dynardo

dynamic software & engineering

Founded: 2001 (Will, Bucher, CADFEM International)

More than 40 employees, offices at Weimar and Vienna

Leading technology companies Daimler, Bosch, Eon, Nokia, Siemens, BMW, are supported by us

Software Development

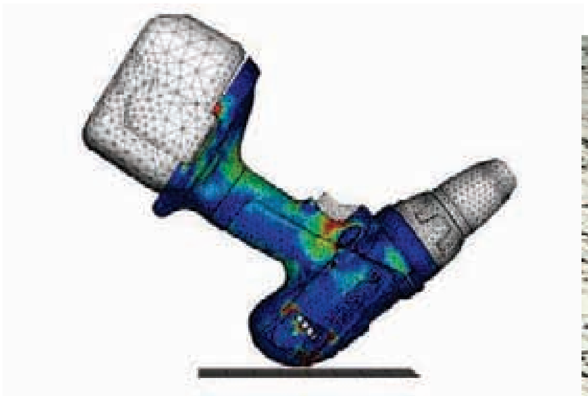
Dynardo is your engineering specialist for CAE-based sensitivity analysis, optimization, robustness evaluation and robust design optimization.

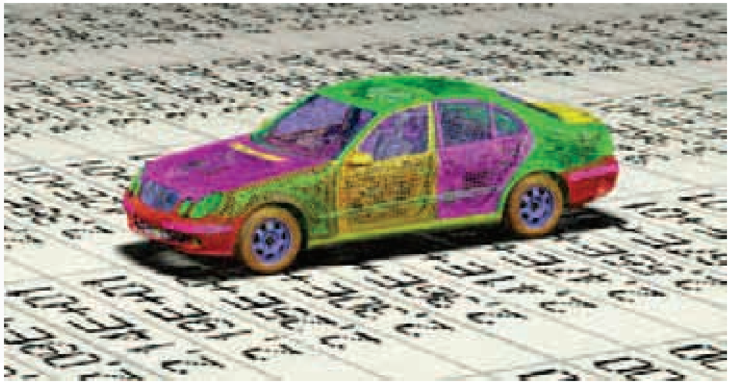
CAE-Consulting

Our expertise:

- Mechanical engineering
- Civil engineering & Geomechanics
- Automotive industry
- Consumer goods industry
- Power generation

Premium Consultancy and Software Company for CAE-based Robustness Evaluation, Reliability Analysis and Robust Design Optimization using Stochastic Analysis





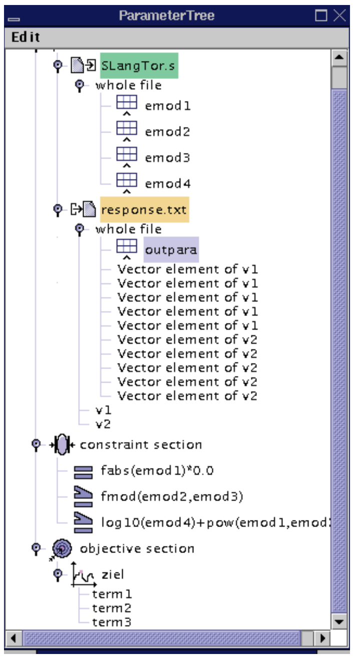
Dynardo is the consulting company which successfully introduced stochastic analysis into complex CAE-based virtual product development processes.
Recently, it is applied in the power generation industry, automotive industry and high-level consumer goods industry

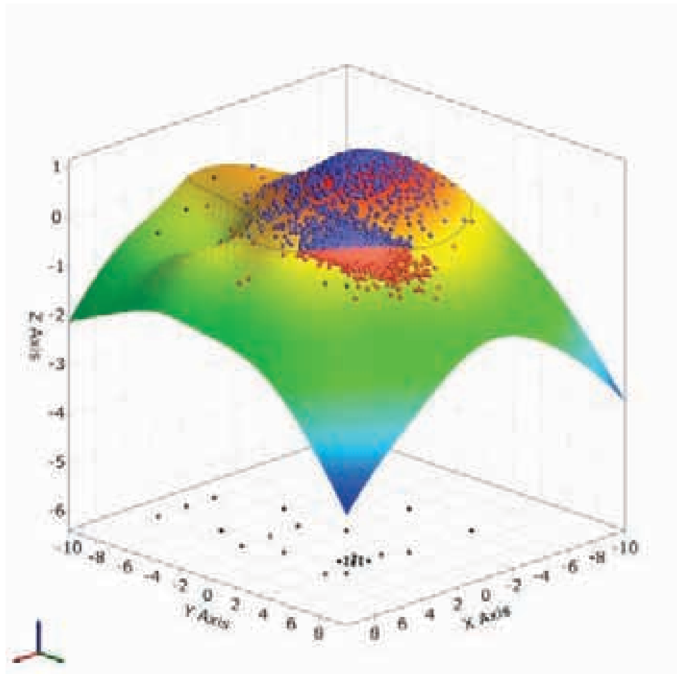
Introduction of optiSLang

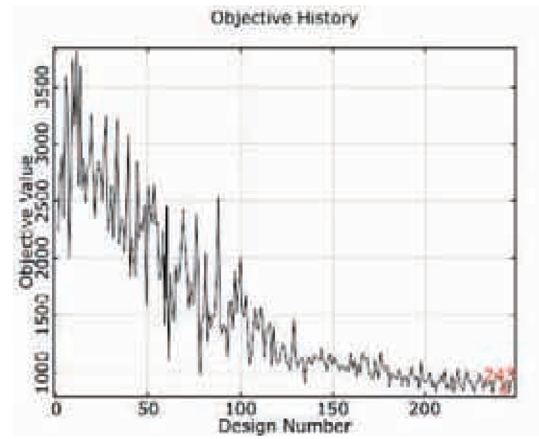
Challenges in Virtual Prototyping

- Virtual prototyping is necessary for cost efficiency
- Test cycles are reduced and placed late in the product development
- CAE-based optimization and CAE-based robustness evaluation becomes more and more important in virtual prototyping
  - Optimization is introduced into virtual prototyping
  - Robustness evaluation is the key methodology for safe, reliable and robust products
  - The combination of optimizations and robustness evaluation will lead to robust design optimization strategies

optiSLang is an algorithmic toolbox for sensitivity analysis, optimization, robustness evaluation, reliability analysis and robust design optimization.







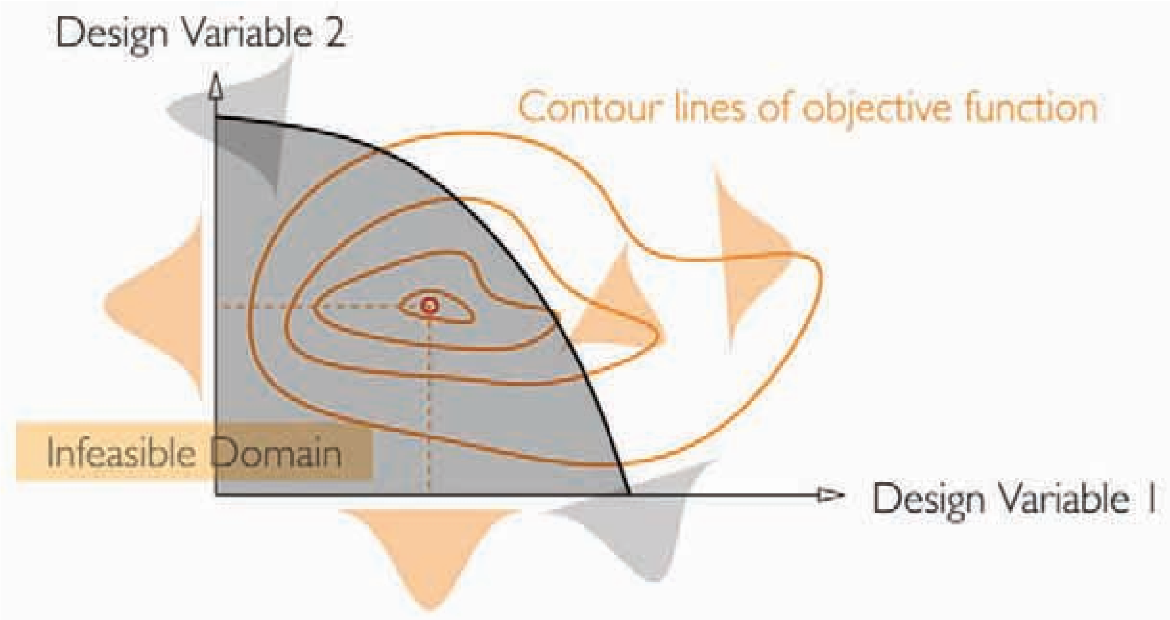
optiSLang is the commercial tool that has completed the necessary functionality of stochastic analysis to run real world industrial applications in CAE-based robust design optimizations.

optiSLang development priority: safe of use and ease of use!

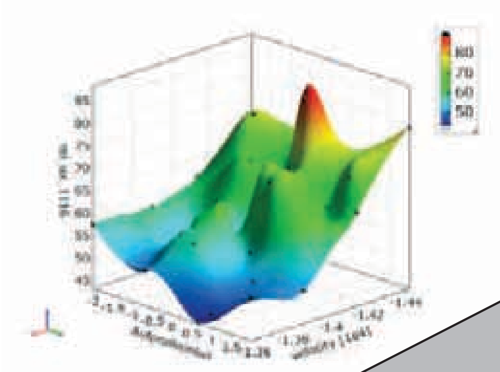
Robust Design

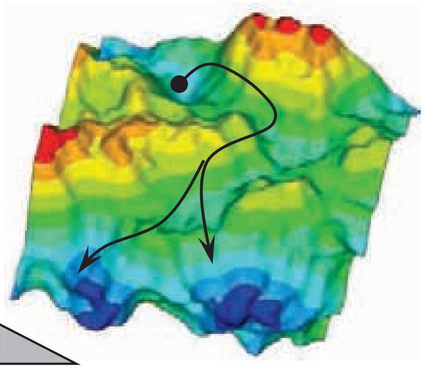
Robust Design Optimization (RDO) optimize the design performance with consideration of scatter of design (optimization) variables as well as other tolerances or uncertainties.

As a consequence of uncertainties the location of the optima as well as the contour lines of constraints scatters.



To proof Robust Designs safety distances are quantified with variance or probability measurements using stochastic analysis.





Robust Design Optimization

Robust Design

Variance based Robustness Evaluation

Probability based Robustness Evaluation, (Reliability analysis)

Optimization

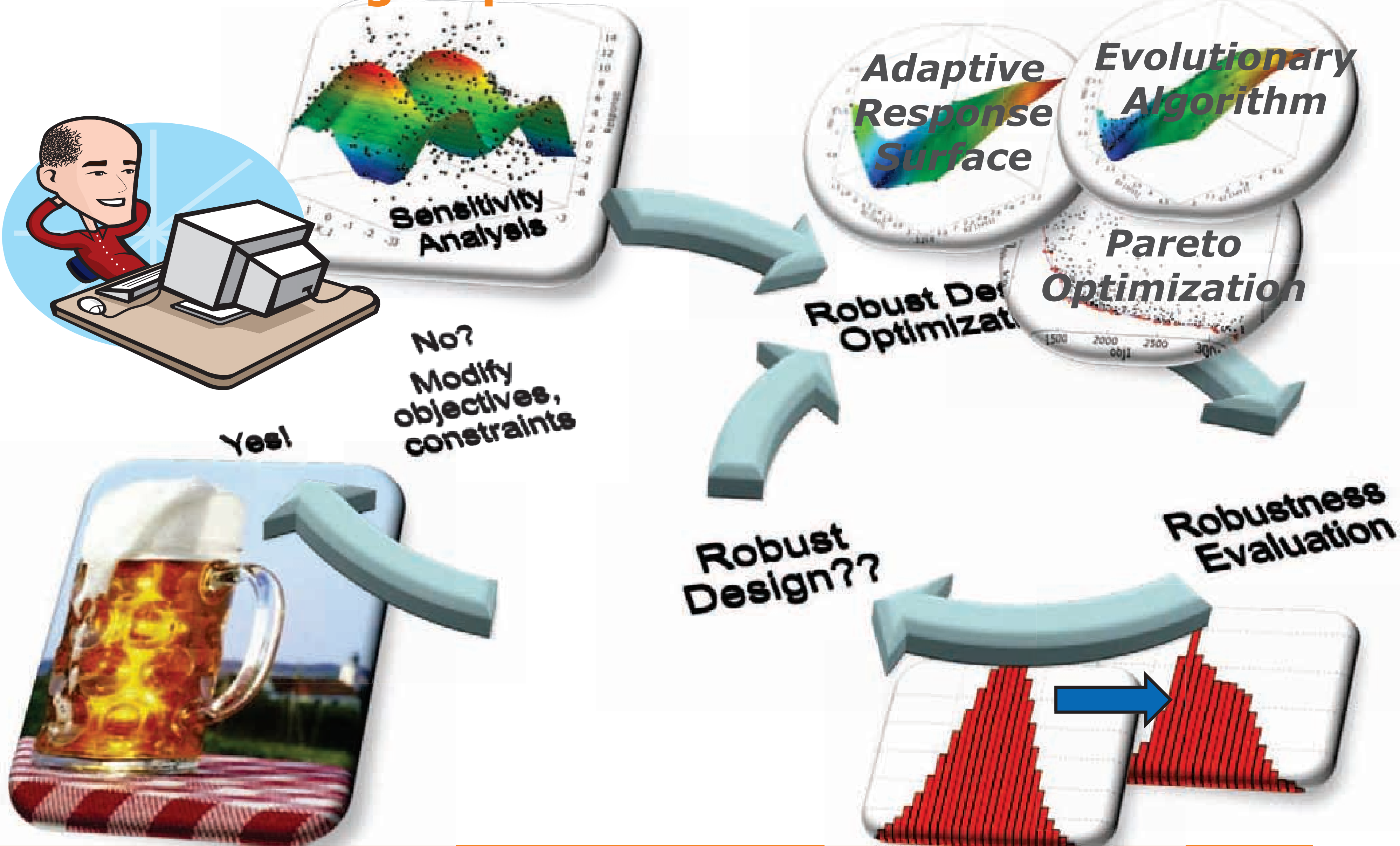
Sensitivity Study

Single & Multi objective (Pareto) optimization

CAE Process (FEM, CFD, MBD, Excel, Matlab, etc.)

Robust Design Optimization Methodology

Robust Design Optimization



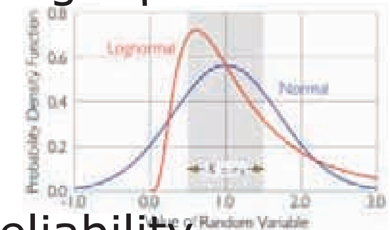
Challenges of RDO in Virtual Prototyping

- With improvements in parametric modeling, CAE (software) and CPU (hardware) there seems to be no problem to establish RDO (DfSS) product development strategies by using stochastic analysis
- There are many research paper or marketing talks about RDO/DfSS.
- But why industrial papers about successful applications are so rare?

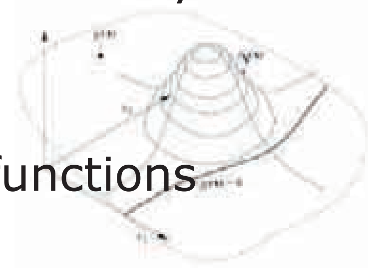
Where is the problem with RDO?

Successful RDO needs a balance between:

- **Reliable definition of uncertainties**
  - ⇒ many scattering variables (in the beginning) of an RDO task
  - ⇒ best translation of input scatter to suitable parametric including distribution functions and correlations between scattering inputs
- **Reliable stochastic analysis methodology**



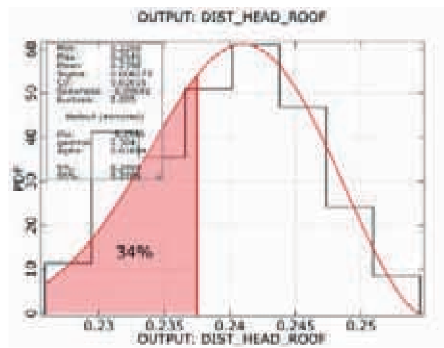
  - ⇒ efficient and reliable methodology to sort out important/unimportant variables
  - ⇒ because all RDO algorithms will estimate robustness/reliability measurements with <u>minimized</u> number of solver runs the proof of the reliability of the final RDO design is absolutely mandatory!
- **Reliable Post Processing**

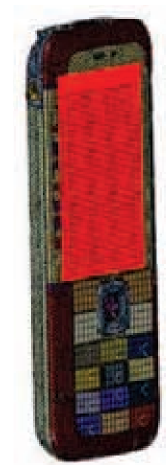


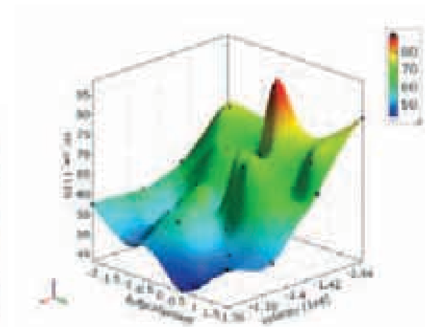
  - ⇒ Filter of insignificant/unreliable results
  - ⇒ Reliable estimation of variation using fit of distribution functions
- **User Friendliness**
  - ⇒ establish automatic flows of best practice which minimize the user input „ease of use" and maximize the „safe of use"
  - ⇒ **Finally non experts of stochastic analysis need be able to perform RDO**

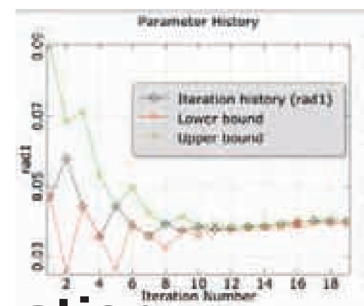
Robust Design Optimization - RDO

Robust Design Optimization combines optimization and Robustness Evaluation. From our experience it is often necessary to investigate both domains separately to be able to formulate a RDO problem. optiSLang offers you either iterative or automatic RDO flows.

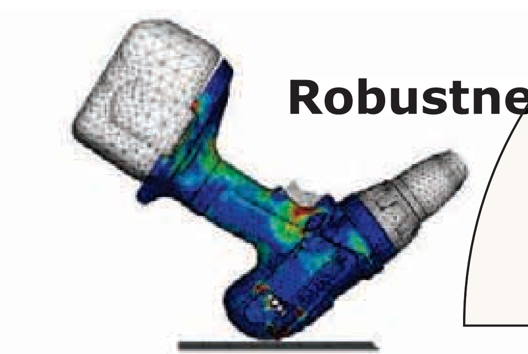


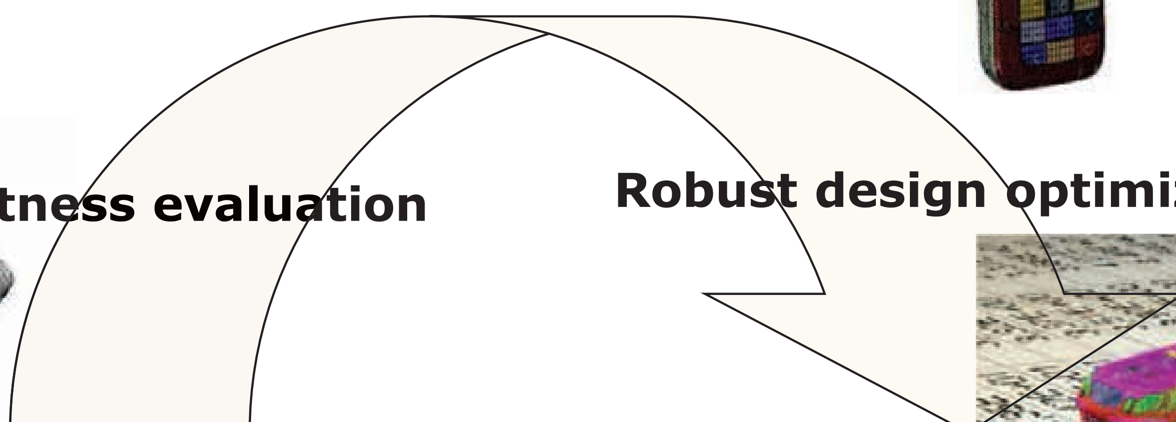


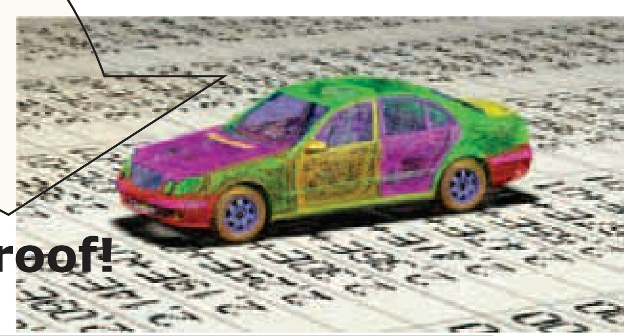




Define safety factors







Robustness evaluation

Robust design optimization

Sensitivity analysis

Robustness proof!

When and How to apply stochastic analysis?

- When material, geometry, process or environmental scatter is significantly affecting the performance of important response values
- When significant scatter of performance is seen in reality

and there is doubt that safety distances may be to small or safety distances should be minimized for economical reasons.

- **Iterative RDO** strategies using optimization steps with safety margins in the design space and checks of robustness in the space of scattering variables

or

- **Automatic RDO** strategies estimating variance based or probability based measurements of variation for every candidate in the optimization space

are possible RDO strategies.

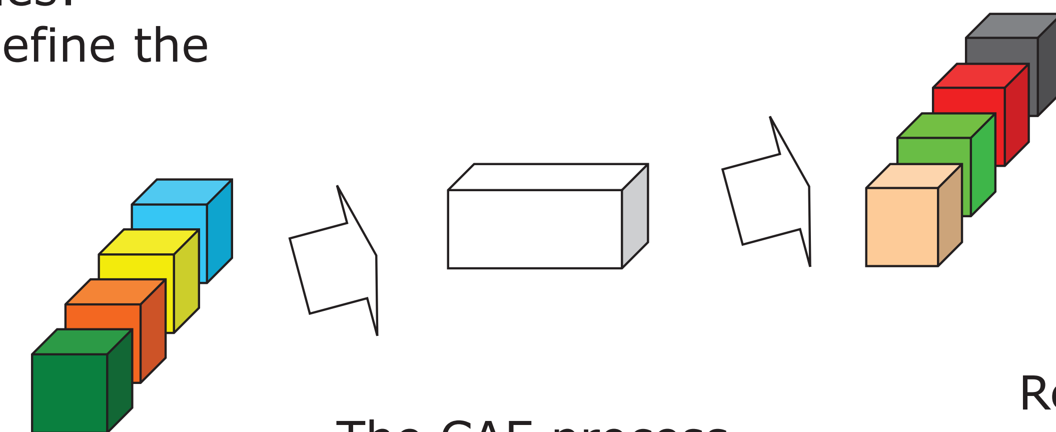
Process Integration

Process Integration

Parametric modeling as base for

- Customer defined optimization design space
- Naturally given robustness/reliability space

Design variables:
Entities that define the design space



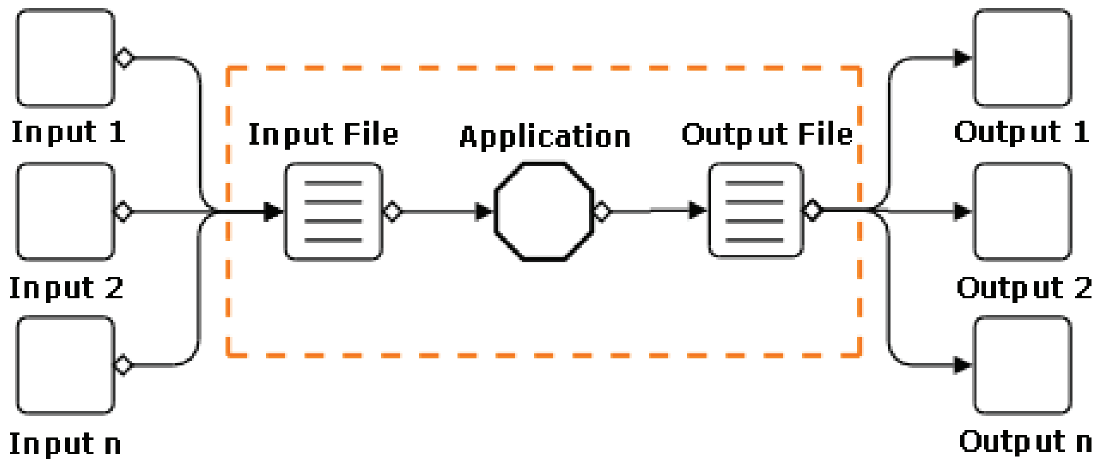
The CAE process generates the results according to the inputs

Result variables:
measures from the system

Scattering variables:
Entities that define the robustness space

optiSLang Process Integration

Arbitrary CAE-processes can be integrated with optiSLang. Default procedure is the introduction of inputs and outputs via ASCII file parsing. Additionally interfaces to CAE-tools exist.



