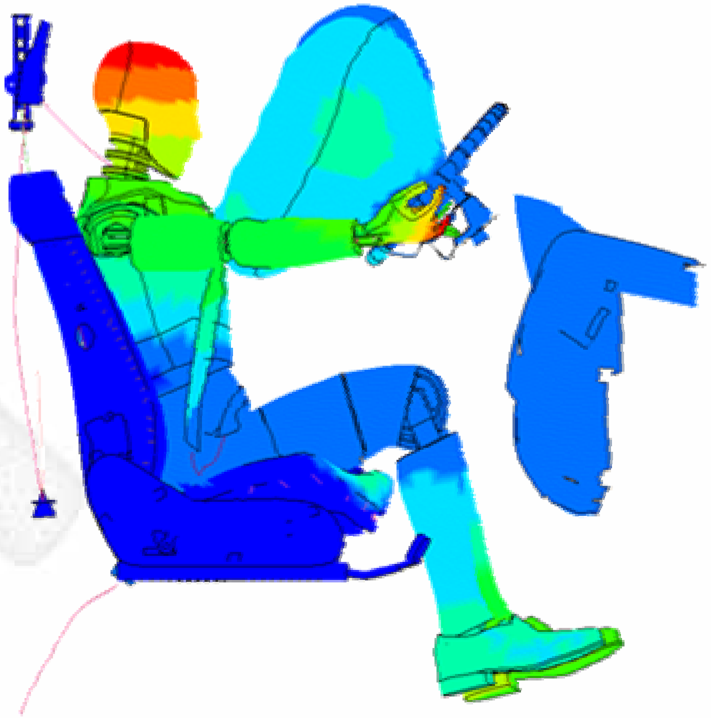
Meta-model space

Residual space

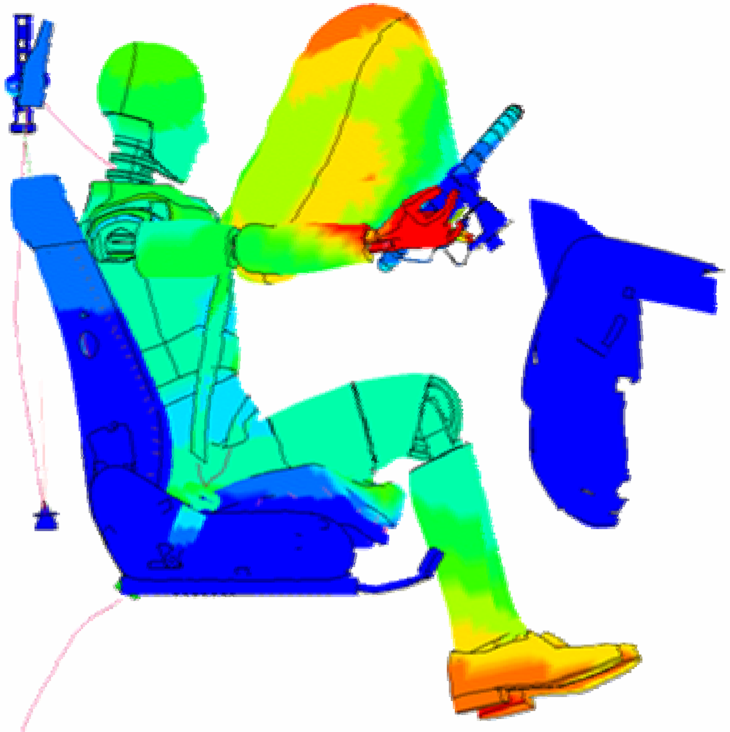
Total Variation

➔ Standard deviation of x-displacements of each node (120 runs)

(a) Deterministic (Meta-Model)



(b) Residual (Outliers)



➔ Version 3.0 - Announced 4th Quarter 2005

- LS-OPT for Windows
  - *Incorporates new Application Program Interface to speed up development/facilitate porting*
- Parameter Identification Module (beta available)
  - *Automated use of test results to calibrate materials/systems*
  - *Simplify input for system identification applications*
  - *Handles "continuous" test curves*
- Improved visualization of stochastic results
  - *Extended LS-PREPOST visualization of design sensitivities and importance of design variables*
- Reliability-based design optimization (RBDO)
  - *Specify probability of failure as design constraints*

→ Version 3.1 - 2006

- Discrete Optimization
  - *Define fixed sets for variables*
  - *Discrete materials (combinatorial problem)*
- 3-D visualization of response surfaces
  - *OpenGL interface*
- GUI features for expressions and special composite functions, e.g. parameter identification, integration, …
- ….

Thanks for your attention!