Available interfaces in optiSLang

- ✓ CATIA v5 interface
- ✓ ANSYS workbench interface
- ✓ Excel Plugin
- ✓ Extraction tool kit (ABAQUS, LS-DYNA)
- ✓ Madymo positioner

Connected CAE-Solver: ANSYS, ABAQUS, NASTRAN, LS-DYNA, PERMAS, Fluent, CFX, Star-CD, MADYMO, Slang, Excel,…

Parametrize Editor

- **optiSLang** reads and writes parametric data to and from ASCII
- **Parameterize functionality**

Input file:

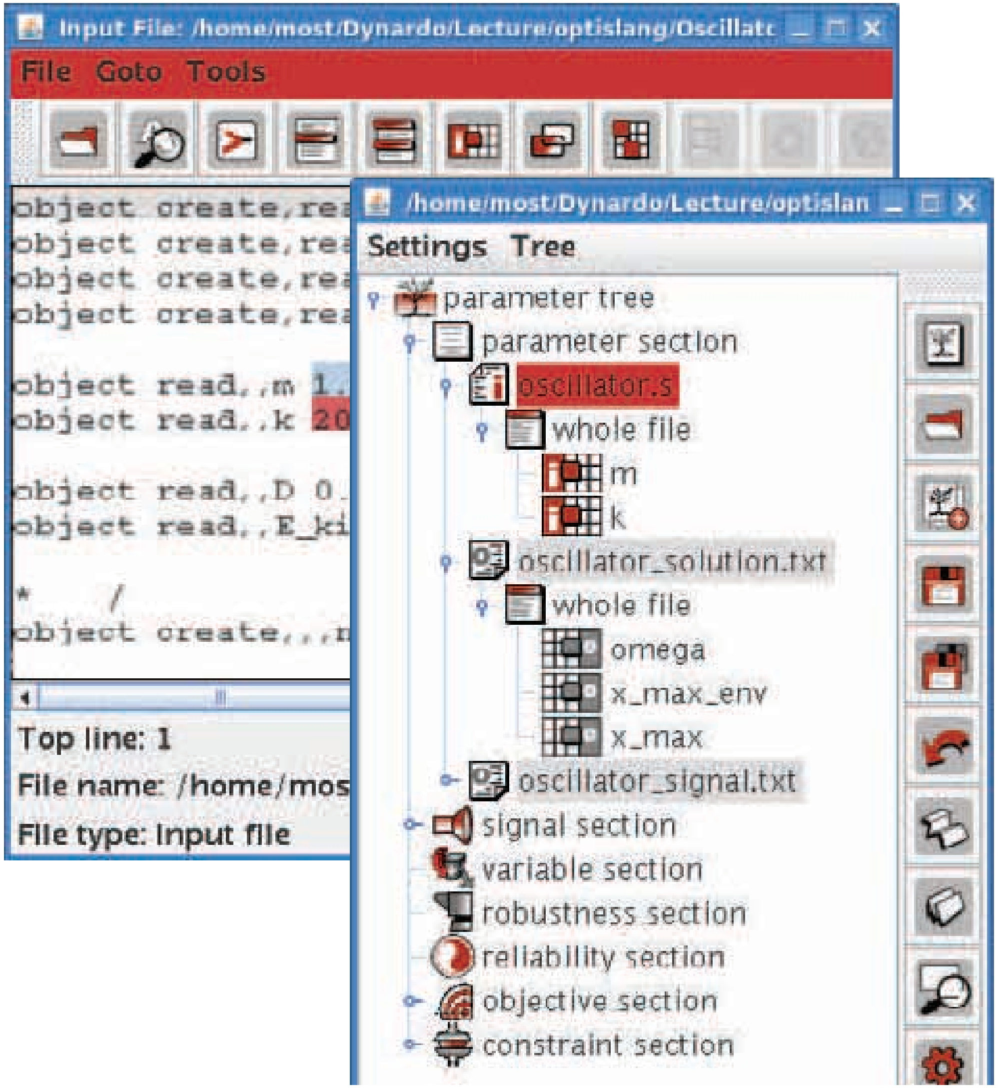
- Optimization parameter
- Robustness parameter
- RDO variable
- Dependent parameter and variables

Output file:

- Response variable
- Response vector
- Signals

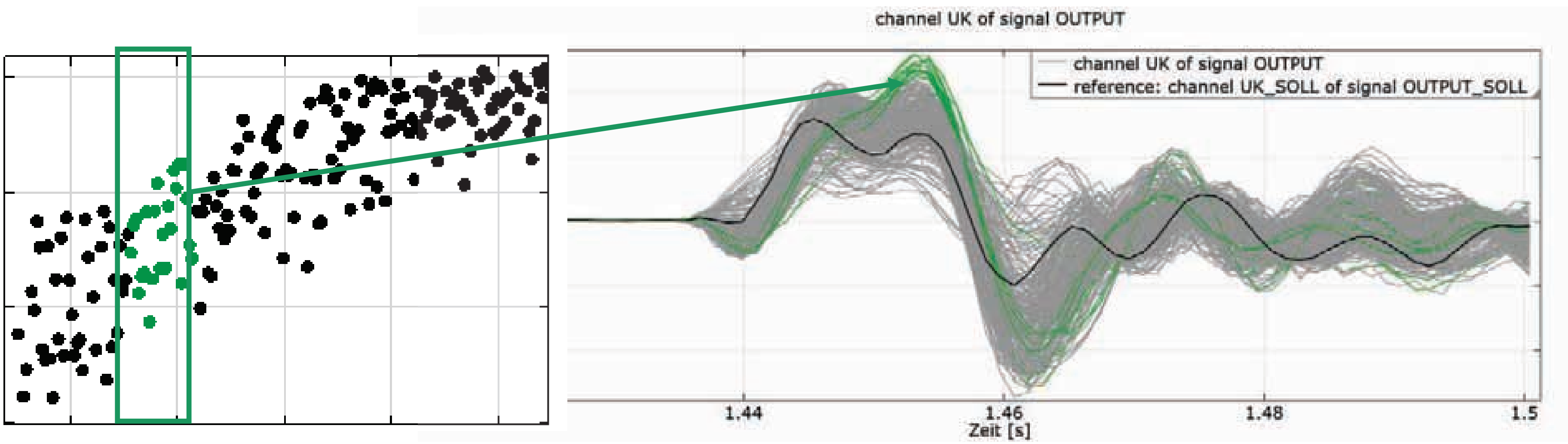
Problem definition section

- Optimization Constraints
- Robustness criteria
- Limit state function
- Multiple objectives/terms

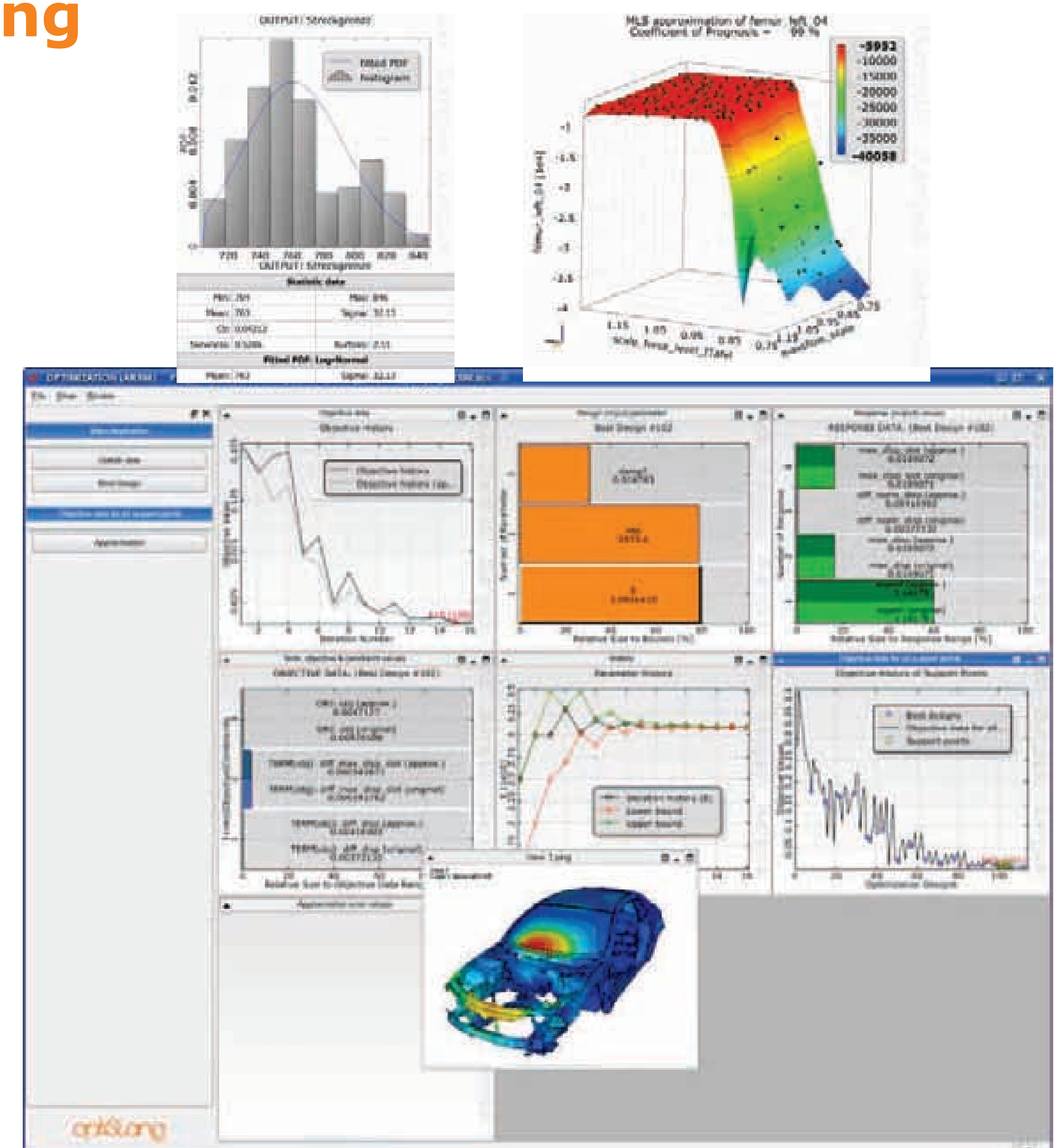


Signals in optiSLang

- Motivation: numerous scripts were written for extraction, processing and visualization of time or frequency signals
- Now signals are available in optiSLang (pre processor, solver, post processor)
  - Definition at parametrize editor (multiple channel signal objects)
  - Response parameters can be extracted via signal processing
  - Response parameters and signals are available for post processing



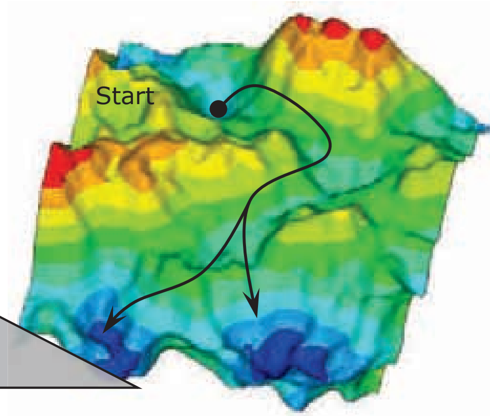
Pre and Post Processing



- The Pre Processing
  - Open architecture, user friendly parametrize editor and *one klick solution* for ANSYS workbench support simulation flow setup
- Solving the RDO Task
  - Easy and safe to use flows with robust default settings allows the engineer to concentrate on his engineering part and let optiSLang do the job of finding the optimal design.
- Post Processing
  - The Interactive case sensitive multi document post processing offers the important plots as default

Sensitivity Analysis

(Design Exploration)



Robust Design Optimization

Robust Design

Variance based Robustness Evaluation

Probability based Robustness Evaluation, (Reliability analysis)

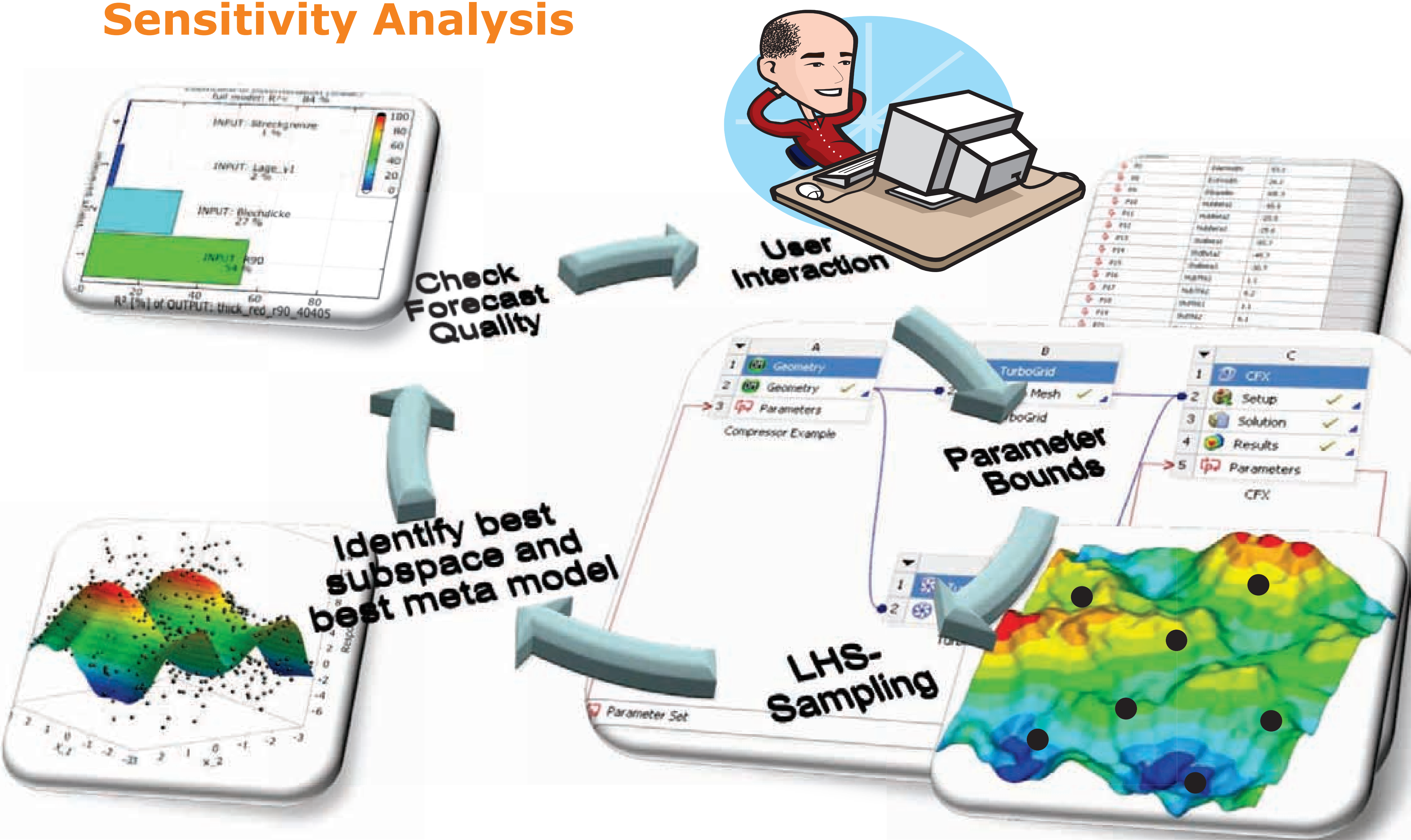
Optimization

Sensitivity Study

Single & Multi objective (Pareto) optimization

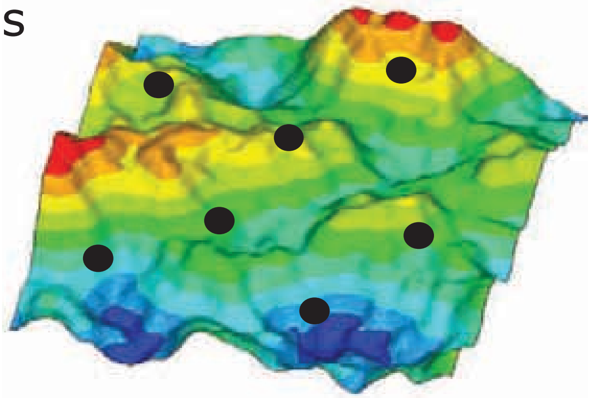
CAE process (FEM, CFD, MBD, Excel, Matlab, etc.)

Sensitivity Analysis



Sensitivity analysis

- Sensitivity analysis scans the design/random space and measures the sensitivity of the inputs with statistical measures



- Application as pre-investigation of an optimization procedure or as part of an uncertainty analysis
- Results of a global sensitivity study are:
  - **Sensitivities** of inputs with respect to important responses
  - **Estimate** the variation of responses
  - **Estimate** the noise of an underlying numerical model
  - **Better understanding** and verification of dependences between input and response variation
- Requirements for industrial applications:
  - Treatment of a large number of inputs
  - Consideration of strongly nonlinear dependencies
  - Manageable numerical/experimental effort

Stochastic Sampling Methods in optiSLang

Plain Monte Carlo Simulation (MCS)

- Independent generation of random samples

Latin Hypercube Sampling (LHS)

- Unwanted correlations removed with classical (fast) method
- Fraction of LHS looses its statistical advantages!
- Requires $N \geq k+1$ samples

Advanced Latin Hypercube Sampling (ALHS)

- Unwanted correlations are strongly minimized by optimization
- Exponentially increasing time effort (more than 50 variables)

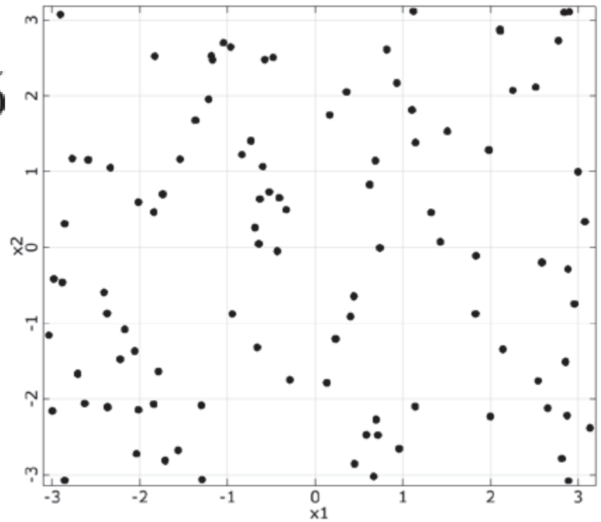
Space-filling Latin-Hypercube Sampling (SLHS)

- Samples are generated to optimally cover design space
- In reduced space, the space filling property may be lost
- Huge time effort for many variables (more than 20 variables)

Stochastic Sampling Methods in optiSLang

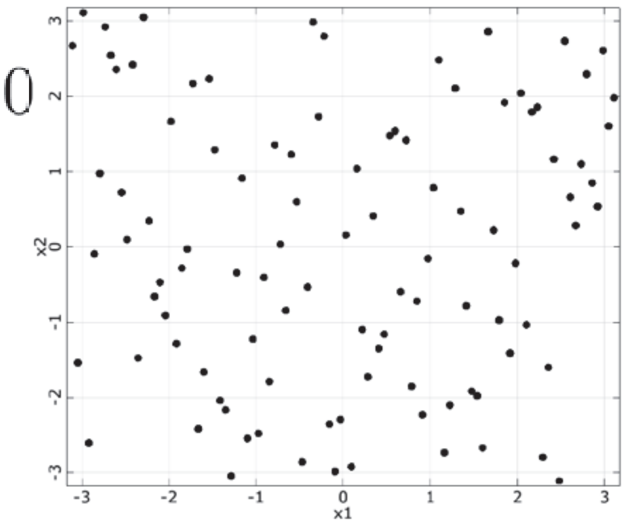
MCS

$\rho = 0.085$



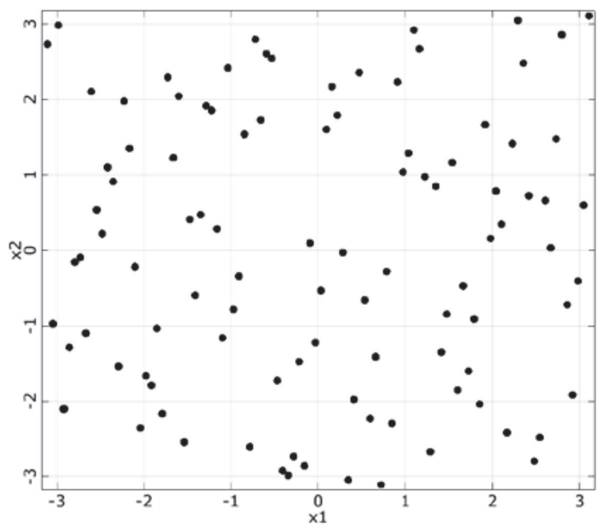
LHS

$\rho = 0.010$



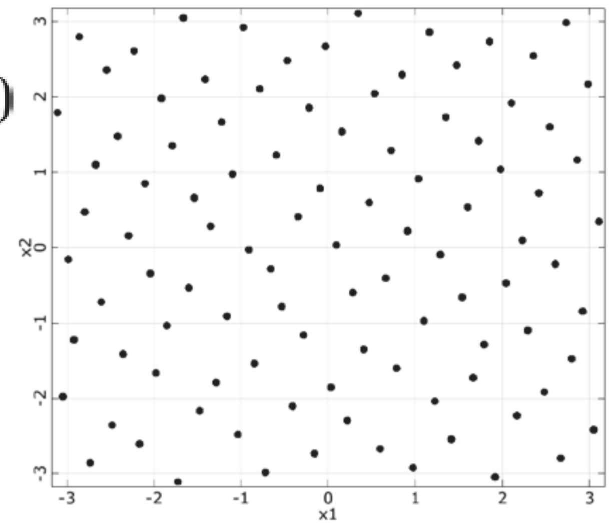
ALHS

$\rho = 0.000$



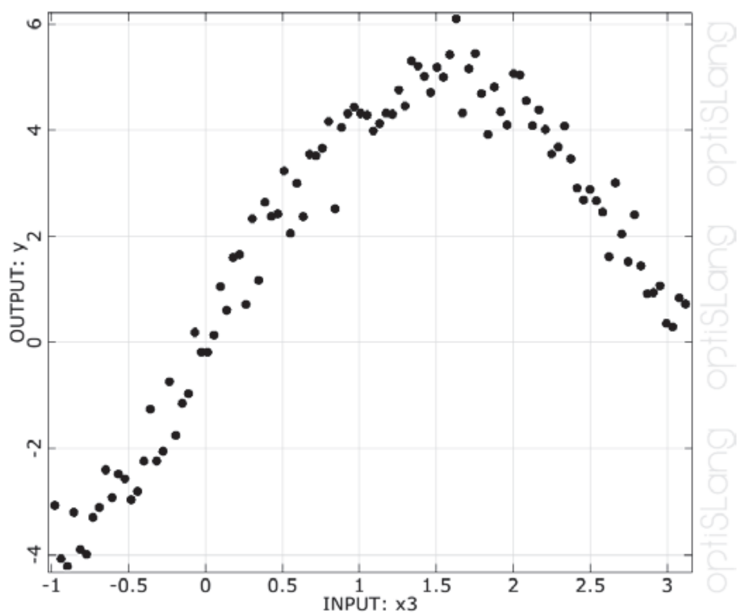
SLHS

$\rho = 0.000$

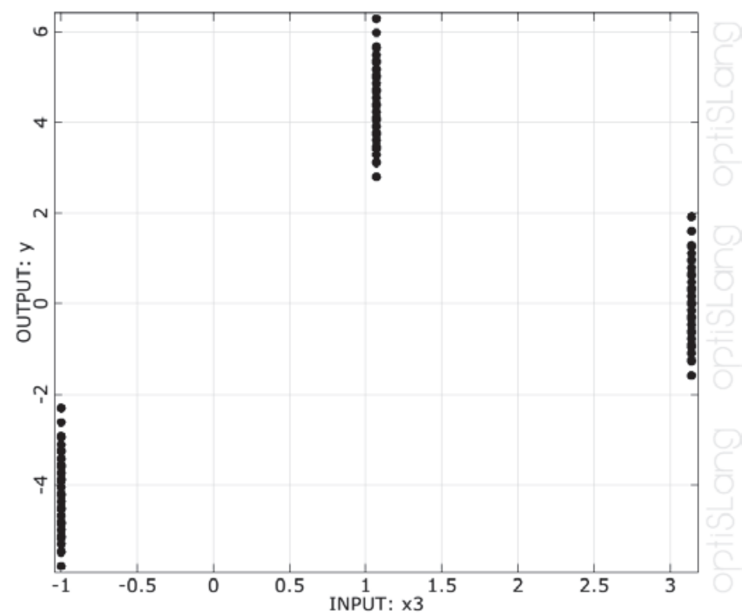


Why do we prefer stochastic sampling ?

- Deterministic designs use maximum 3 levels for each variable
- LHS has *N* levels for each variable
- ➢ If we reduced the variable space be removing unimportant variables, deterministic designs loose the information of these variables, but with LHS this is not the case
- Example: 4 minor and 1 major important input variables:



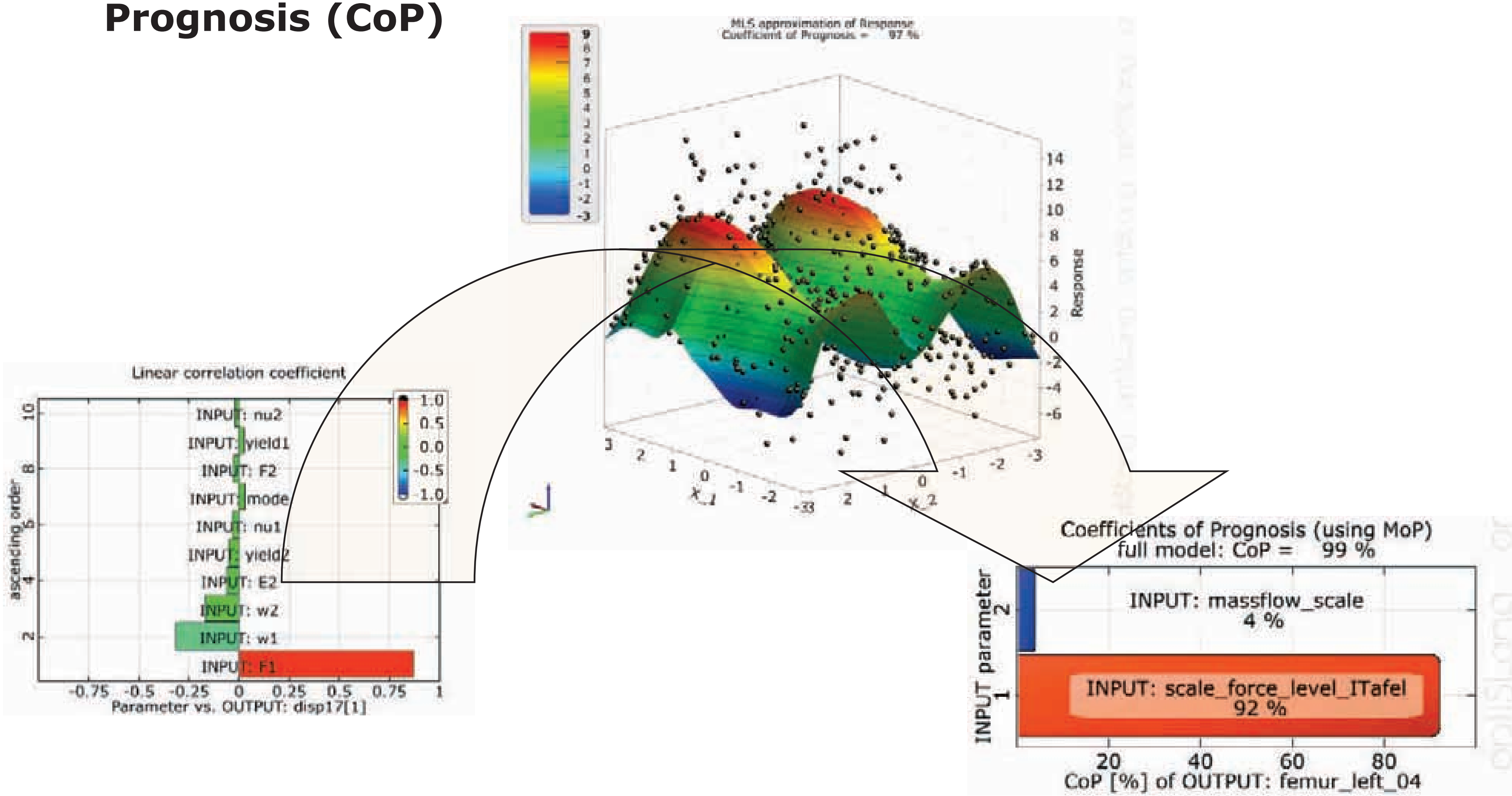
LHS, 100 samples



Full factorial, 243 designs

Identifying important parameters

From tornado chart of linear correlations to the Coefficient of Prognosis (CoP)

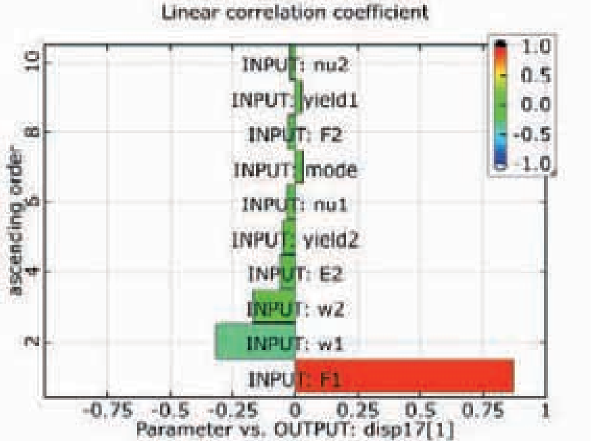


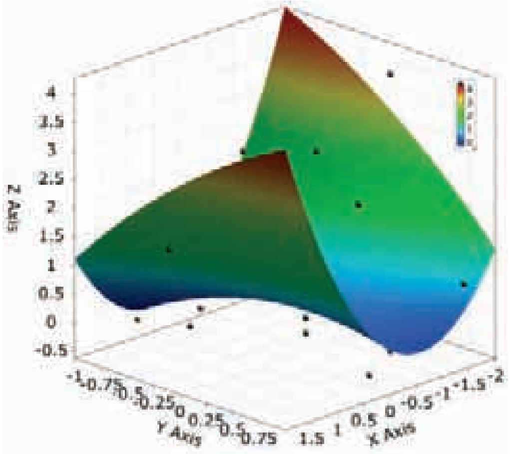
Will, J.; Most, T.: Metamodel of optimized Prognosis (MoP) – an automatic approach for user friendly design optimization; Proceedings ANSYS Conference 2009, Leipzig, Germany, www.dynardo.de

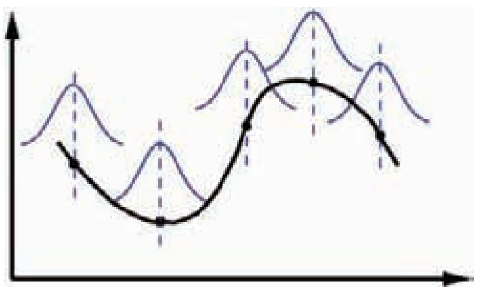
Statistical measurements

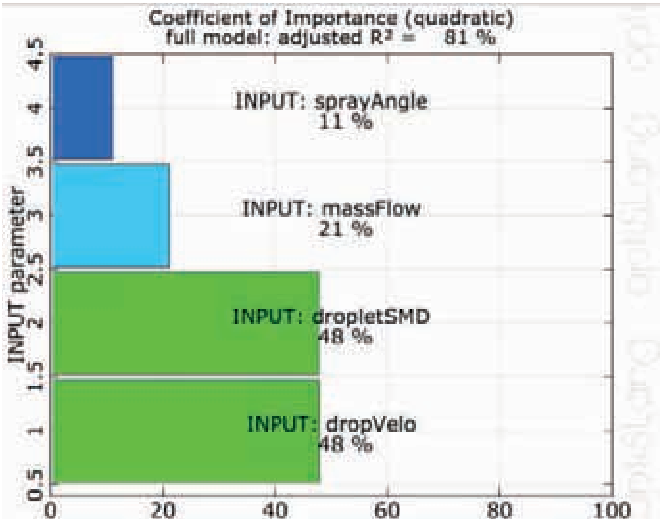
Correlation Measurements

- Coefficients of pairwise linear/quadratic correlation is the simplest correlation measurement
- Multi-dimensional non-linear correlation can be detected using advanced meta models (Neural networks, Moving least squares,..)







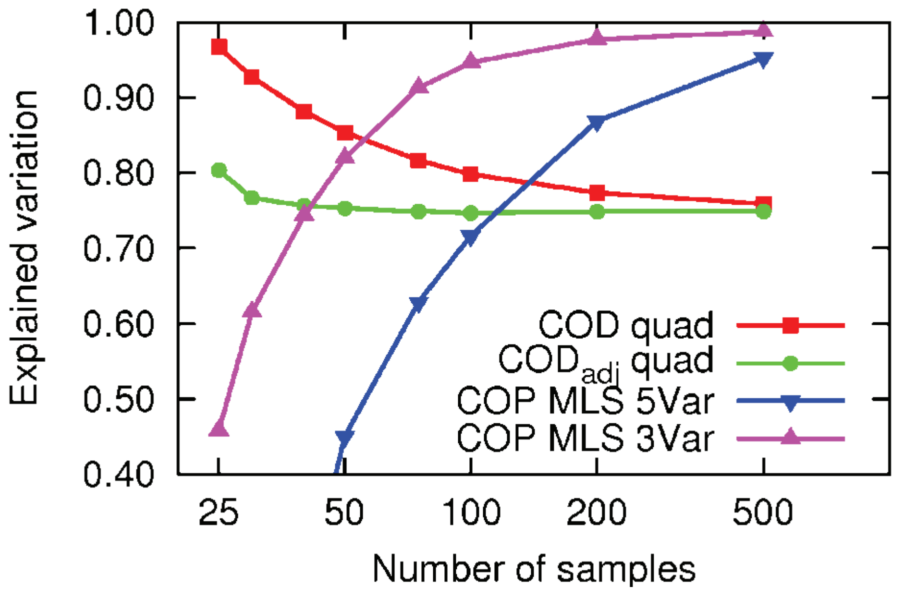


Goodness of fit Measurements (CoD)

- Goodness of Fit (Coefficient of Determination - CoD) summarize correlations on the meta models

Dynardo‘s Coefficient of Prognosis (CoP)

- CoD is only based on how good the regression model fits through the sample points, but not on how good the prediction quality is
- Approximation quality is too optimistic for small number of samples
- For interpolation models (MLS, Neural Networks, Radial basis functions,..) with perfect fit, CoD is equal to one
- CoP measures the forecast quality of regression model using an independend test data set



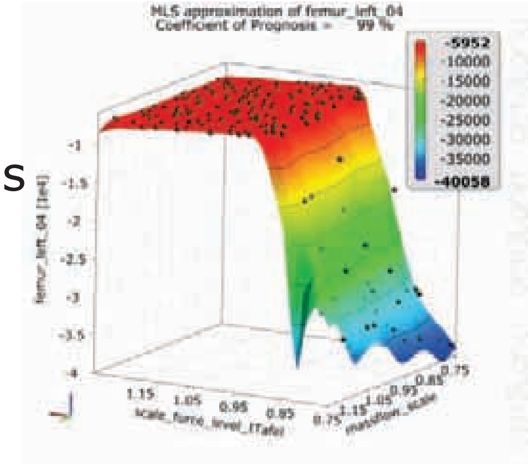
- Prediction quality is better if unimportant variables are removed from the approximation model

To minimize necessary number of sample optiSLang includes **filter technology** to select significant variables (significance, importance & correlation filter)

Meta model of optimal Prognosis (MoP)

- optiSLang provides a automatic flow to reduce variables and generate the best possible response surface for every response with a given number of solver calls [Meta model of optimal Prognosis (MoP)] and checks Prognosis quality of the meta model.

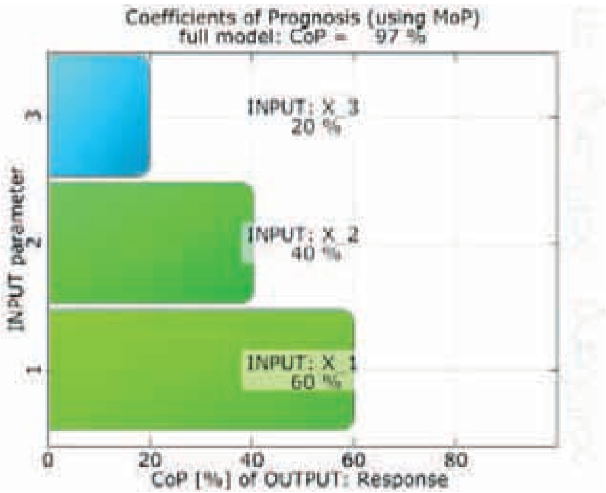
- MoP solve following important tasks
  - We reduce the variable space using filter technology= best subspace
  - We check multiple non linear correlations by checking multiple MLS/Polynomial regression = best Meta Model
  - We check the forecast (prognosis) quality using a test sample set = Coefficient of Prognosis (CoP)
  - CoP/MoP allows to minimize the number of solver runs
  - Final MOP can be used for optimization purpose

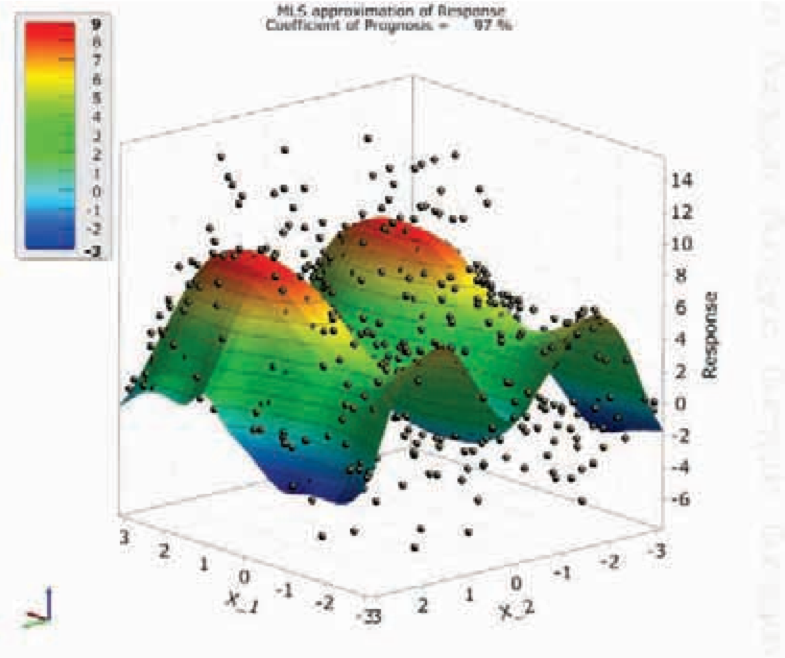


MOP allows "No Run to Much"

With MOP functionality we can start to check after 50..75 runs independent on the number of input variables (5 or 100)

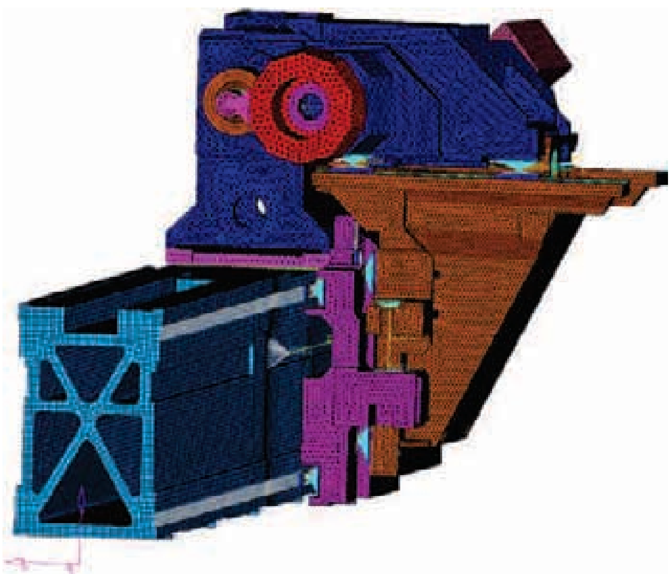
⇒ can we explain the variation
⇒ which input scatter is important
⇒ how large is the amount of unexplainable scatter (potentially noise, extraction problems or high dimensional non linear mechanisms)

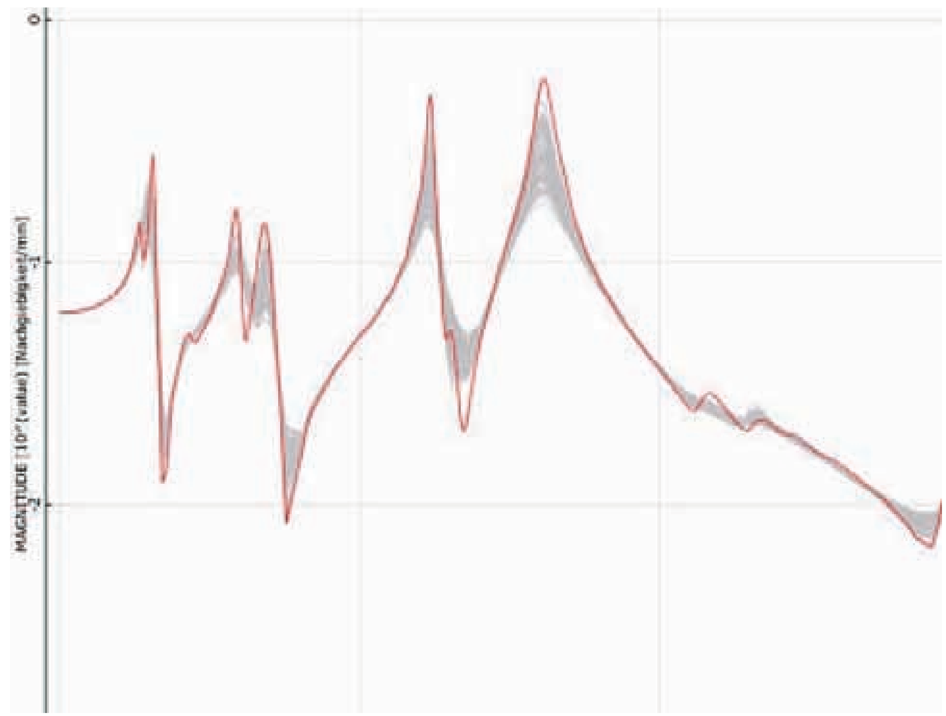




Sensitivity Analysis

Determining the sensitivity of stiffness and damping variation due to the tool center point position: 104 varying parameter





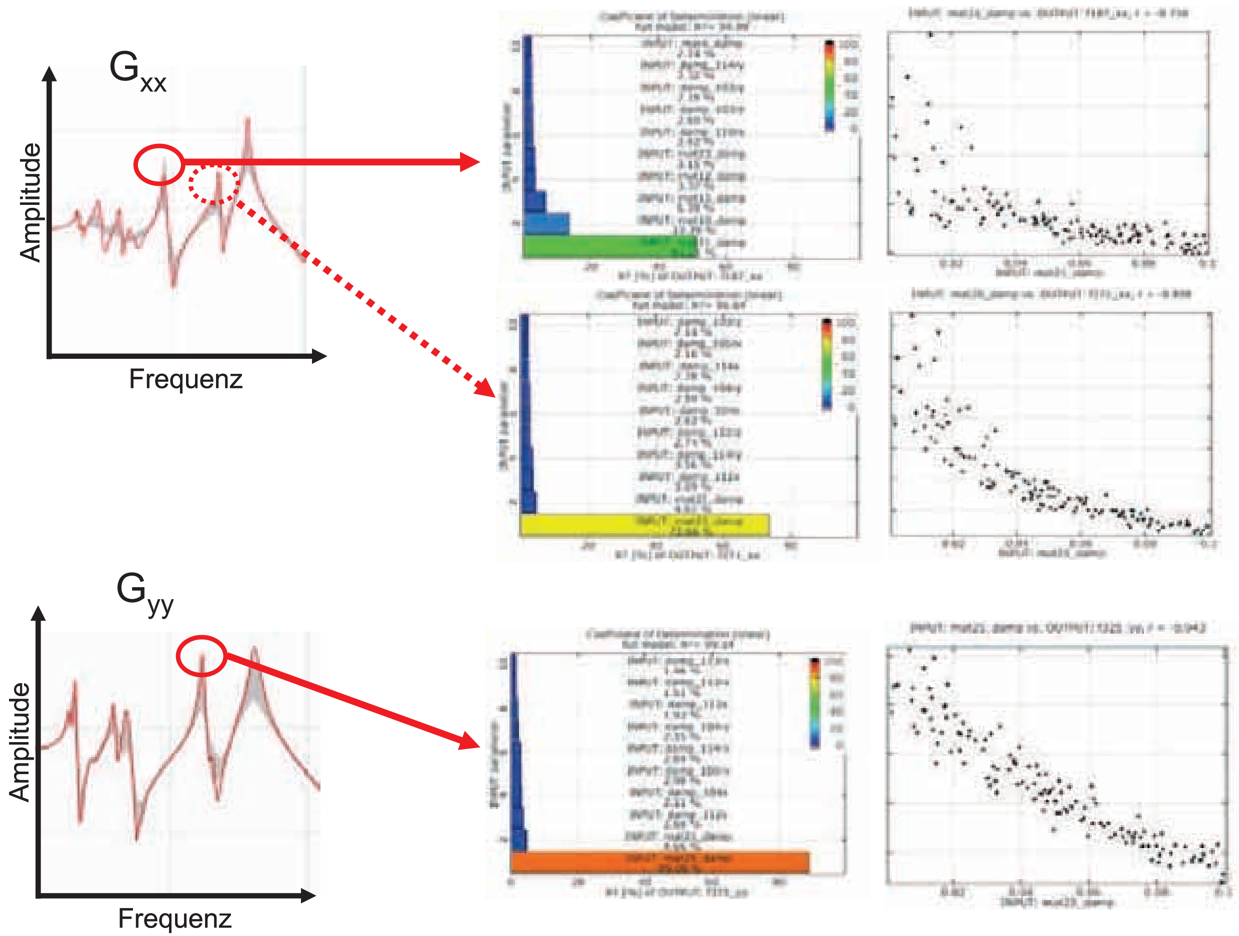
Solver PERMAS: frequency analysis up to 1000 Hz

SimCAT INDEX HELLER

Broos, A.; Kehl, G.; Melchinger, A.; Röck, S.; Will, J.: optiSLang in der Entwicklung von Werkzeugmaschinen, Proceedings WOST 3.0, 2006, www.dynardo.de

Sensitivity Analysis

Better understanding of dynamics, e.g. specially damping mechanisms:

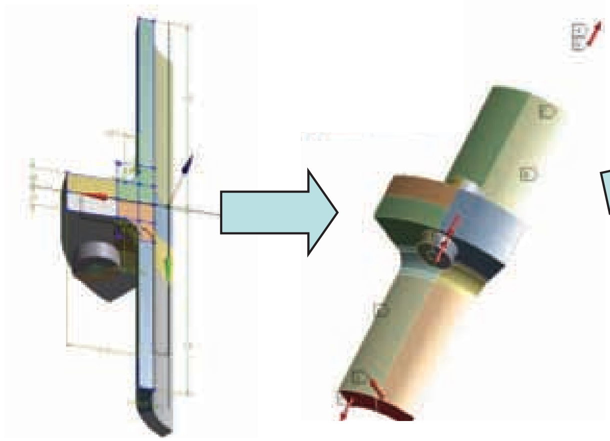


SimCAT
INDEX
HELLER

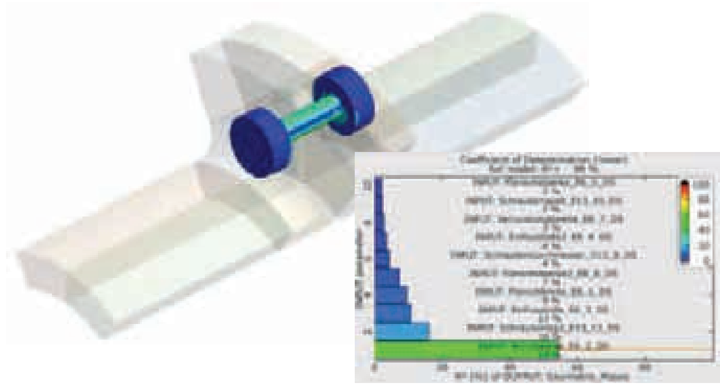
Will, J.: Variation Analysis as Contribution to the Assurance of Reliable Prognoses in Virtual Product Development, Proceeding NAFEMS Seminar "Reliable Use of Numerical Methods in Upfront Simulations" March 2007, Wiesbaden, Germany, www.dynardo.de

Multidisciplinary Optimization

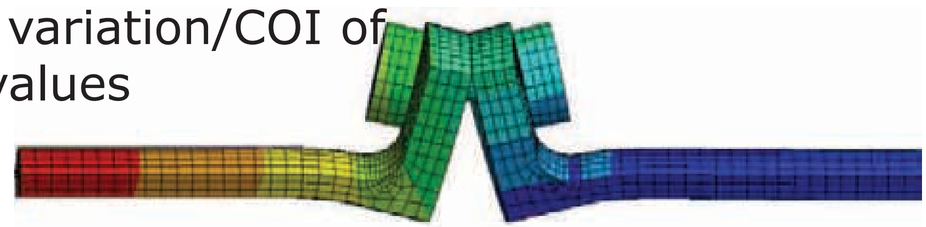
Multidisciplinary Optimization with optiSLang



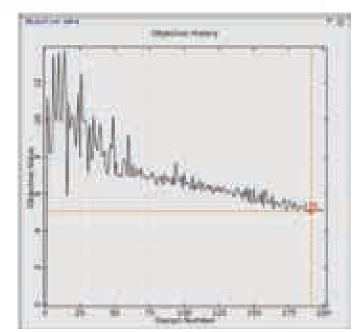
CAD and CAE Parameter definition



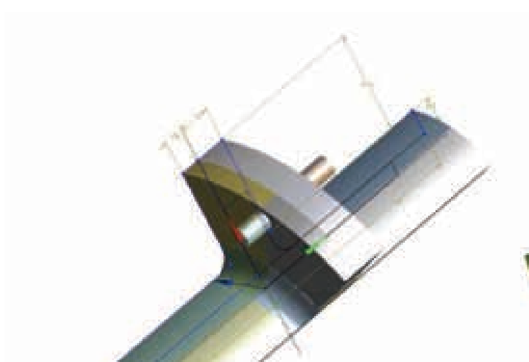
Sensitivity study – identify the most important parameter and check variation/COI of response values

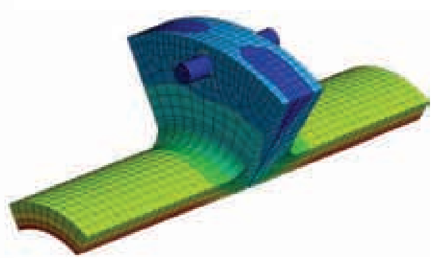


minimize



Define optimization goal and optimize





Validate optimized design in CAE and CAD

Deterministic optimization problem

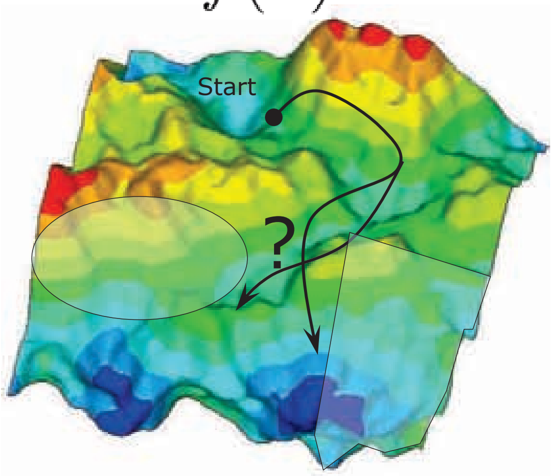
- Design variables
  Variables defining the design space (continuous, discrete, binary)

- Objective function
  Function $f(\mathbf{x})$ has to be minimized

- Constraints, State variables
  Constrain the design space, Equality/Inequality restrictions are possible

- Most optimizers require constraints and objectives with same order of magnitude (use scaling if not fulfilled)

$f(\mathbf{x})$



$$f\left(x_1, x_2, \dots, x_N\right) \rightarrow \min$$

$$g_k(x_1, x_2, \dots x_N) = 0; \;\; k = 1, m_e$$

$$h_l(x_1, x_2, \dots x_N) \geq 0; \;\; l = 1, m_u$$

$$x_i \in [x_l, x_u] \subset \mathbb{R}^N$$

$$x_l \leq x_i \leq x_u$$

Example: damped oscillator

- Time-dependent displacement function

$$x(t) = e^{-D\omega_0 t}\frac{v_0}{\omega}\sin(\omega t),$$

- Optimization goal: Minimize maximum amplitude after 5s free vibration

$$|x(t \geq 5\mathrm{s})|_{max} \rightarrow \min$$

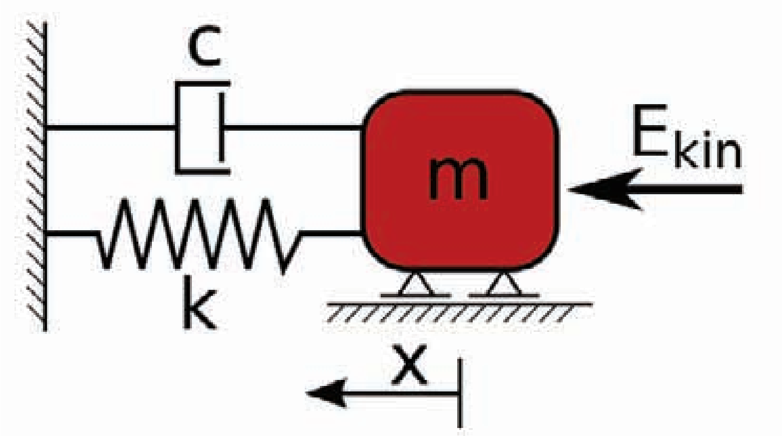
- Optimization constraint:

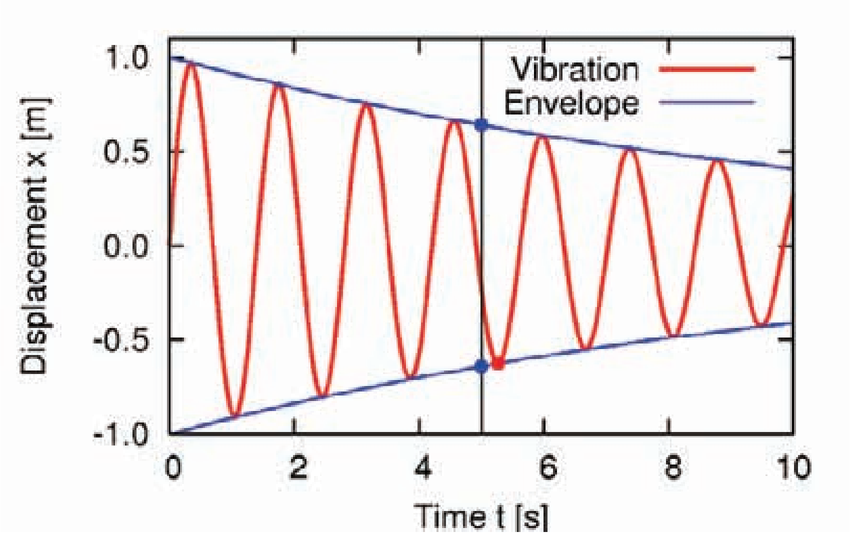
$$w \leq 8\frac{1}{\mathrm{s}}$$

- Optimization parameter bounds & constant parameters:

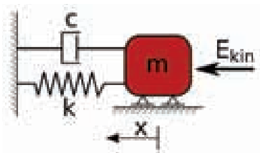
$$m \in [0.1, 5.0 \text{ kg}] \qquad D = 0.02$$

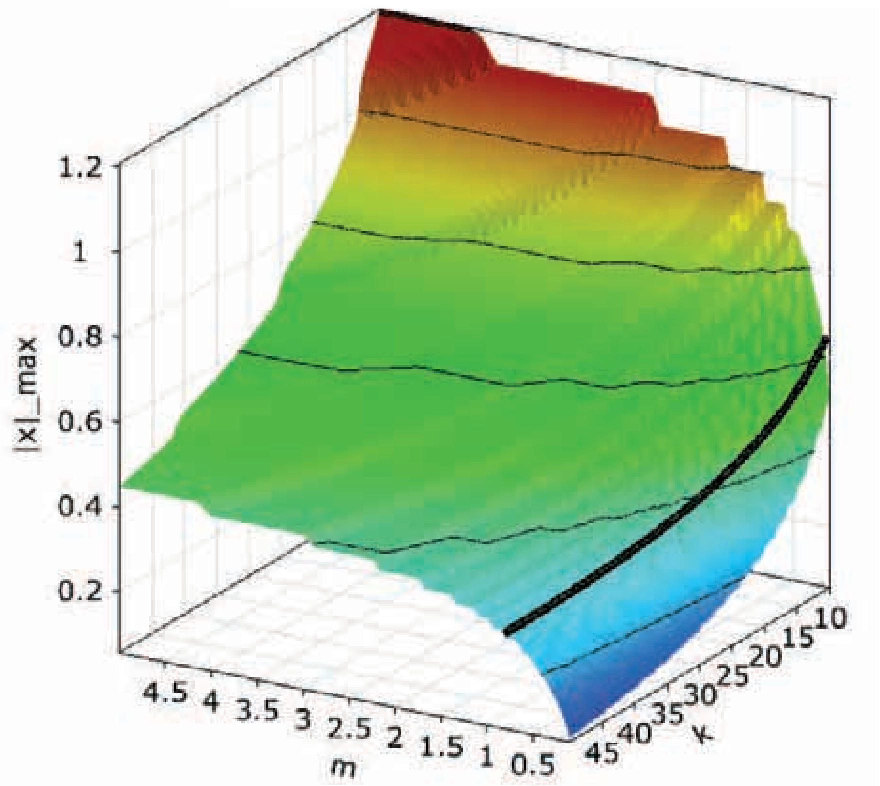
$$k \in [10, 50 \text{ N/m}] \qquad E_{kin} = 10 \text{ Nm}$$

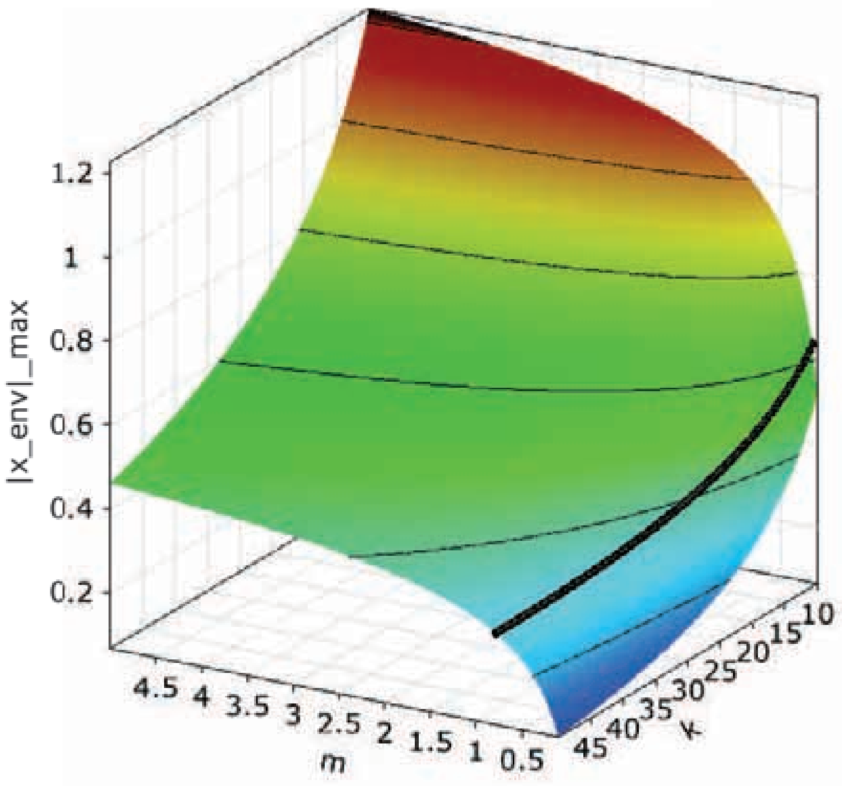




Objective function

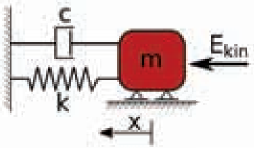


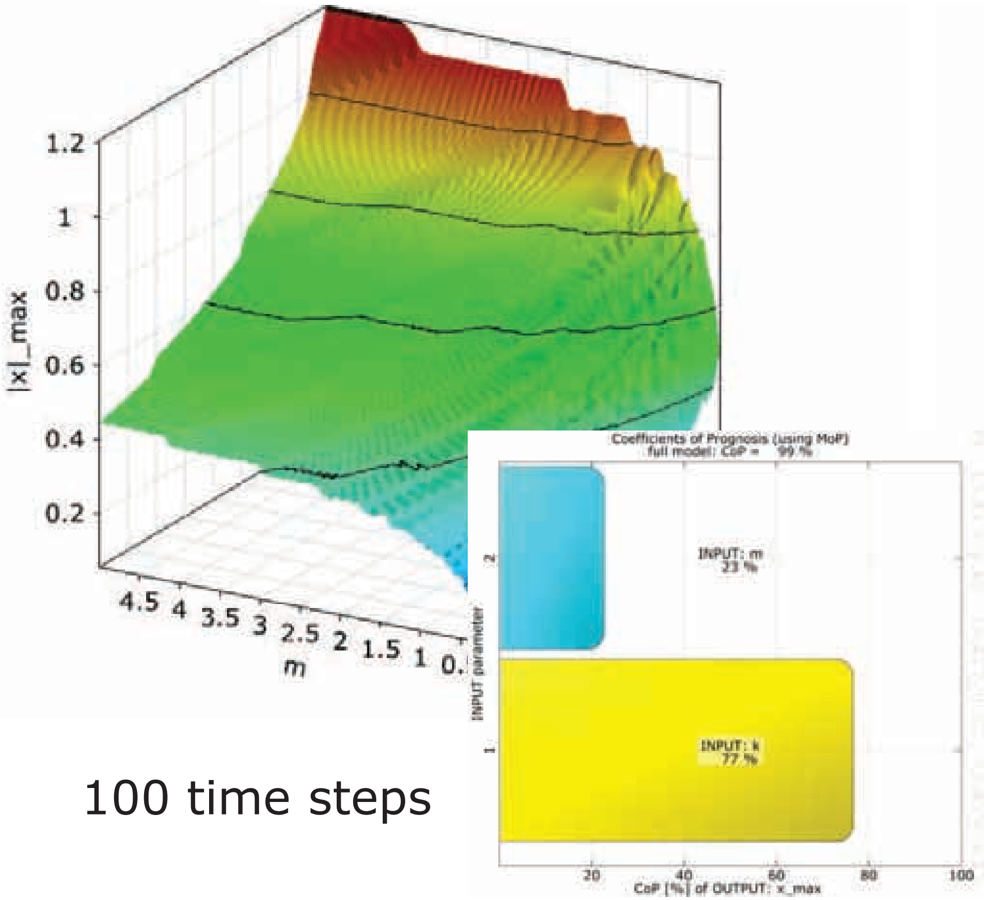




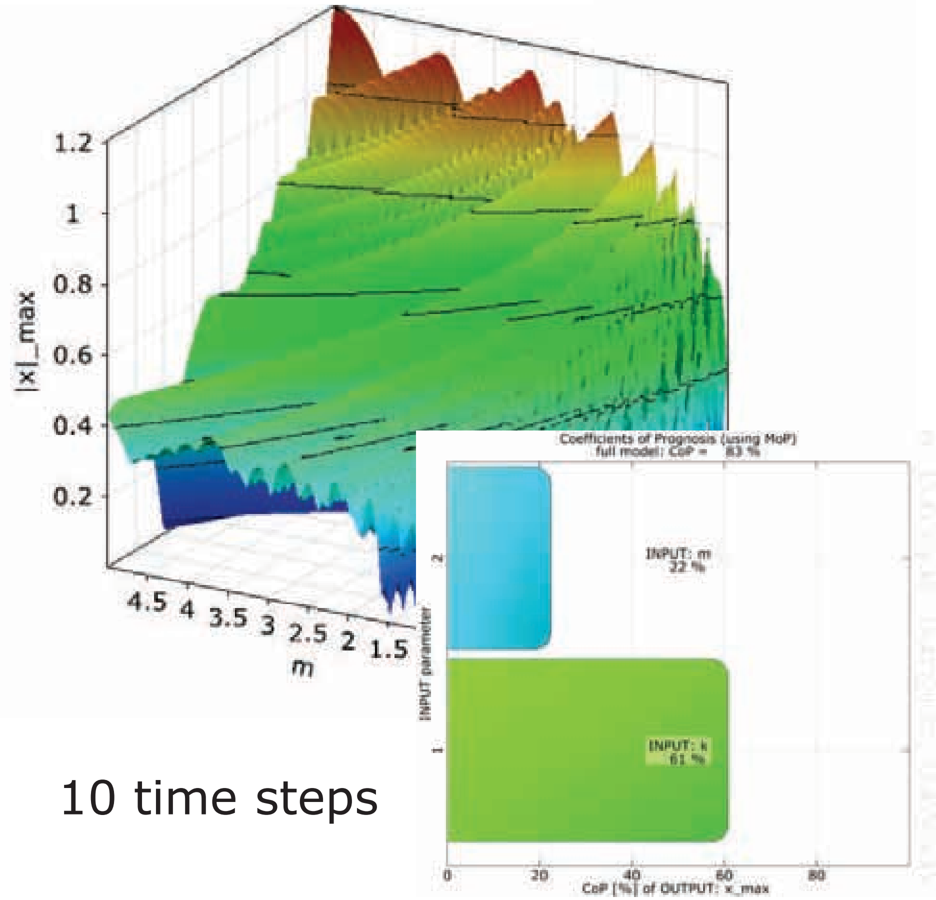
- Stepped objective function by using maximum elongation
- Smooth objective if amplitude is approximated with envelope

Solver validation with MOP





100 time steps



10 time steps

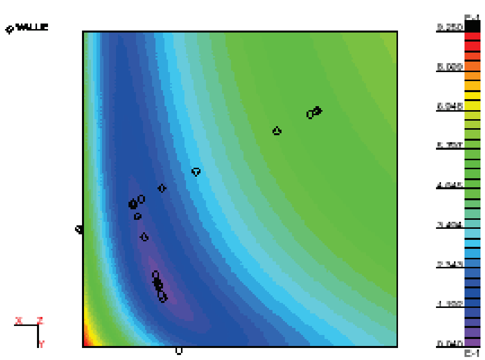
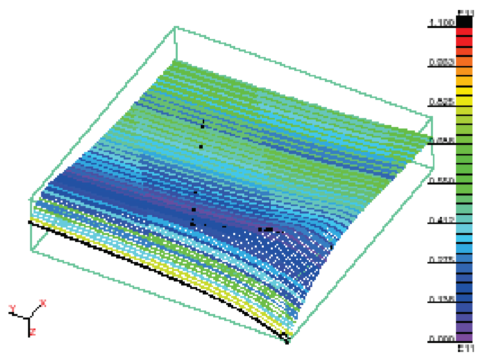
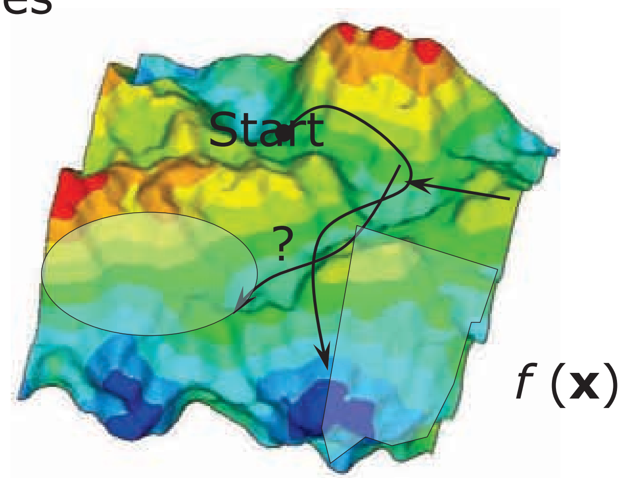
- If time discretization is too coarse, objective function is distorted
- MOP(100 LHS): 100 time steps CoP=99%, 10 time steps CoP=83%

Gradient based Optimization

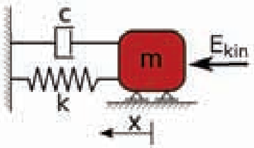
- NLPQL (Nonlinear Programming Quadratic Line Search – Prof. Schittkowski)
- Recommended area of application: reasonable smooth problems

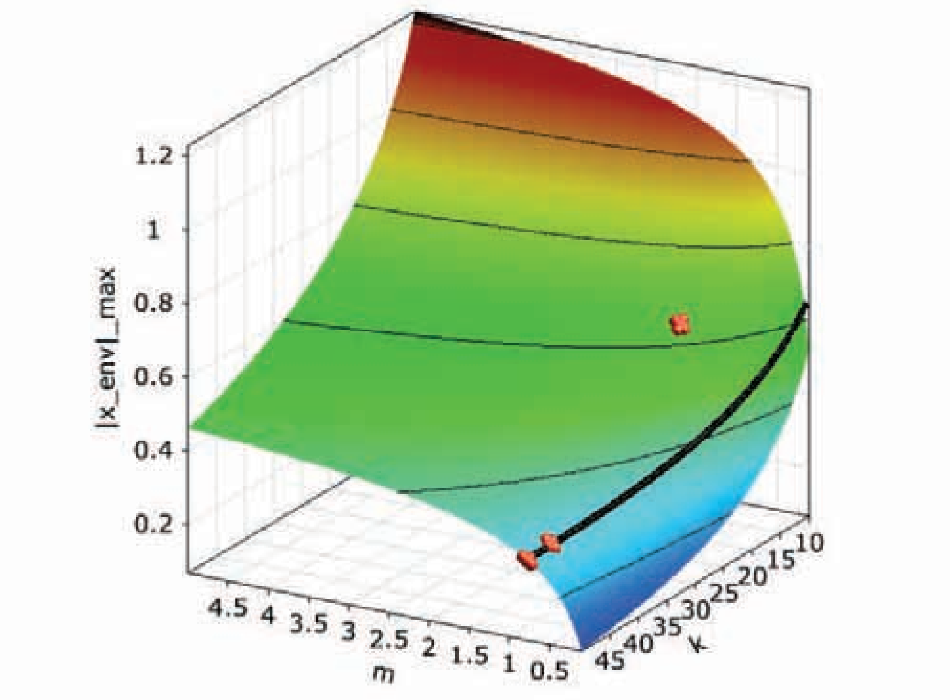
+ Fast convergence in case of:
- Function & gradients can be evaluated with sufficiently high precision
- The problem is smooth and well scaled

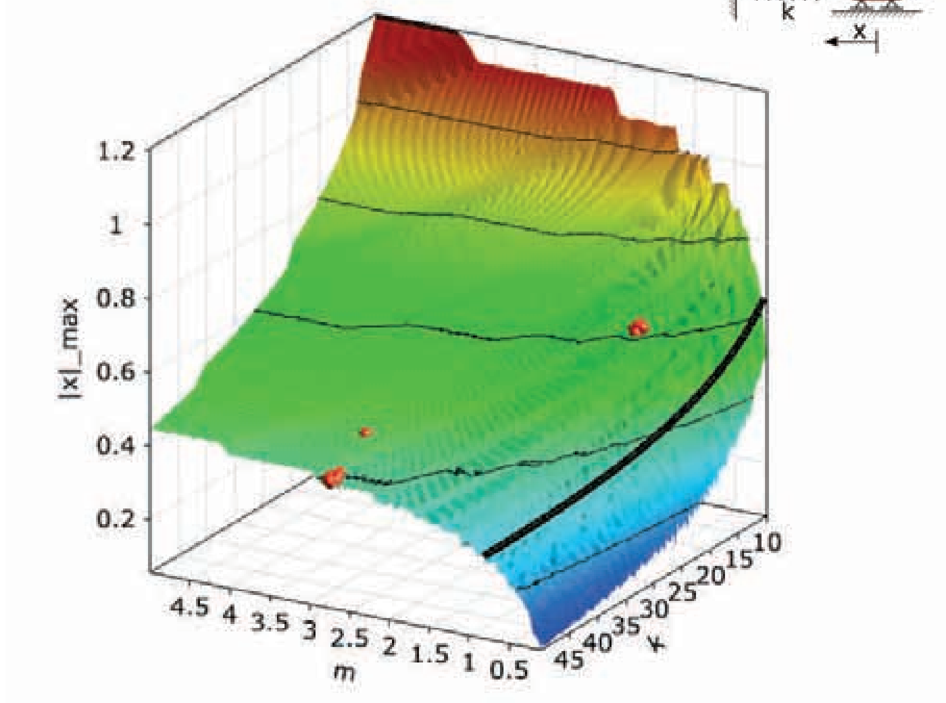
\- Local optima, expensive gradients
- Use with care for binary/discrete variables

NLPQL on original and approximated objective function







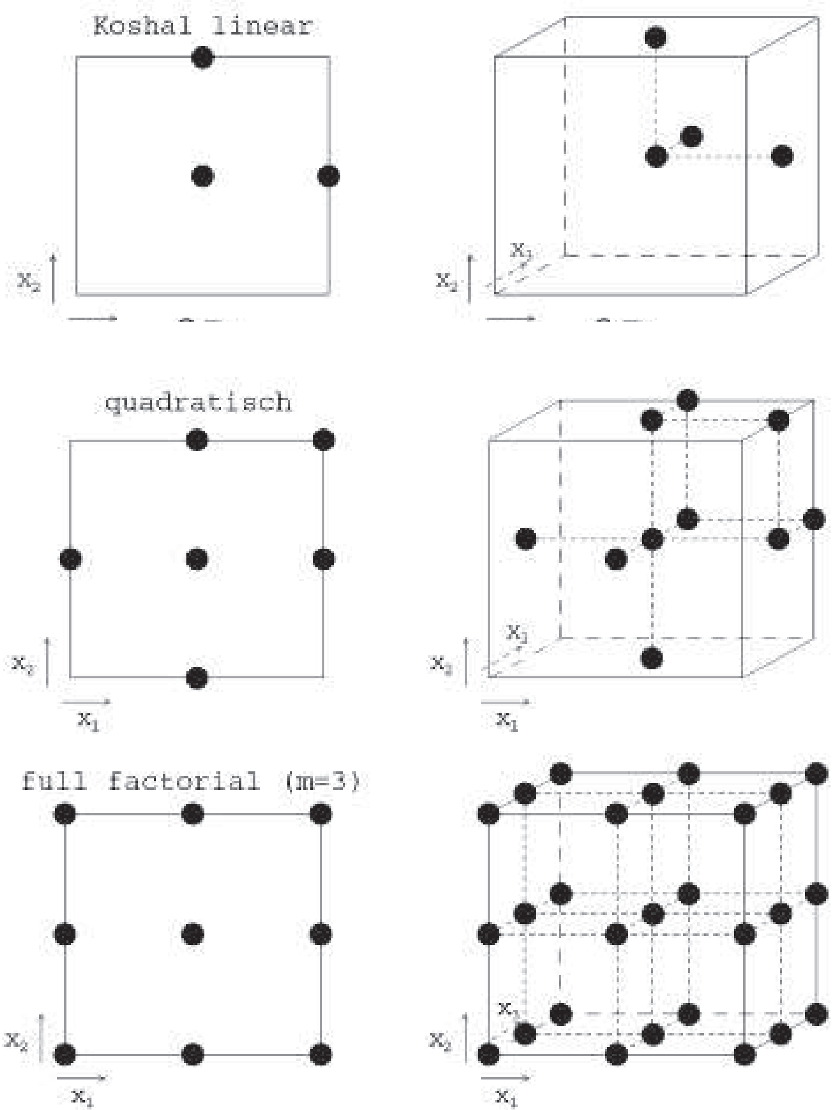
Envelope (18 solver calls)

$$m_{opt} = 0.78 \text{ kg}$$
$$k_{opt} = 50.0 \text{ N/m}$$
$$\omega_{opt} = 8.00 \text{ 1/s}$$
$$|\hat{x}|_{max}^{opt} = 0.28 \text{ m}$$

Direct, 100 time steps (29 calls)

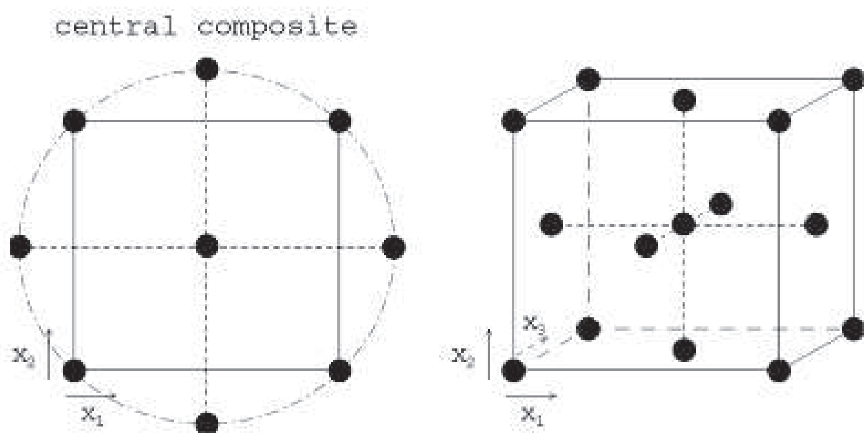
$$m_{opt} = 2.77 \text{ kg}$$
$$k_{opt} = 48.9 \text{ N/m}$$
$$\omega_{opt} = 4.20 \text{ 1/s}$$
$$|x|_{max}^{opt} = 0.39 \text{ m}$$

Design of Experiment



<u>Method principles & properties:</u>

- Values for input parameters sampled at deterministic points
- Number of simulations strongly depends the on number of input parameters (*k*)

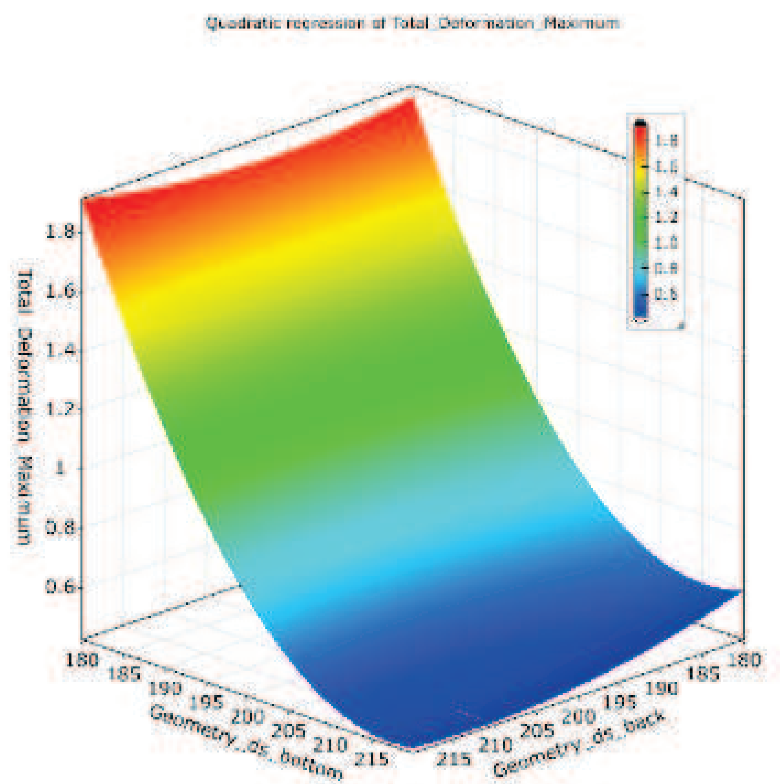


Global Response Surface Methods

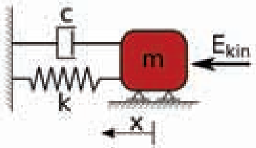
+ Global polynomial response surface approximation is effective for a small set of variables $n \leq 5 .. 7$

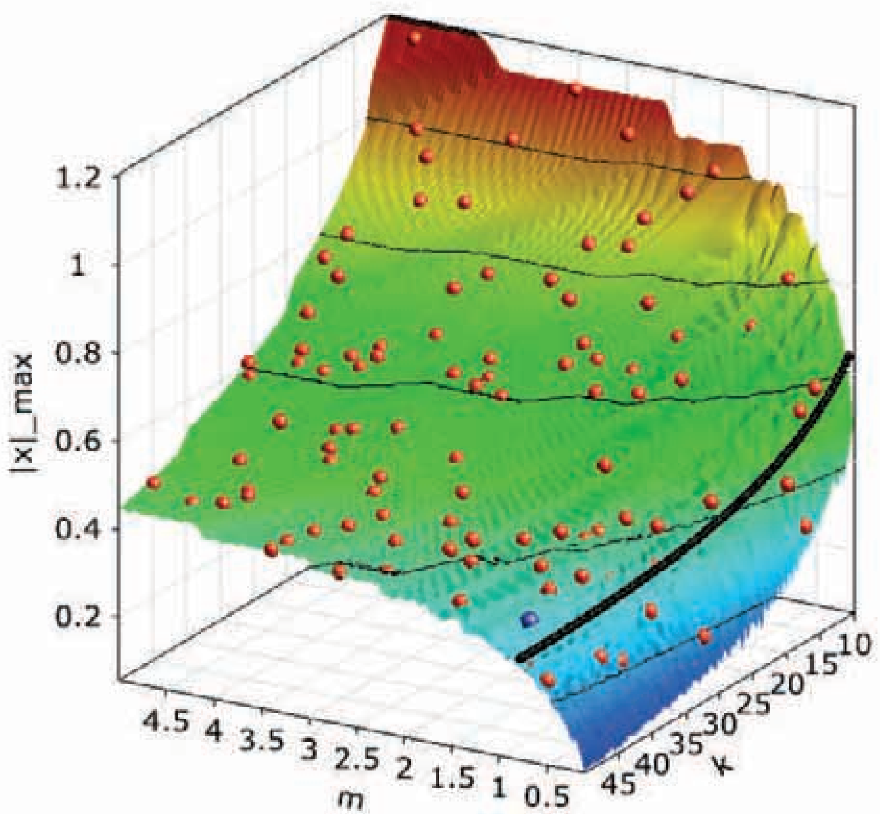
- Number of necessary support points for reasonably precise RS becomes very high in dimensions > 10

	Number of support points[a]						
	Linear approximation			Quadratic approximation[b]			
Number of Variables n	Koshal Linear	D–optimal[c] (linear)	Full factorial ($m=2$)	Koshal Quadr.	D–optimal[d] (quadr.)	Full factorial ($m=3$)	Central composite (CCD)
1	2	2	2	3	3	3	3
2	3	4	4	6	9	9	9
3	4	6	8	10	15	27	15
4	5	8	16	15	23	81	25
5	6	9	32	21	32	243	43
6	7	11	64	28	42	729	77
7	8	12	128	36	54	2187	143
8	9	14	256	45	68	6561	273
9	10	15	512	55	83	19683	531
10	11	17	1024	66	99	59049	1045
11	12	18	2048	78	117	177147	2071
12	13	20	4096	91	137	531441	4121
13	14	21	8192	105	158	1594323	8219
14	15	23	16384	120	180	4782969	16413
15	16	24	32768	136	204	14348907	32799



Scanning the design space with LHS



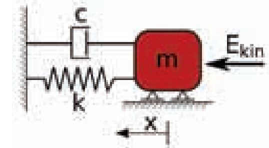


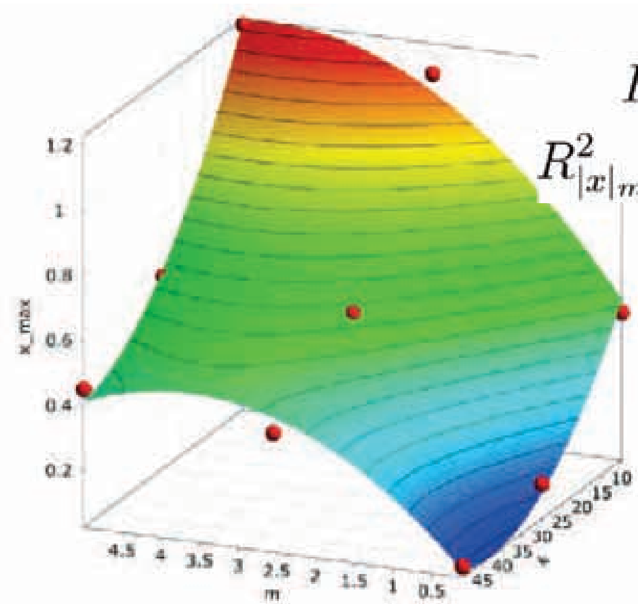
- 100 Latin Hypercube samples
- Best design:

$$m_{best} = 1.01 \text{ kg}, \qquad k_{best} = 45.4 \text{ N/m}$$

$$\omega_{best} = 6.71 \text{ 1/s}, \quad |x|_{max}^{best} = 0.32 \text{ m}$$

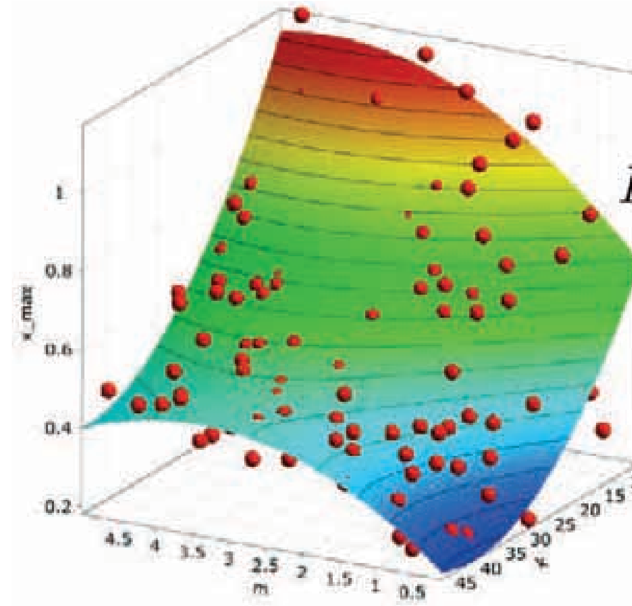
Quadratic polynomial regression, D-optimal and LHS DOE





$$R^2_\omega = 80\%$$
$$R^2_{|x|_{max}} = 90\%$$

D-optimal (9 solver calls)



$$R^2_\omega = 86\%$$
$$R^2_{|x|_{max}} = 96\%$$

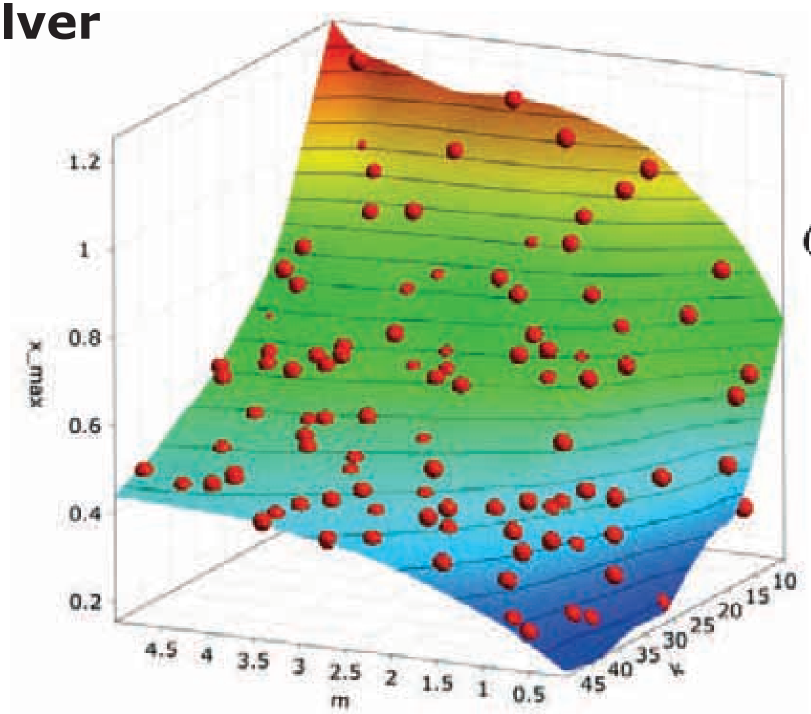
LHS (100 solver calls)

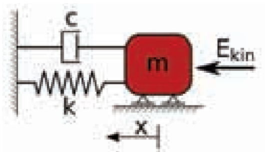
$$m_{opt} = 3.31 \text{ kg}$$
$$k_{opt} = 50.0 \text{ N/m}$$
$$\omega_{opt} = 3.89(7.94) \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.42(0.32) \text{ m}$$

$$m_{opt} = 0.76 \text{ kg}$$
$$k_{opt} = 42.1 \text{ N/m}$$
$$\omega_{opt} = 7.43(7.98) \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.31(0.28) \text{ m}$$

Always verify best design with solver!

Using MOP as solver





$$CoP_\omega = 98\%$$

$$CoP_{|x|_{max}} = 99\%$$

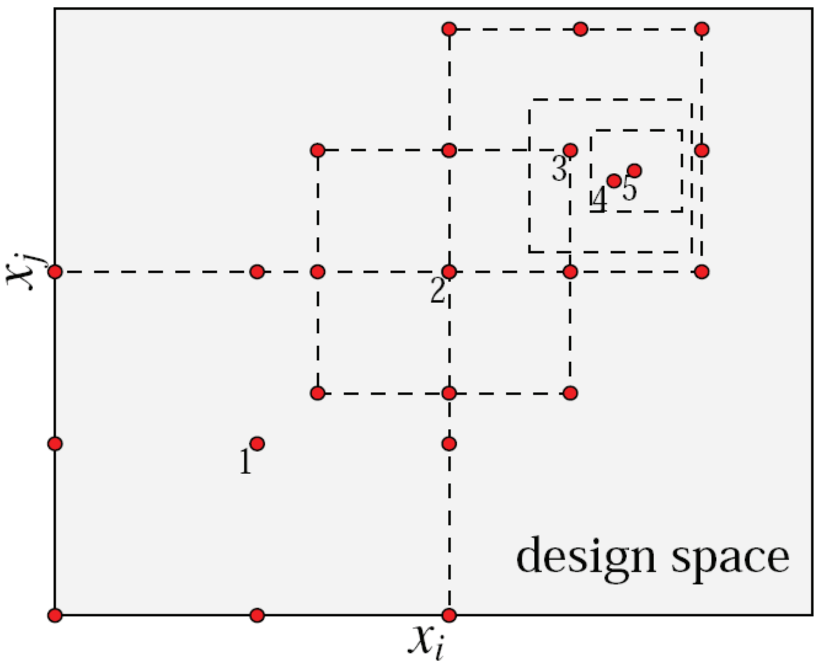
- Reuse of samples from sensitivity analysis
- Smoothing of noisy objective function
- High CoPs (≥90%) are required for objective **and** constraints
- **Always verify best design with solver!**

$$m_{opt} = 0.77 \text{ kg}, \qquad \omega_{opt} = 8.04(8.00) \text{ 1/s}$$

$$k_{opt} = 50.0 \text{ N/m}, \quad |x|^{opt}_{max} = 0.27(0.25) \text{ m}$$

Adaptive Response Surface Methods (Local)

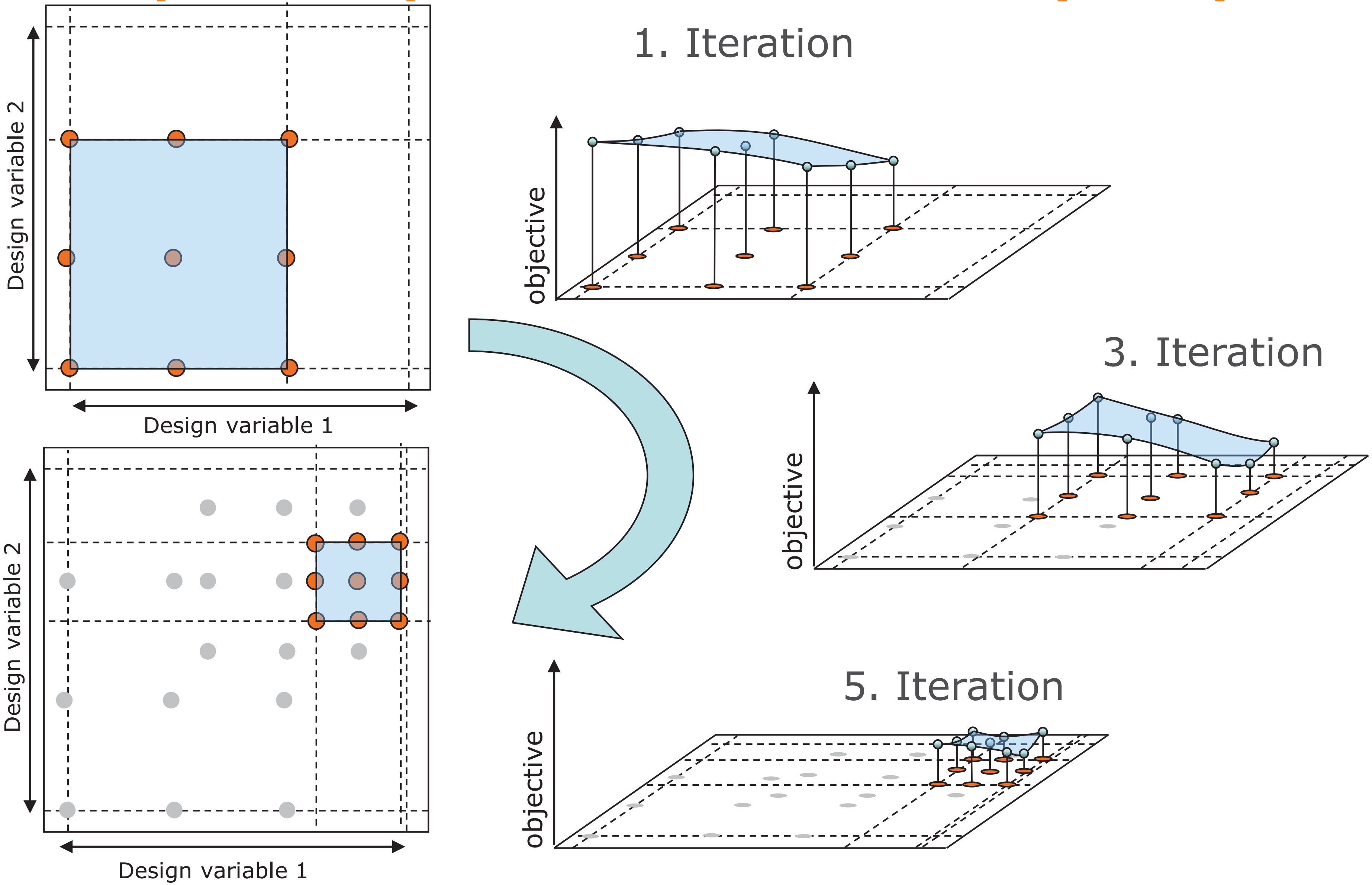
Adaptive design of experiment – design space



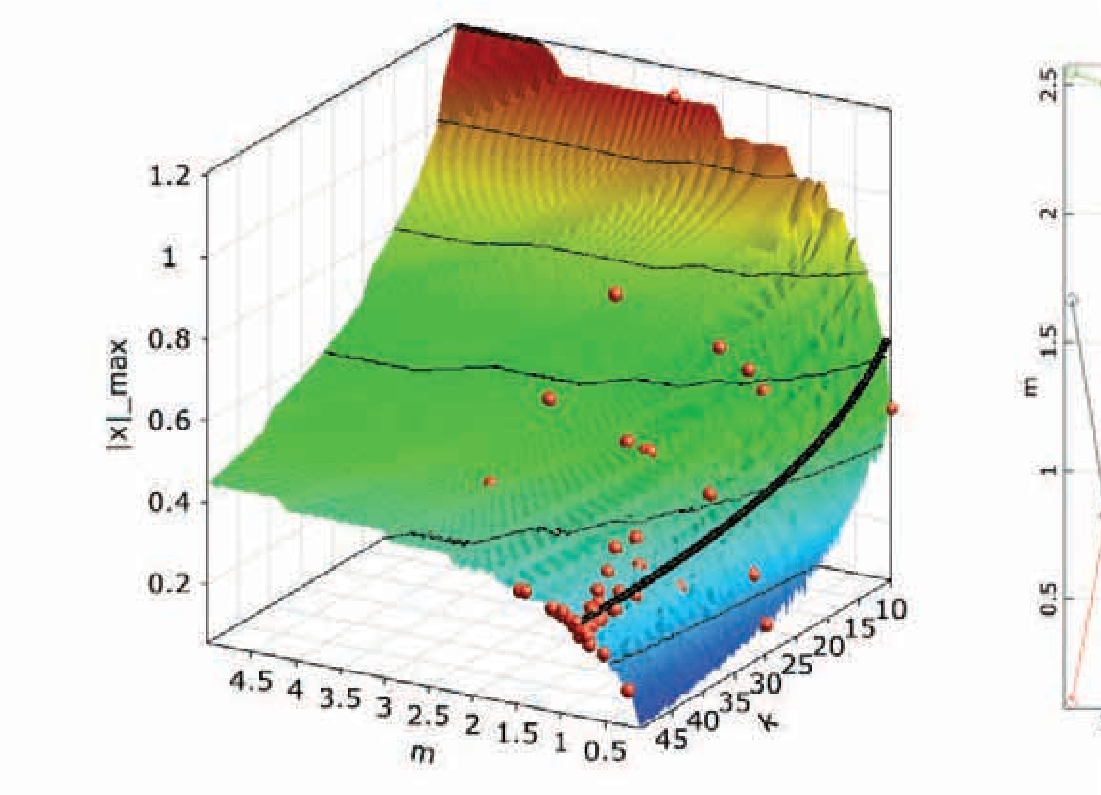
- Starting with a large subregion
- Iteration moves and shrinks the subspace till a solution converges to an optimum
- Approximation of the responses with low level trial function (e.g. linear and quadratic polynomial functions)

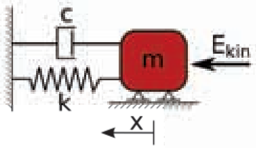
+ Fast catch of global trends, smoothing of noisy answers
+ Adaptive RSM with D-optimal linear DOE/approximation functions for optimization problems with up to 5..15 continuous variables is possible

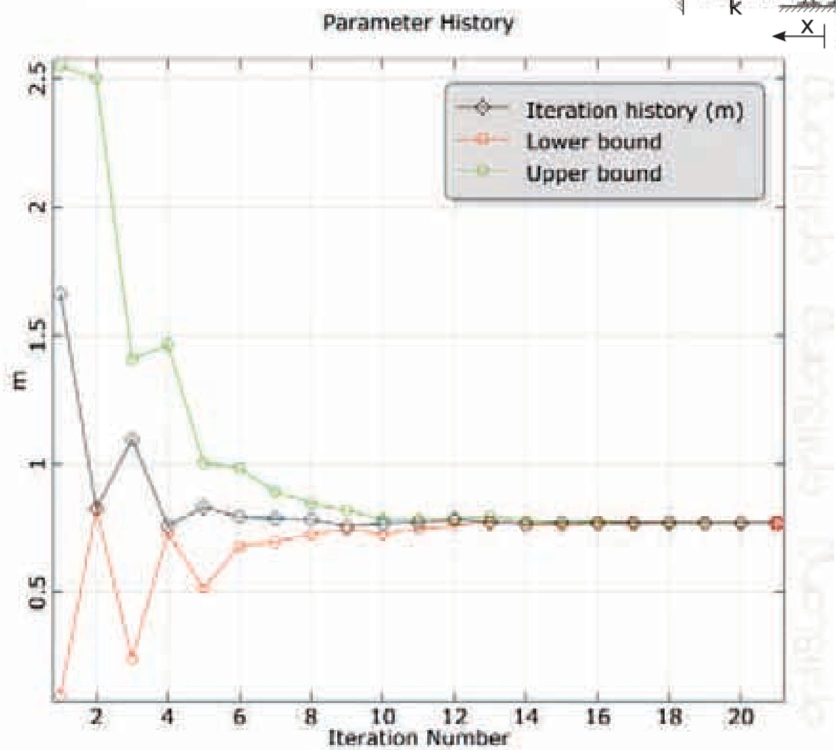
Adaptive Response Surface Methods (Local)



Local ARSM with linear polynomial







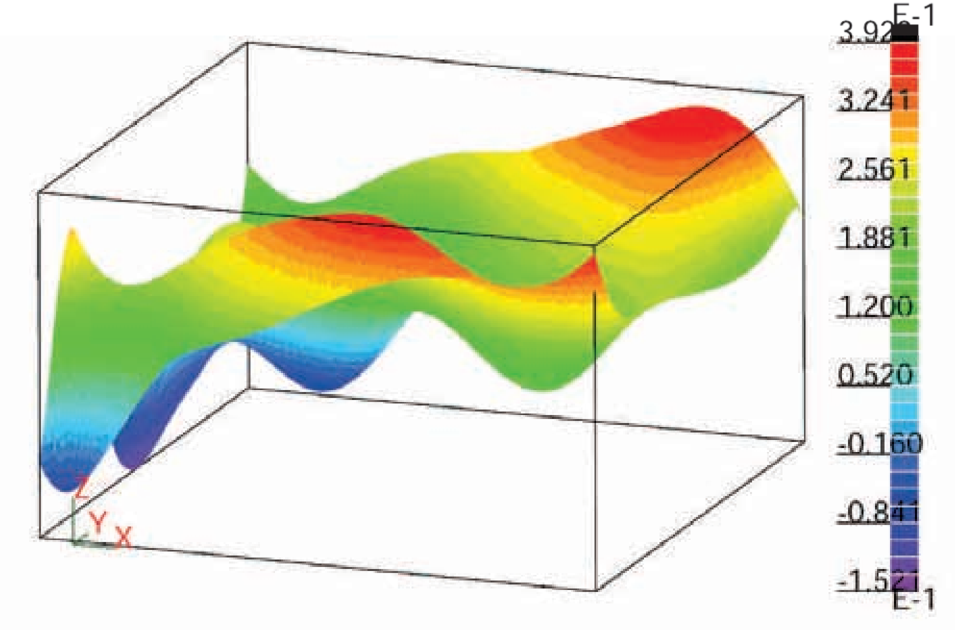
- ARSM (local) with linear D-optimal design
- Good convergence for noisy objective function
- 105 solver calls

$$m_{opt} = 0.77 \text{ kg}$$
$$k_{opt} = 49.3 \text{ N/m}$$
$$\omega_{opt} = 7.99 \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.25 \text{ m}$$

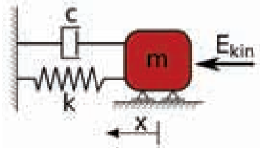
Adaptive Response Surface Method (Global)

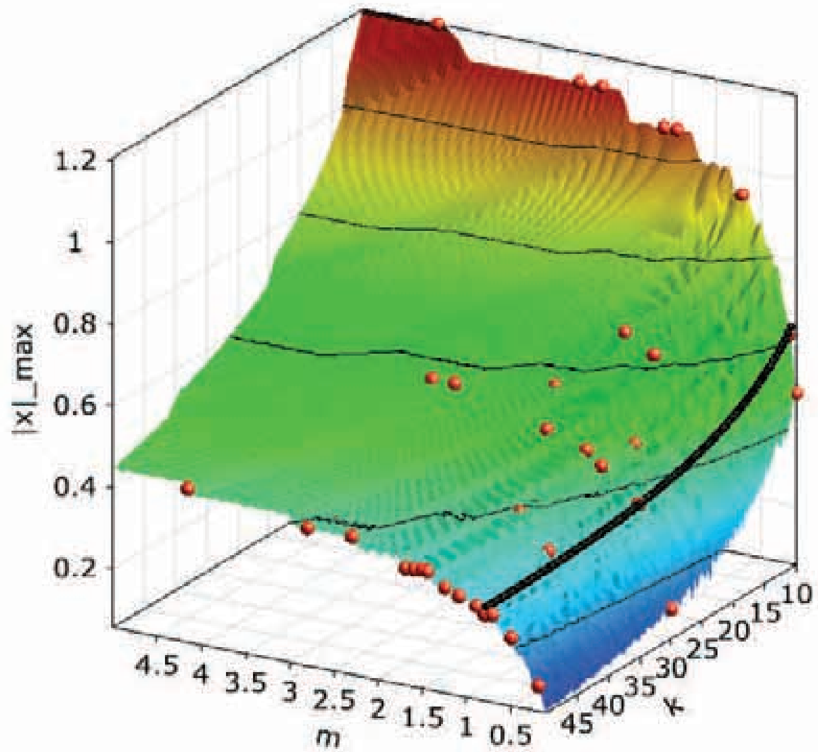
- Global Moving least square approximation
- Interpolation can be forced by regularized weighting function
- Adaptive DOE with reuse of all calculated designs

- Better approximation of local effects than polynomial functions
- Global optimization on approximation function



Global ARSM with Moving Least Squares



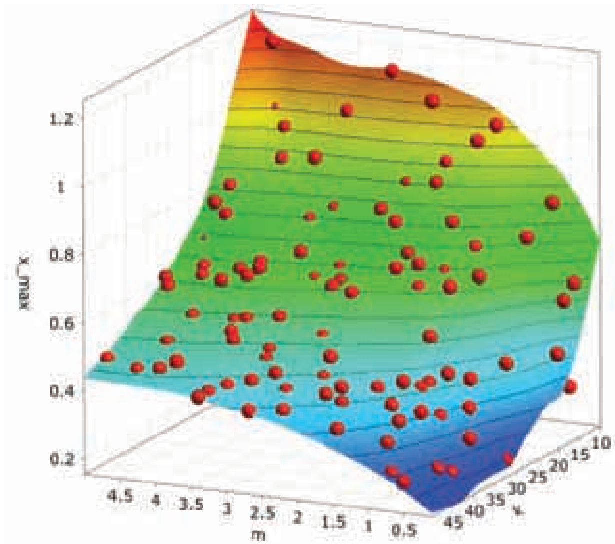


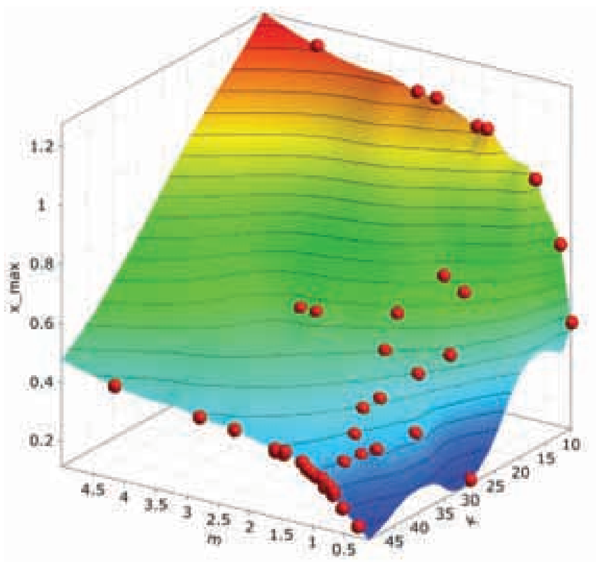
- ARSM (global) with linear D-optimal and interpolating MLS
- 62 solver calls, mainly in important region of design space

$$m_{opt} = 0.78\ \text{kg}, \qquad k_{opt} = 49.5\ \text{N/m}$$
$$\omega_{opt} = 7.99\ 1/\text{s}, \quad |x|_{max}^{opt} = 0.25\ \text{m}$$

Response Surface Methodology

- Based on design of experiment (DOE)
- Global polynomial response surface approximation are effective for a small amount of variables $k \leq 5$, but not very accurate
- MOP gives sufficient results if CoP is high enough
- Adaptive (local) response surfaces are effective for a medium amount of variables $k \leq 15$, but only result in local approximation
- Adaptive (global) response surfaces (moving least square) stay global and localize at the same time. They may be still effective for medium amount of variables $k \leq 10$ .. 20

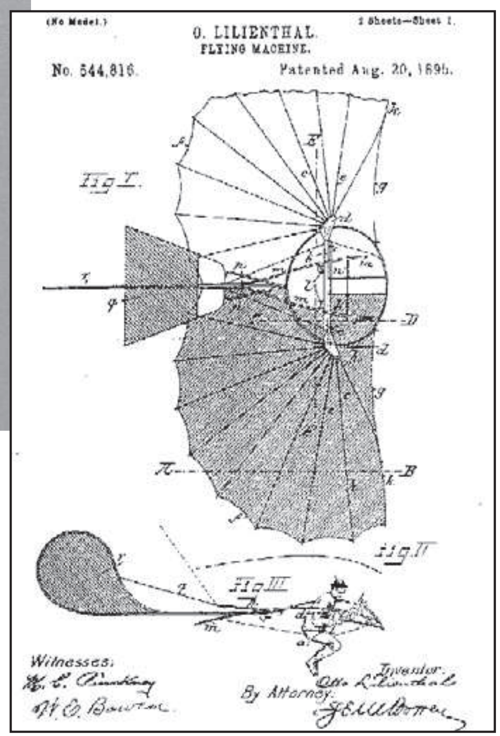




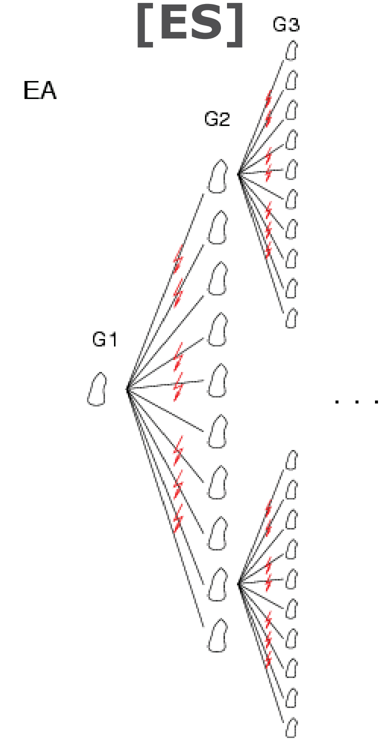
Evolutionary Algorithms (EA)

Imitates Evolution ("Optimization") in Nature:

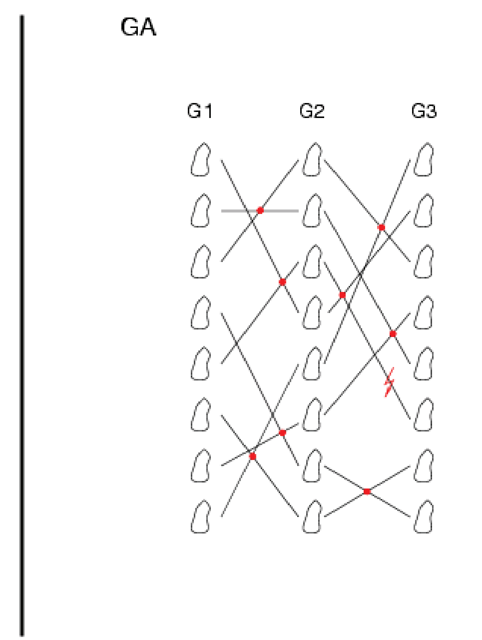
- Survival of the fittest
- Evolution due to mutation, recombination and selection
- Developed for optimization problems where no gradient information is available, like binary or discrete search spaces



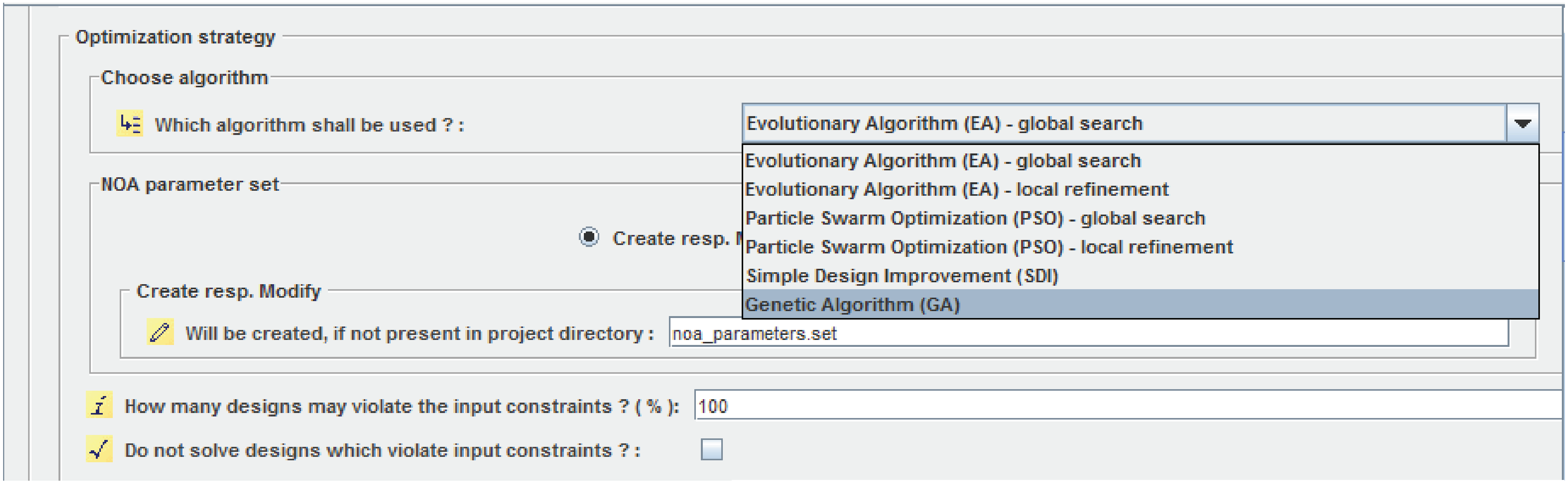
Evolution Strategies [ES]



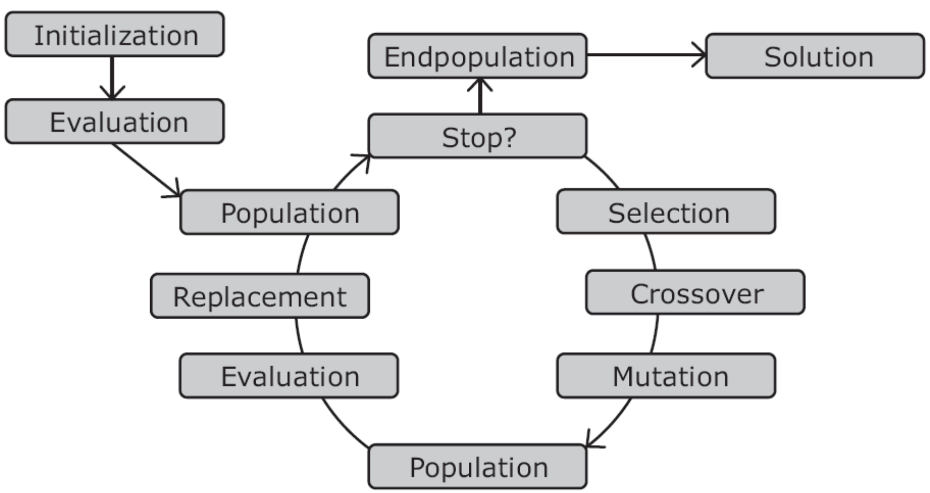
Genetic Algorithms [GA]



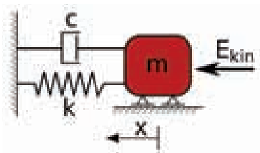
Toolbox for Natural inspired Optimization

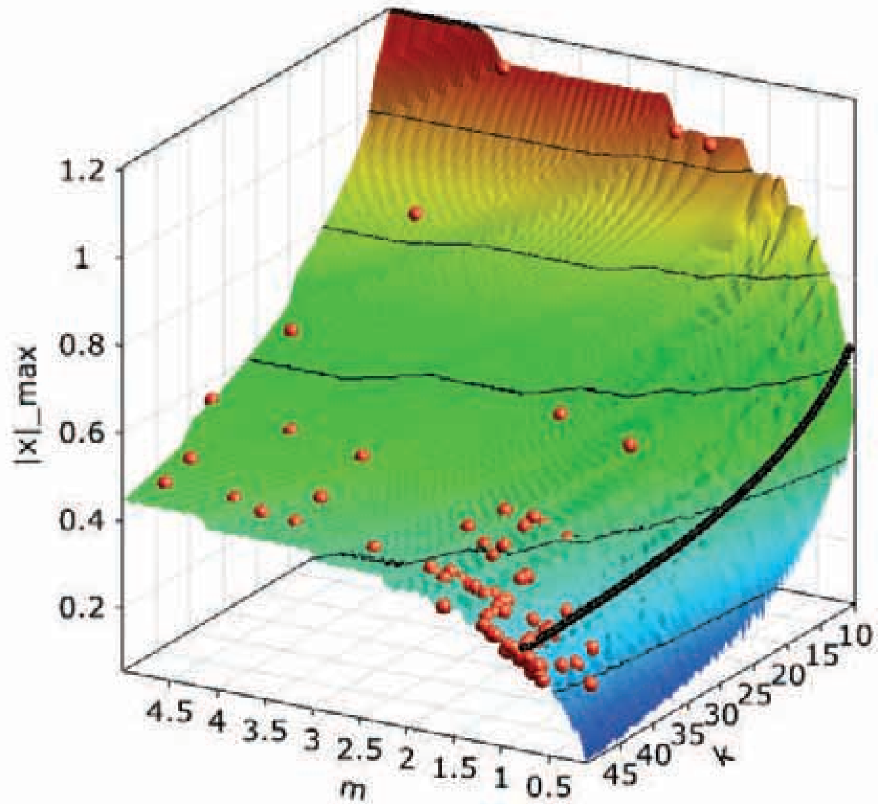


- Global and local search for EA
- Global and local search for PSO
- Simple design improvement (loc search)
- Genetic algorithm (global searcl adaptive mutation to reduce number of infeasible designs)



Genetic algorithm

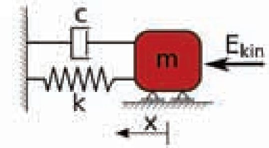


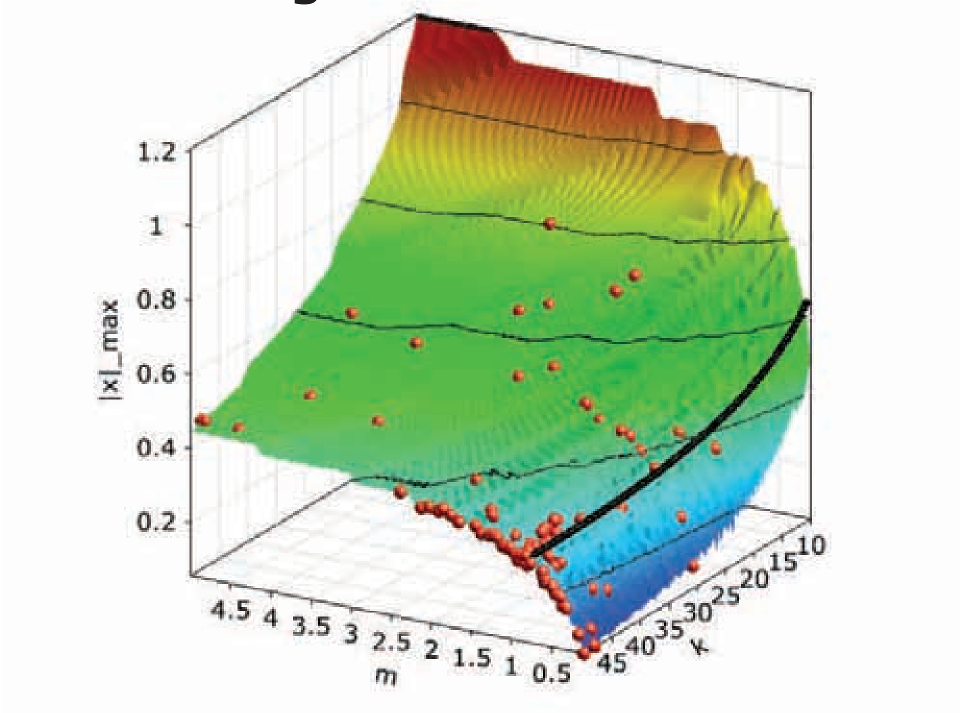


- 99 solver calls

$$m_{opt} = 0.81 \text{ kg}, \qquad k_{opt} = 49.8 \text{ N/m}$$
$$\omega_{opt} = 7.86 \text{ 1/s}, \quad |x|_{max}^{opt} = 0.26 \text{ m}$$

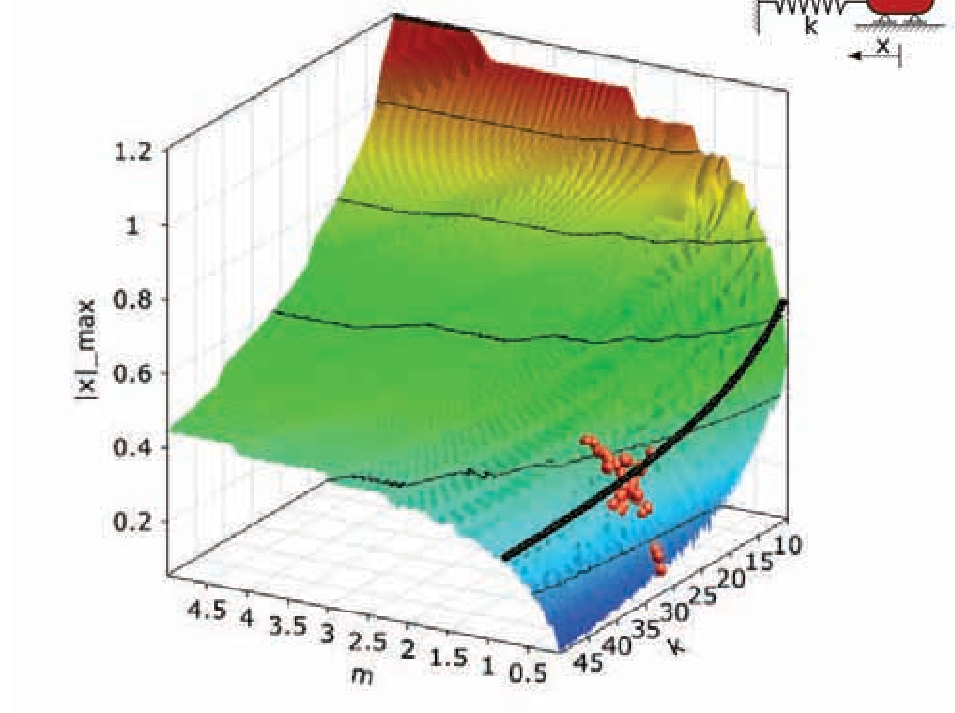
EA with global and local search





Global search (102 solver calls)

$$m_{opt} = 0.81 \text{ kg}$$
$$k_{opt} = 50.0 \text{ N/m}$$
$$\omega_{opt} = 7.88 \text{ 1/s}$$
$$|x|_{max}^{opt} = 0.26 \text{ m}$$



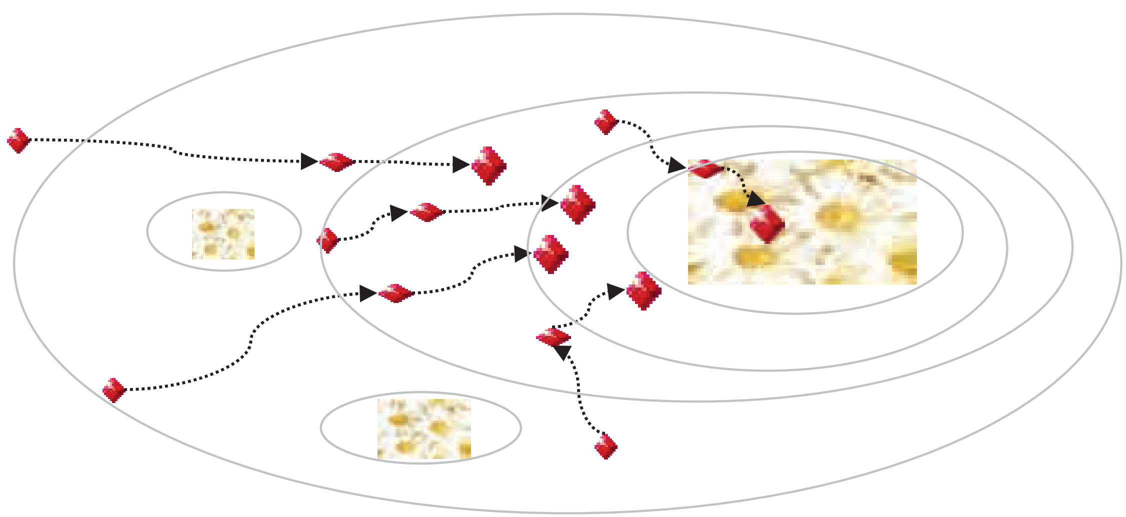
Local search (51 solver calls)

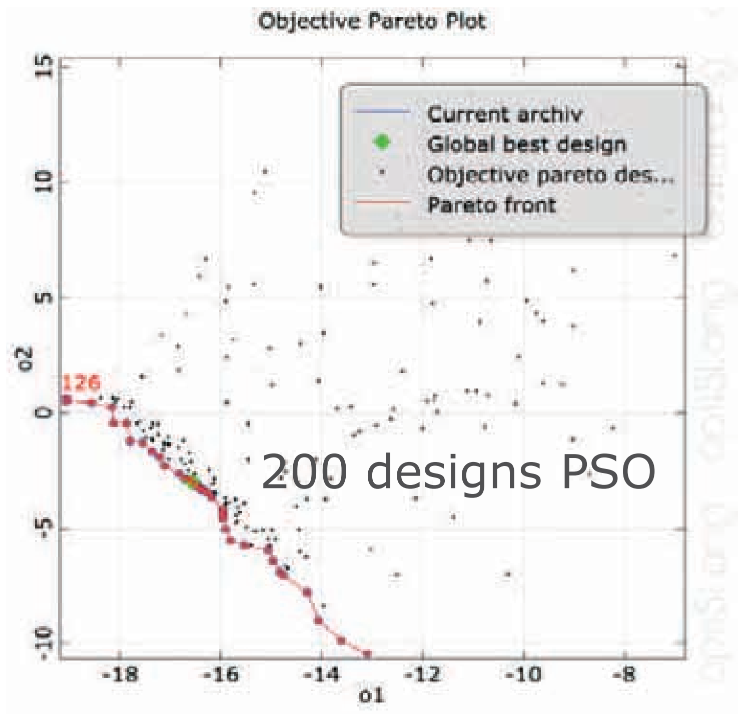
$$m_{opt} = 0.51 \text{ kg}$$
$$k_{opt} = 32.4 \text{ N/m}$$
$$\omega_{opt} = 7.99 \text{ 1/s}$$
$$|x|_{max}^{opt} = 0.31 \text{ m}$$

Particle Swarm Optimization (PSO)

- swarm intelligence based biological algorithm
- imitates the social behaviour of a bees swarm searching for food

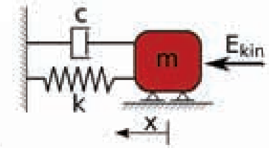
- **Selection** of swarm leader including archive strategy
- **Adaption of** fly direction
- **Mutation of** new position
- Available for **single/multi objective Optimization**

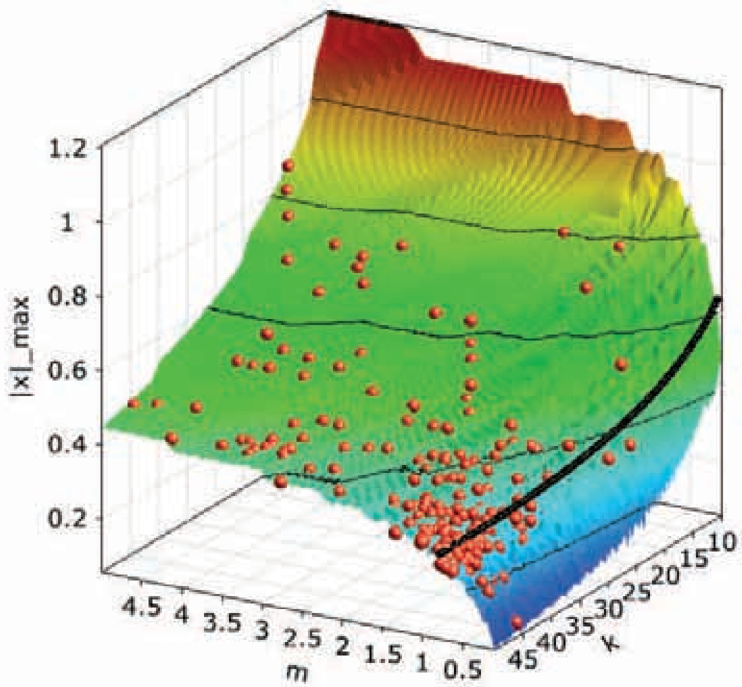




dynardo

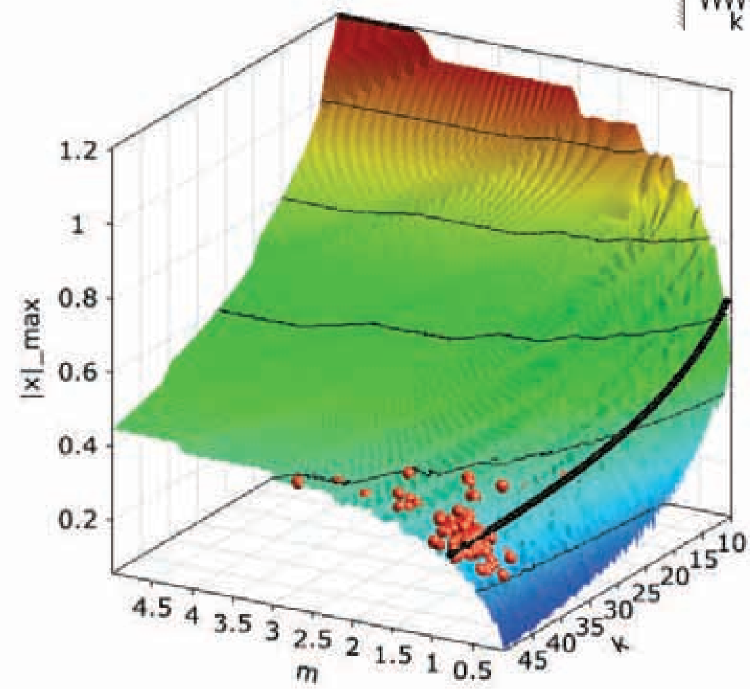
PSO with global and local search





PSO global (220 solver calls)

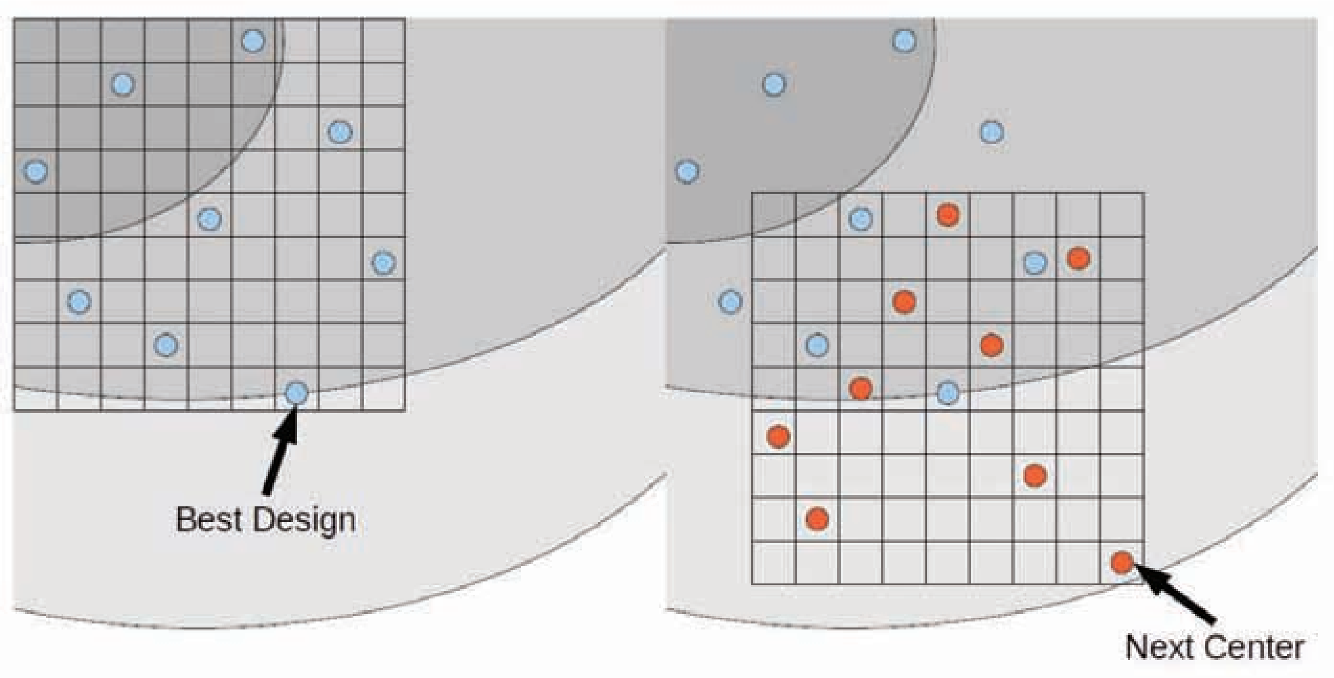
$$m_{opt} = 0.72 \text{ kg}$$
$$k_{opt} = 46.0 \text{ N/m}$$
$$\omega_{opt} = 8.00 \text{ 1/s}$$
$$|x|_{max}^{opt} = 0.262 \text{ m}$$



PSO local (198 solver calls)

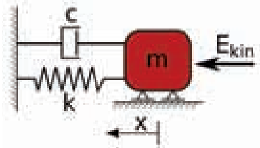
$$m_{opt} = 0.73 \text{ kg}$$
$$k_{opt} = 46.9 \text{ N/m}$$
$$\omega_{opt} = 7.99 \text{ 1/s}$$
$$|x|_{max}^{opt} = 0.258 \text{ m}$$

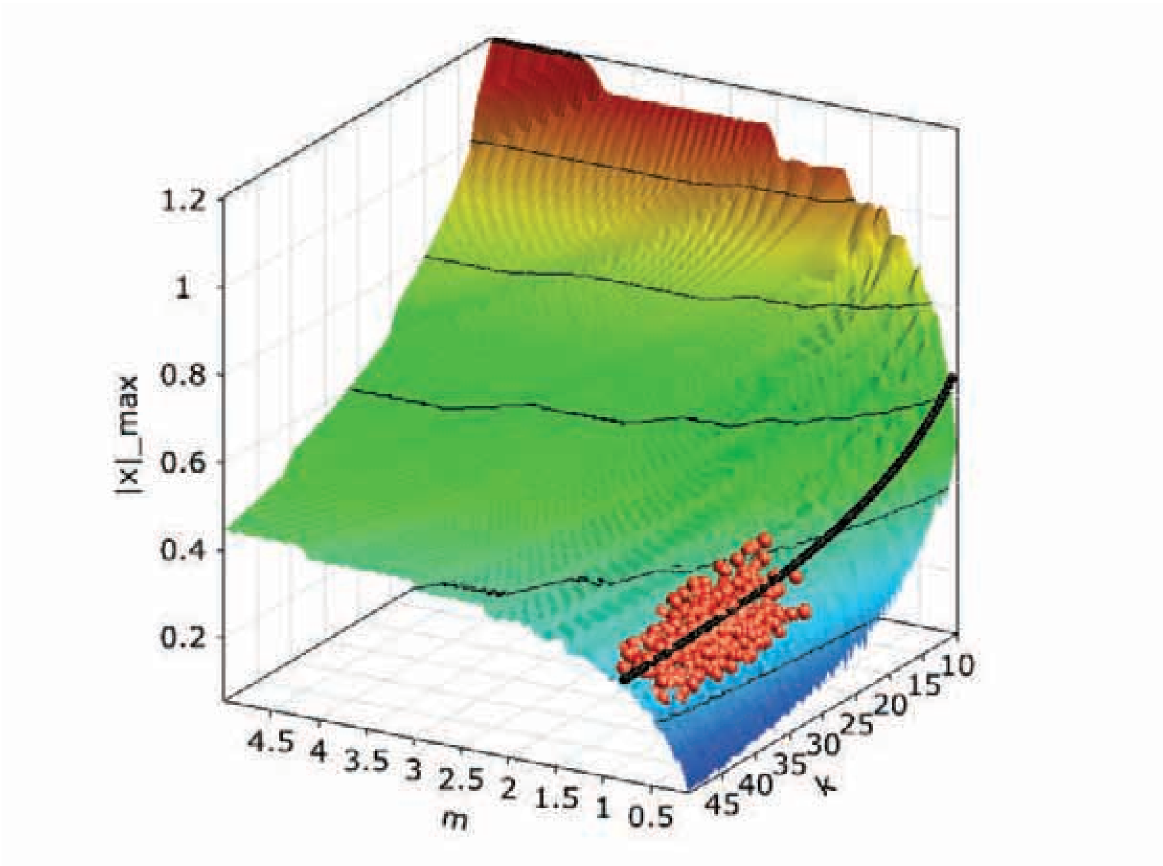
Simple Design Improvement



- Improves a proposed design without extensive knowledge about interactions in design space
- Start population by uniform LHS around given start design
- The best design is selected as center for the next sampling
- The sampling ranges decrease with every generation

Simple Design Improvement



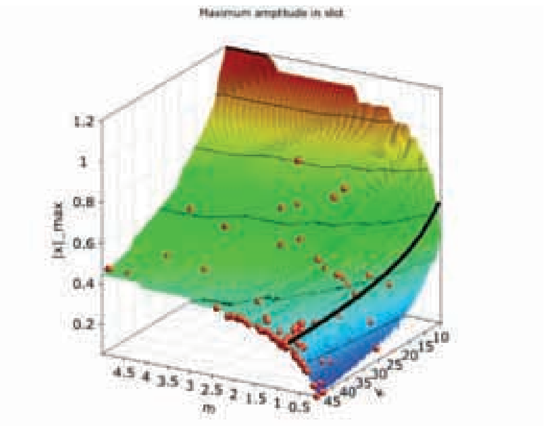


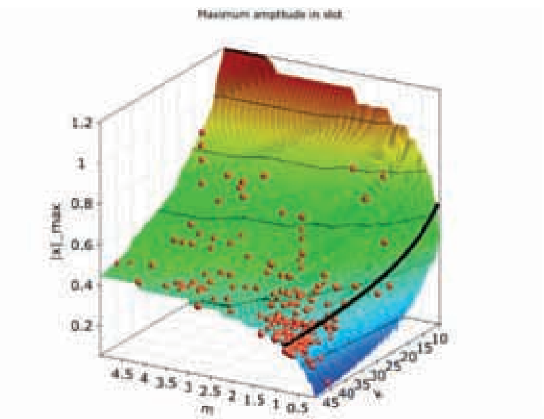
- 318 solver calls

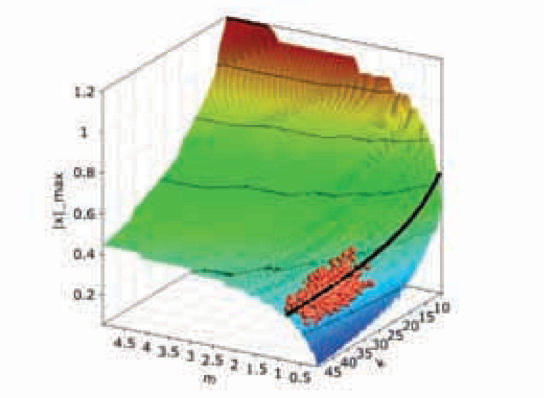
$$m_{opt} = 0.70 \text{ kg}, \qquad k_{opt} = 44.9 \text{ N/m}$$
$$\omega_{opt} = 8.00 \text{ 1/s}, \quad |x|^{opt}_{max} = 0.26 \text{ m}$$

Nature inspired Optimization

- Evolutionary algorithm
  - Suitable for global and local search
  - Search for new designs and evolutionary improvement of designs
- Genetic algorithm
  - Search for new designs
  - Search for feasible design islands with additional local optimization (e.g. NLPQL)
- Particle swarm optimization
  - Suitable for global and local search
  - Risk of local optimum is higher as with EA
  - Local convergence closer to optimum
- Simple design improvement
  - Very robust but low efficiency
  - Not developed to find optimal design

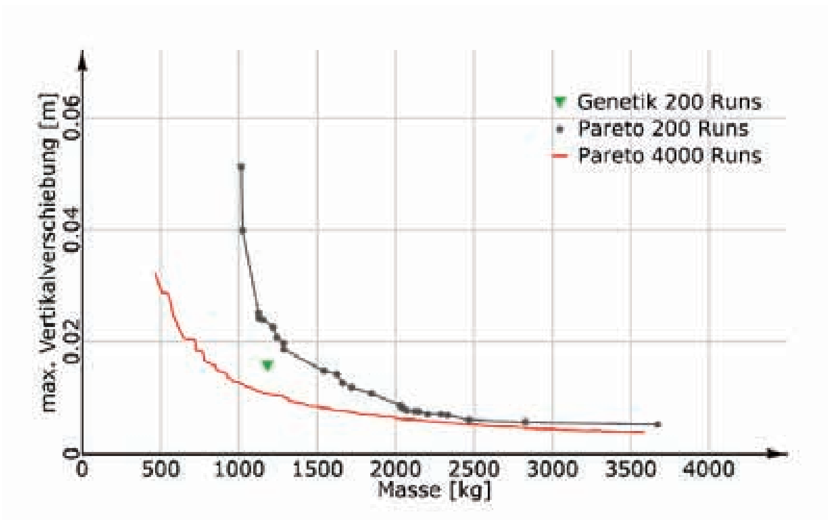


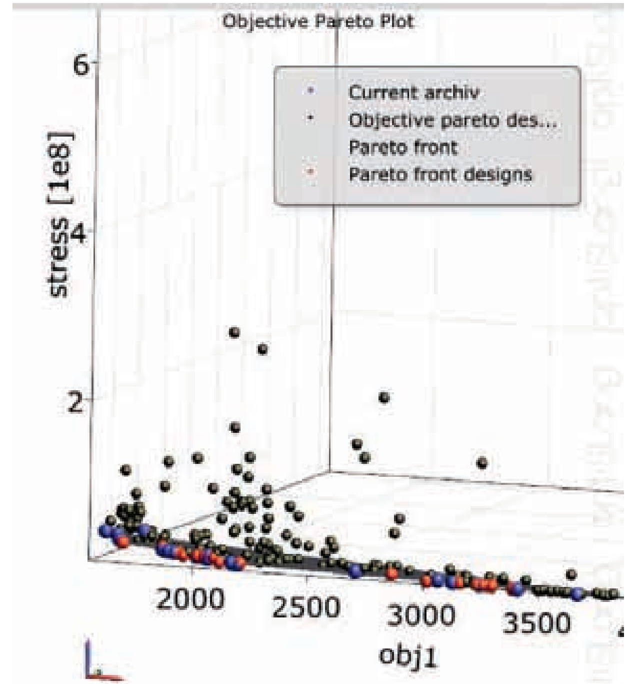




Multi Criteria Optimization Strategies

Pareto Optimization using Evolutionary Algorithms (SPEA2)





- Only in case of conflicting objectives, a Pareto frontier exists and Pareto optimization is recommended (optiSLang post processing supports 2 or 3 conflicting objectives)
- Effort to resolute Pareto frontier is higher than to optimize one weighted optimization function

Gradient-based algorithms

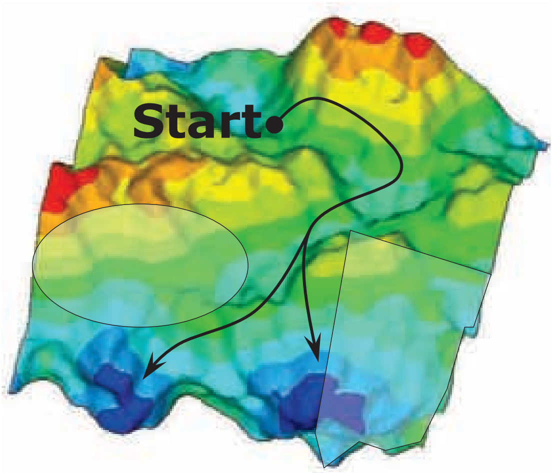
- Most efficient method if gradients are accurate enough
- Consider its restrictions like local optima, only continuous variables and no solver noise

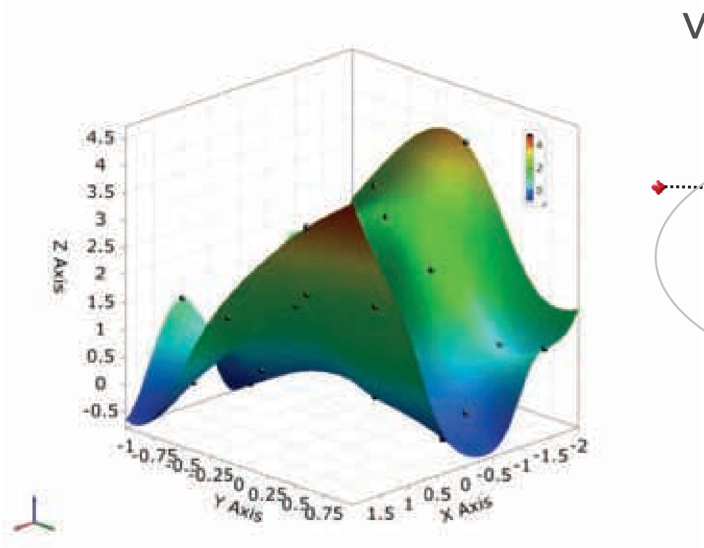
Response surface method

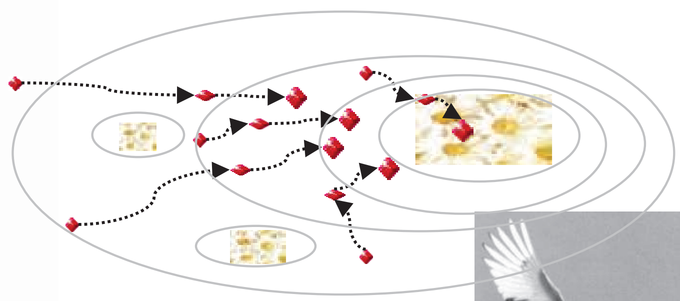
- MOP allows a fast check for design improvement
- Adaptive RSM is the method of choice for a small set of continuous variables (<15)

Natural inspired Optimization

- GA/ES/PS copy mechanisms of nature to improve individuals
- Method of choice for Pareto Optimization Tasks
- Very robust against numerical noise, non-linearities, number of variables,…



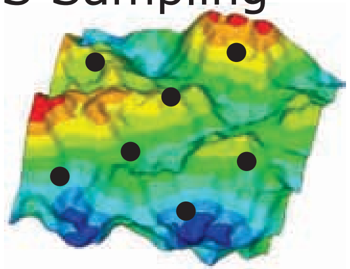




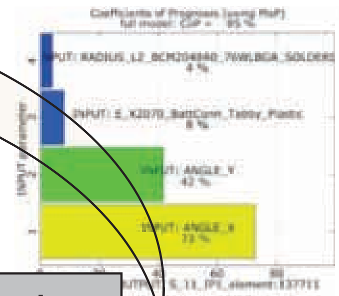
When to use which algorithm?

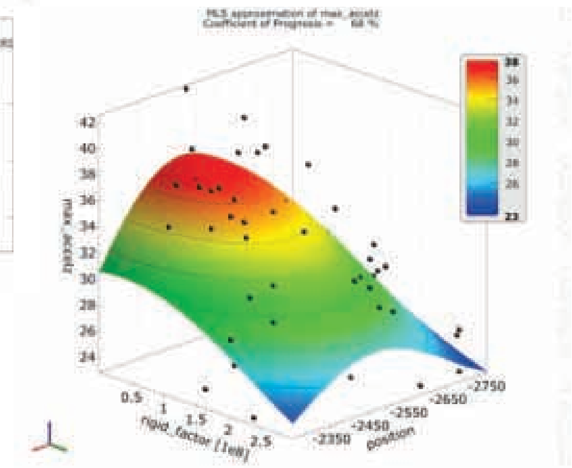
Sensitivity Analysis and Optimization

1) Start with a sensitivity study using the LHS Sampling



2) Identify the important parameters and responses using meta model technique
- understand the problem
- reduce the problem

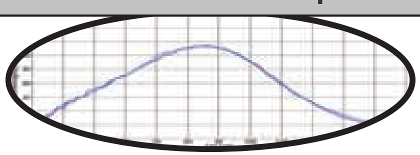




Scan the whole Design Space

Understand the Problem using CoP/MoP

Search for Optima



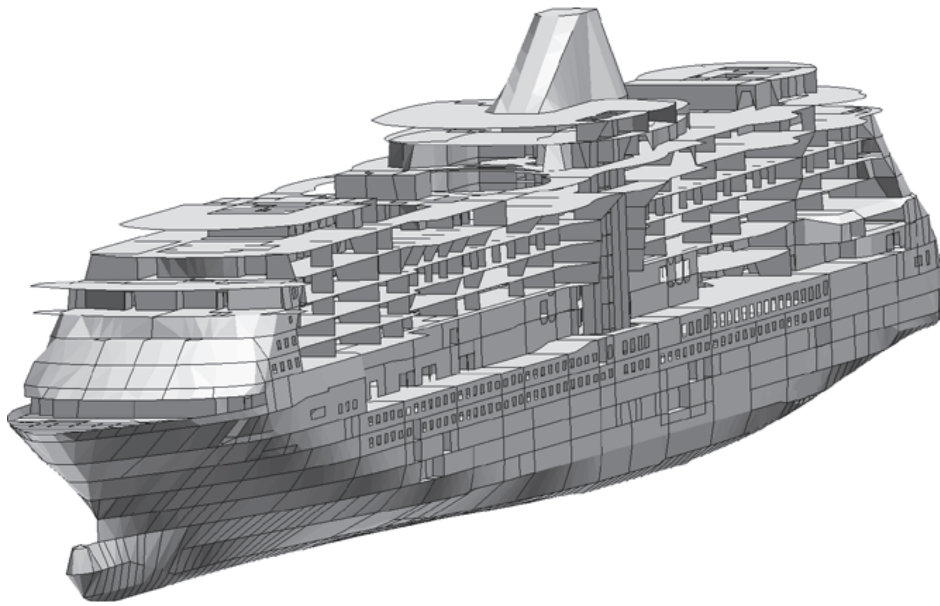
3) Run gradient based or biological based optimization algorithms at optimal meta model (MOP)

4) Run an ARSM, gradient based or biological based optimization algorithms with additional solver runs

Optimization of a Large Ship Vessel

EVOLUTIONARY ALGORITHM

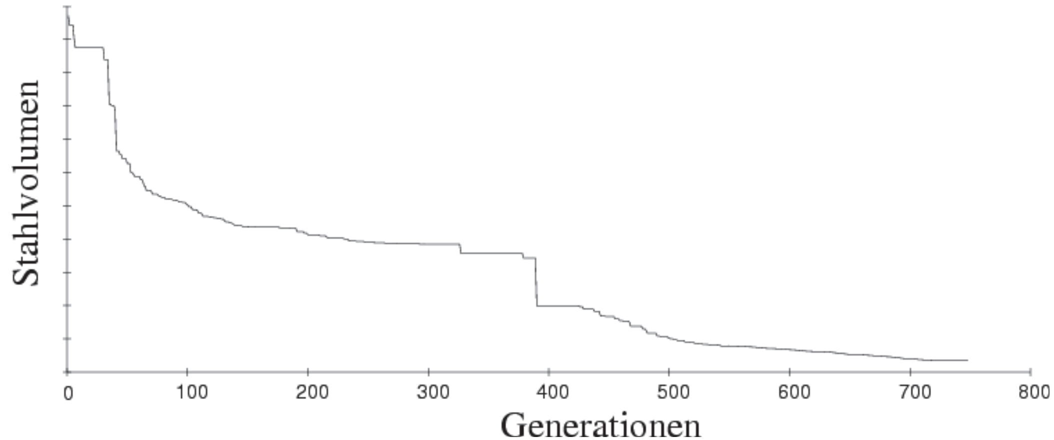
- Optimization of the total weight of two load cases with constrains (stresses)
- **30.000** discrete Variables
- Self regulating evolutionary strategy
- Population of 4, uniform crossover for reproduction
- Active search for dominant genes with different mutation rates



Solver: ANSYS

Design Evaluations: 3000

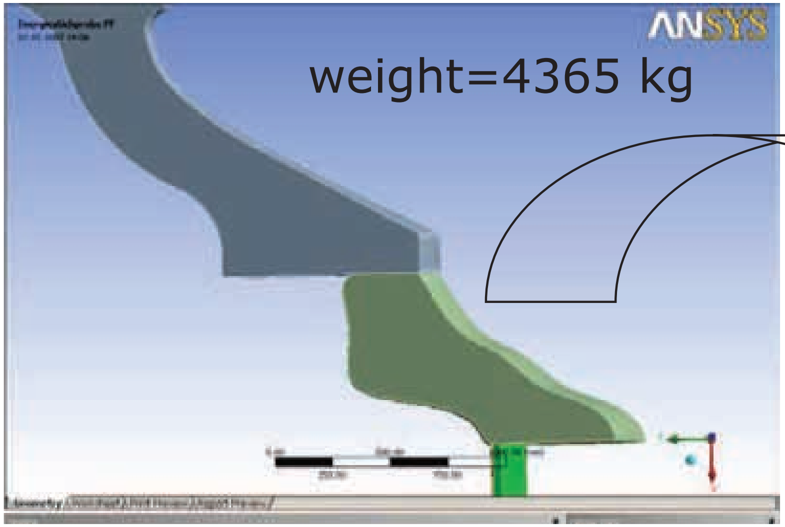
Design Improvement: > 10 % 0



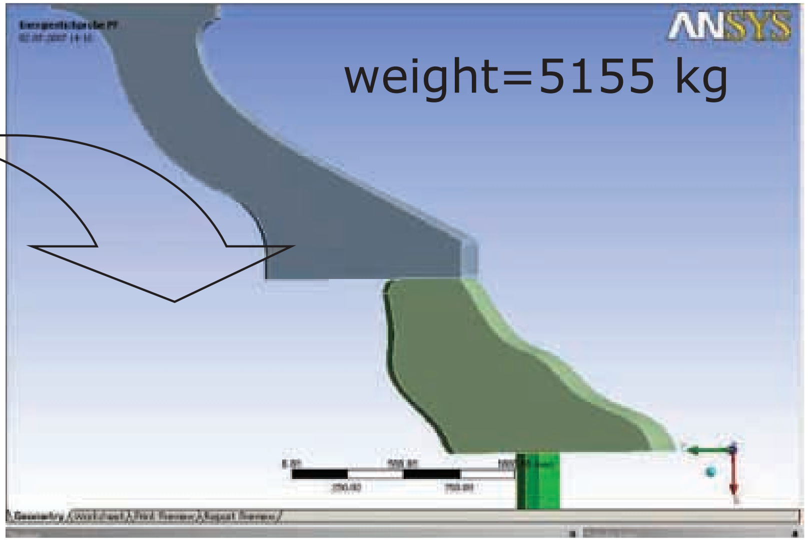
Riedel, J.: Gewichtsoptimierung eines Passagierschiffes, Bauhaus Universität Weimar, Institutskolloquium, 2000, Germany, www.dynardo.de]

Optimization of see hammer

Dynamic performance optimization under weight and stress constraints using 30 CAD-parameter. With the help of sensitivity study and optimization (ARSM), the performance of a deep sea hammer for different pile diameters was optimized.



Initial Design valid for
two pile diameter



Optimized design valid for
four pile diameter

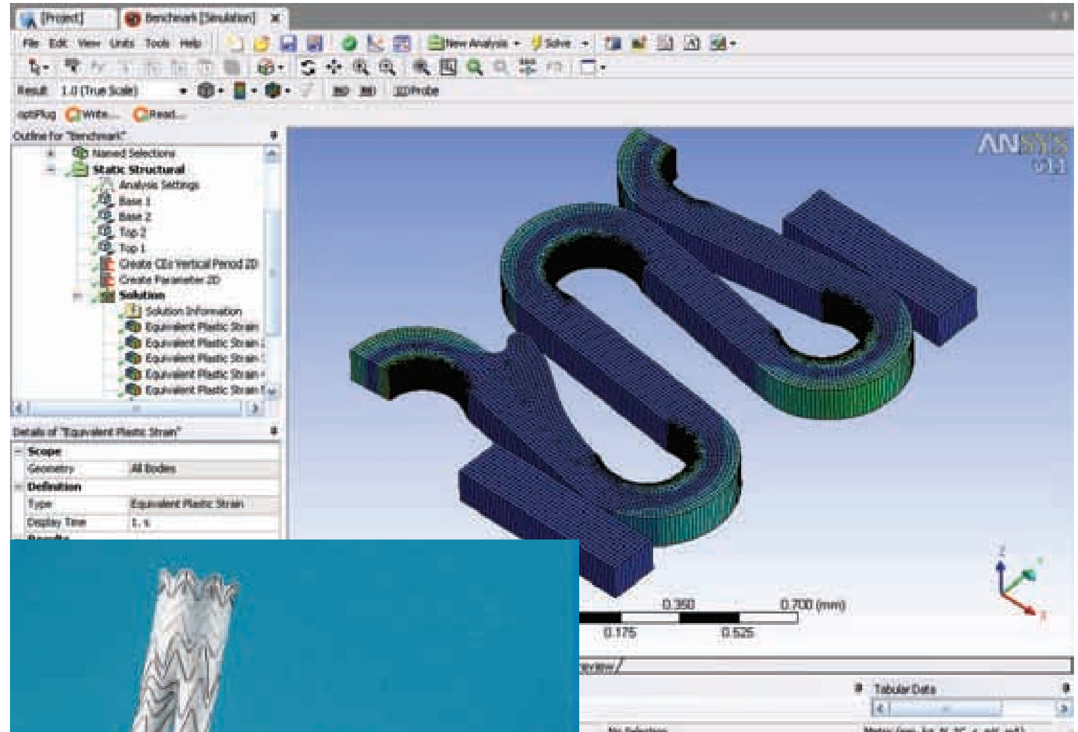
Design Evaluations: 200 times 4 loadcase
CAE: ANSYS workbench
CAD: ProEngineer

Optimization of a stant

Performance optimization under geometry constrains constraints using 15 CAD-parameter. With the help of sensitivity study and optimization (ARSM), the performance was optimized.

- Step wise approach to generate a successful design space for optimization

Design Evaluations:
Process chain: Solid Edge – ANSYS – optiSLang



by courtesy of

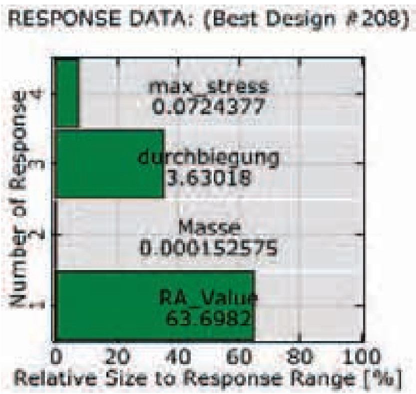
CORTRONIK

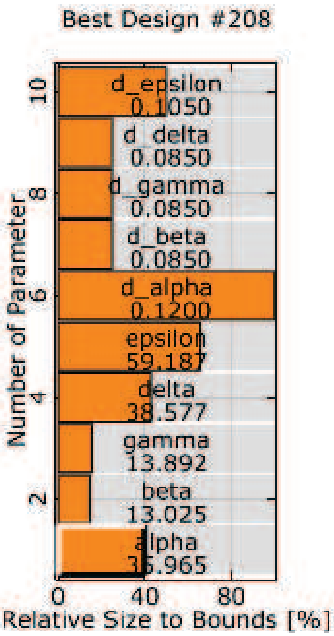
Optimization of Tennis Racket

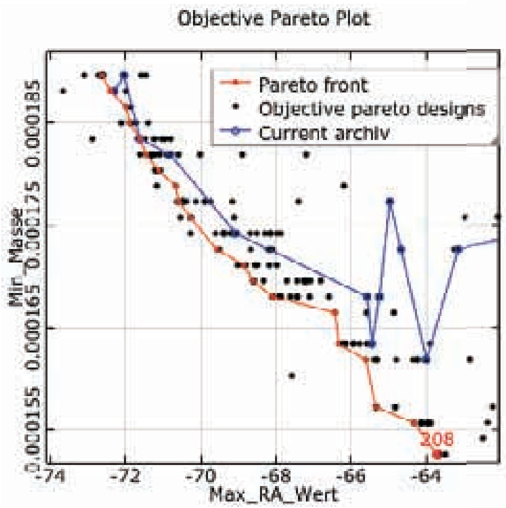
The challenge in tennis racket optimization is to find a optimal design of the composite structure.

Consideration of production constrains of multiple composite layer orientation and thickness lead to a discrete optimization task with conflicting goals of mass and stiffness (playability).

Therefore optiSLang Pareto optimization using Evolutionary Algorithms was used.





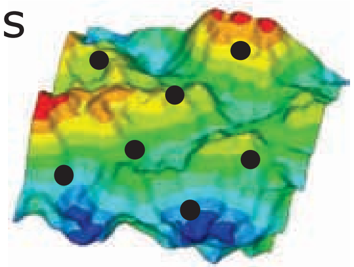


Design Parameter ≥10
Design Evaluations: 200
CAE: ANSYS Workbench

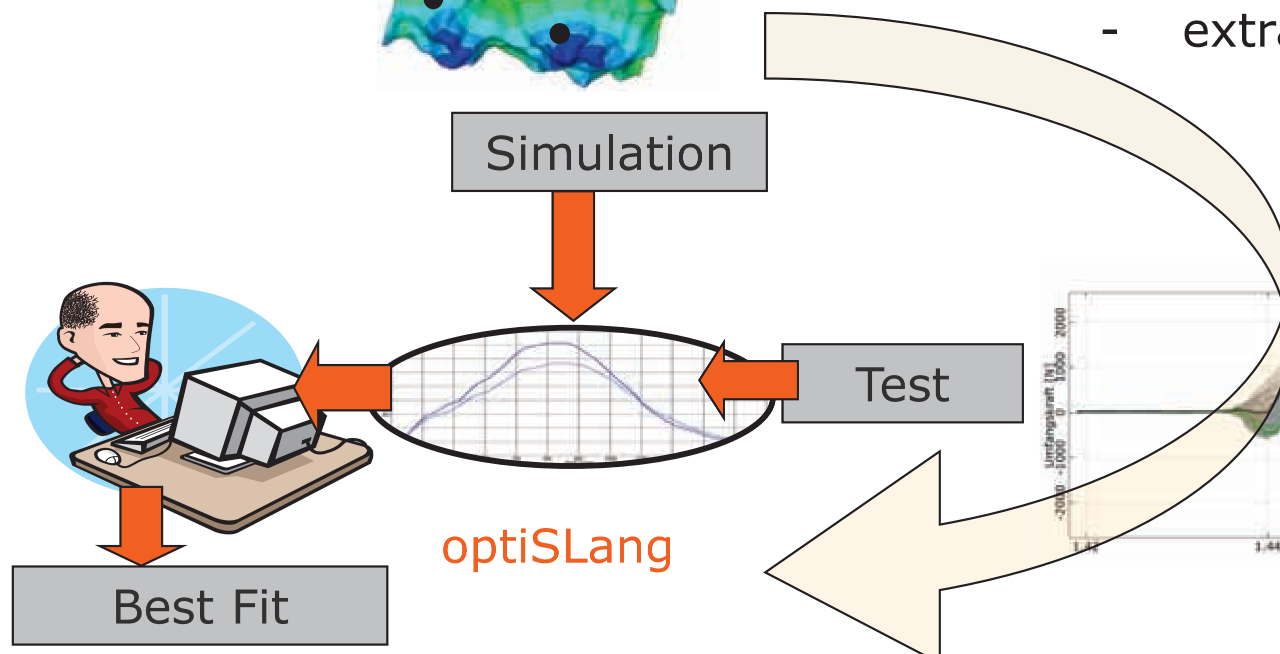
Parameter Update and System Identification

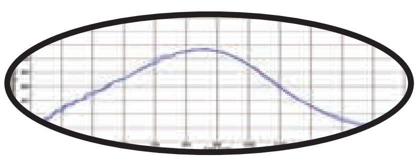
Calibration using optiSLang

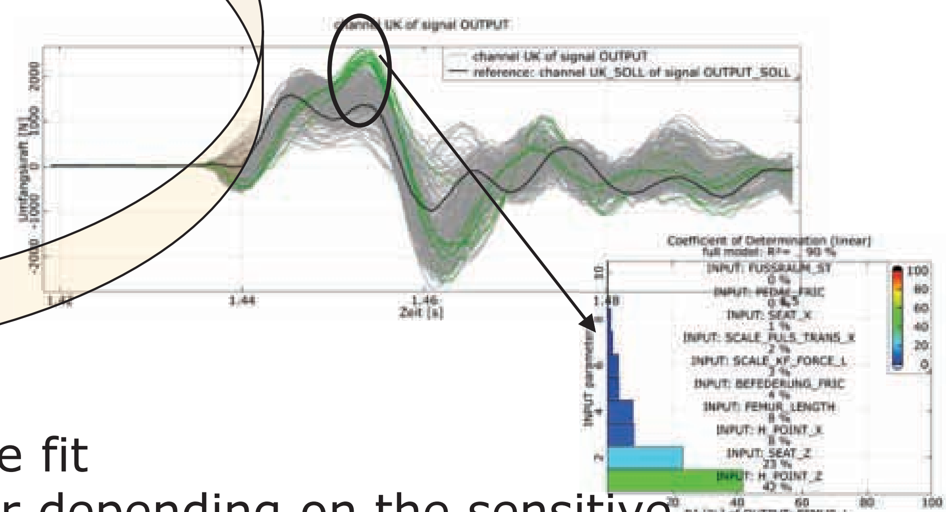
1) Define the Design space using continuous or discrete optimization variables



2) Scan the Design Space
- Check the variation
- Identify sensible parameters and responses
- Check parameter bounds
- extract start value

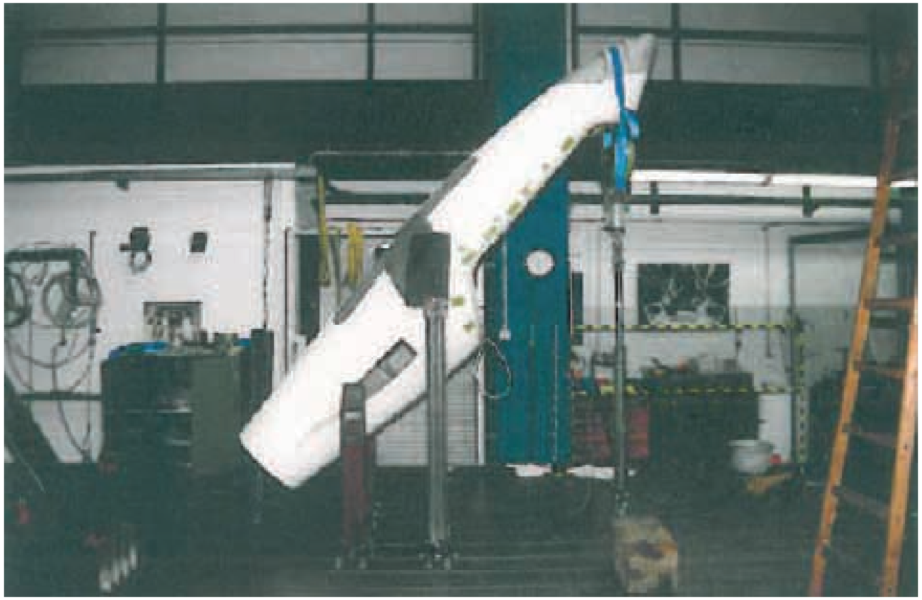






3) Find the best possible fit
- choose an optimizer depending on the sensitive optimization parameter dimension/type

Calibration and Optimization of carbon fiber airplane cockpit body using ANSYS and optiSLang

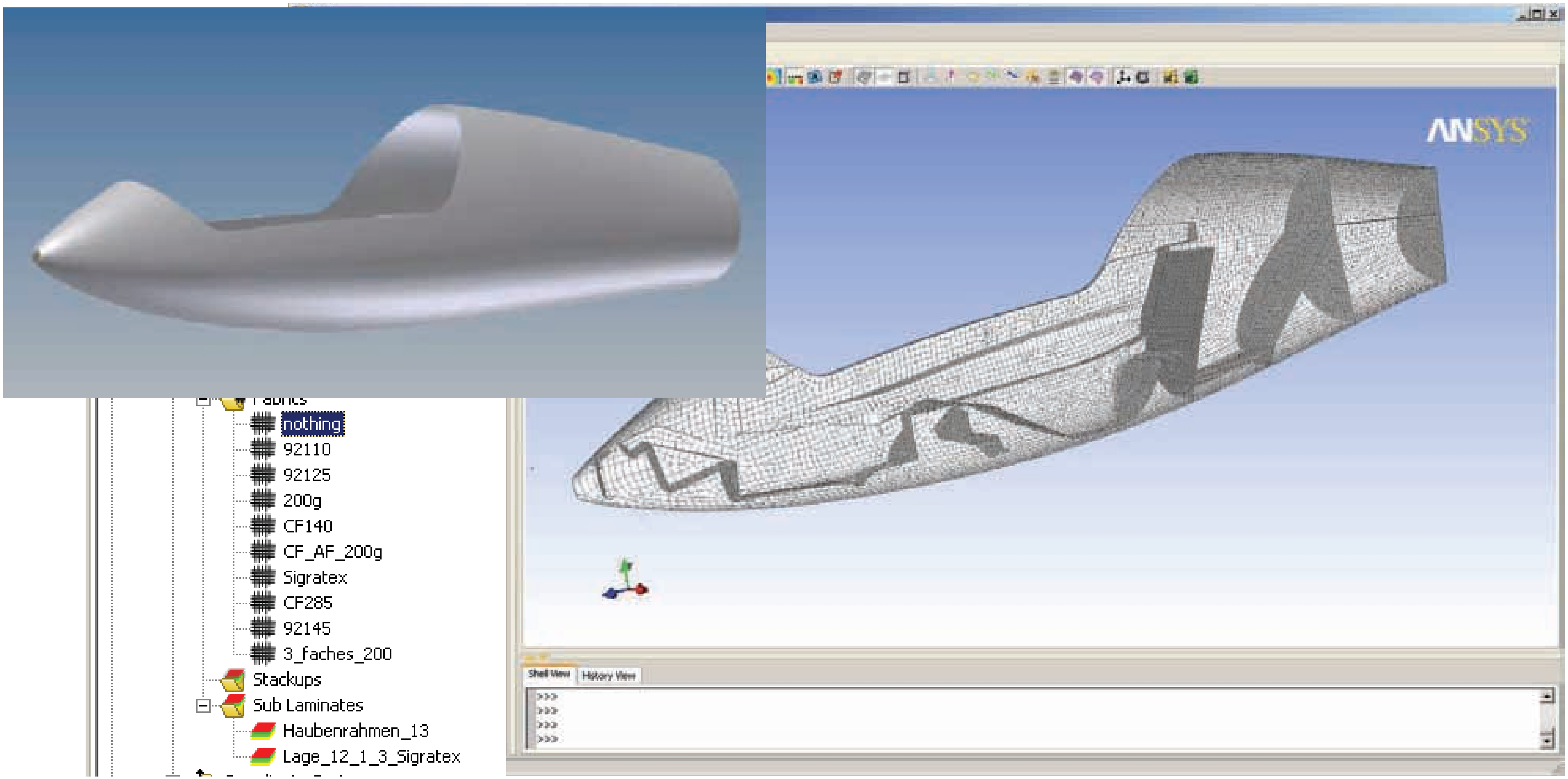


Body was tested regarding crash performance (German TÜV)

1. Calibration of test results

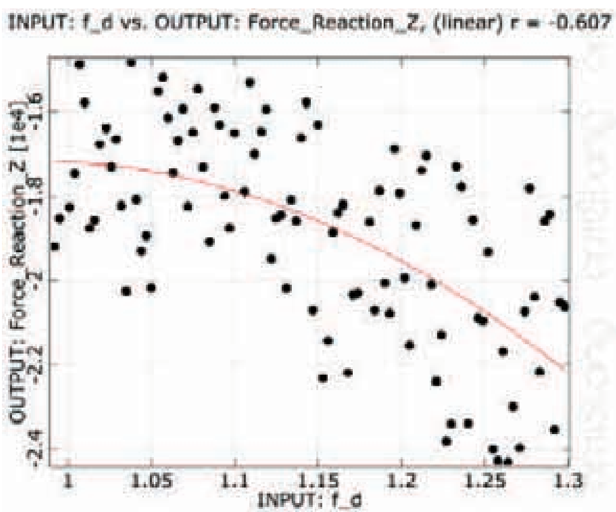
2. Optimization of Crash performance of the airplane cockpit carbon fiber body to withstand the next higher crash loading class

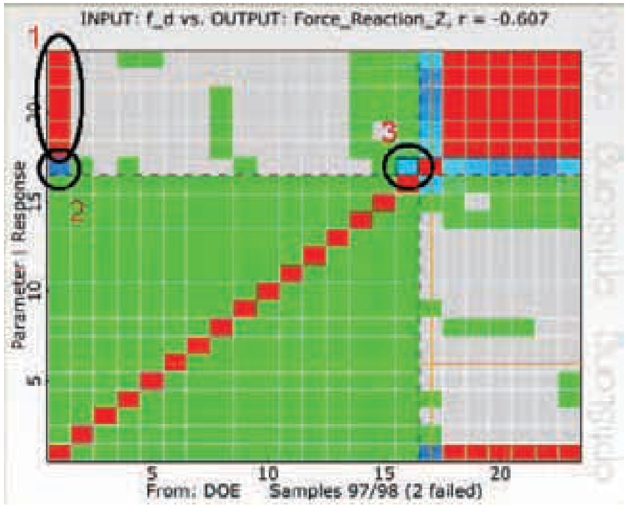
Parametrization of carbon body using ANSYS ACP



- geometric modeling using ANSYS WB
- carbon fiber material definition (stiffness/strength/damage) using ANSYS Composit Modeller (ACP)

Calibration of test results





Via sensitivity study the important model parameter are identified, via Evolutionary optimization the test is calibrated:

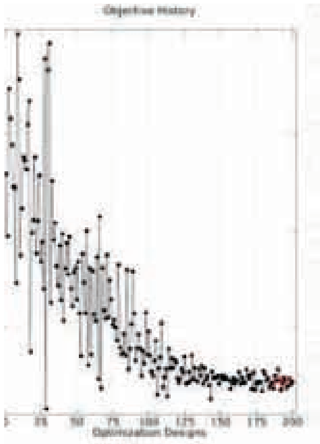
- very good fit of test results!
- identified model is qualified for optimization
- the safety margin of the calibrated model is large enough

identified fabric thickness factor 1.275 ! Fabric thickness (160g): 0.21mm → 0.267mm

Very good agreement between test and simulation

- delta deformation maximum 2-3mm

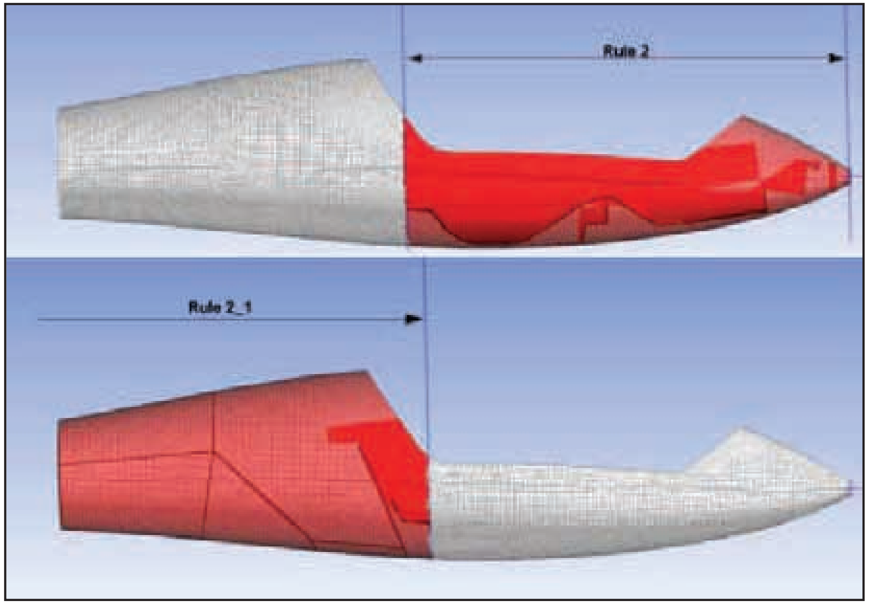
Optimization for higher crash loading

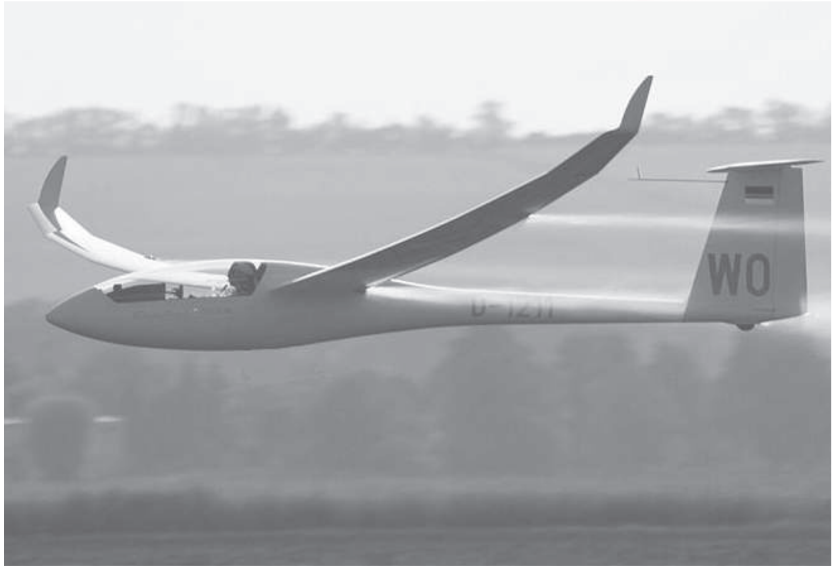


objective: minimum Mass
constraints: maximum load, no critical damage of structur (irf-values)

With optimization of position, orientation and thickness of important fabric layers the load could be improved by 50% having a mass increase 1.6% only!

For optimization evolutionary algorithms with Default Settings are used.





picture: Andreas Lutz, Bernd Weber
Schempp-Hirth Flugzeugbau

Part 7
Applications

Sensitivity of Passive Safety Systems

How Sensitive Is the CAE Model?

To protect occupants from the risk of serious injury in event of a side impact, passenger vehicles are designed to fulfil legislative and consumer impact test requirements.

Facing increasing competition in virtual product engineering using sensitivity analysis, optimization and robustness evaluation become necessary.

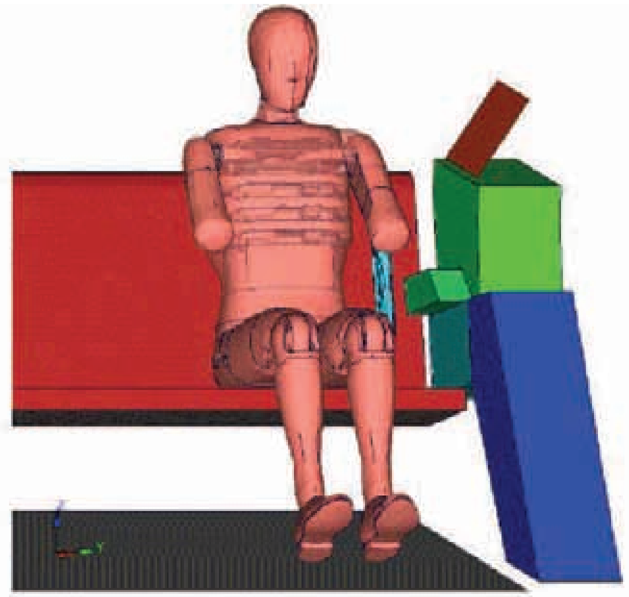


Figure 5. Sled model with EuroSID2

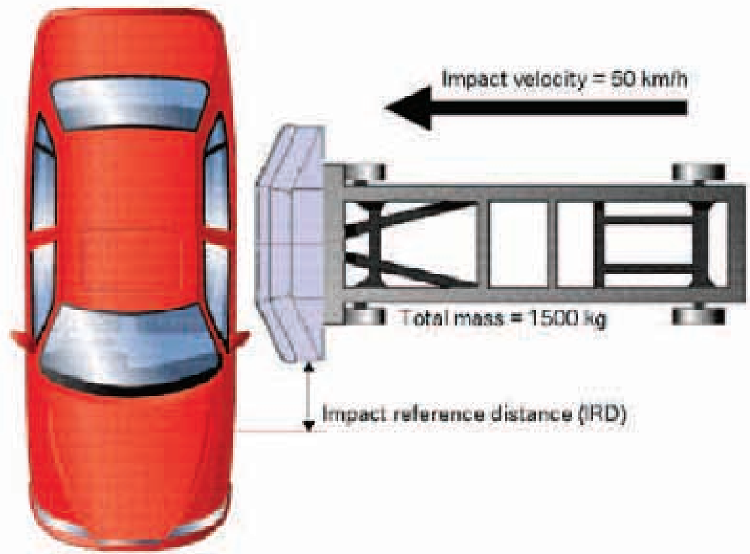


Figure 2. Side impact IIHS barrier schematic

by courtesy of BMW

Ionescu, V.; Wernicke, P.:Assessement of side impact simulation using ABAQUS/Explicit, Proceeding SAE Conference, 2006

Sensitivity of Passive Safety Systems

Which Design Variable Shows Importance?

In an early phase of the product development, a simplified model of the side crash resistance is used.

Sensitivity analysis, using the stochastic sampling procedure and statistical post processing, identifies the most important design variables and estimates the variation of responses.

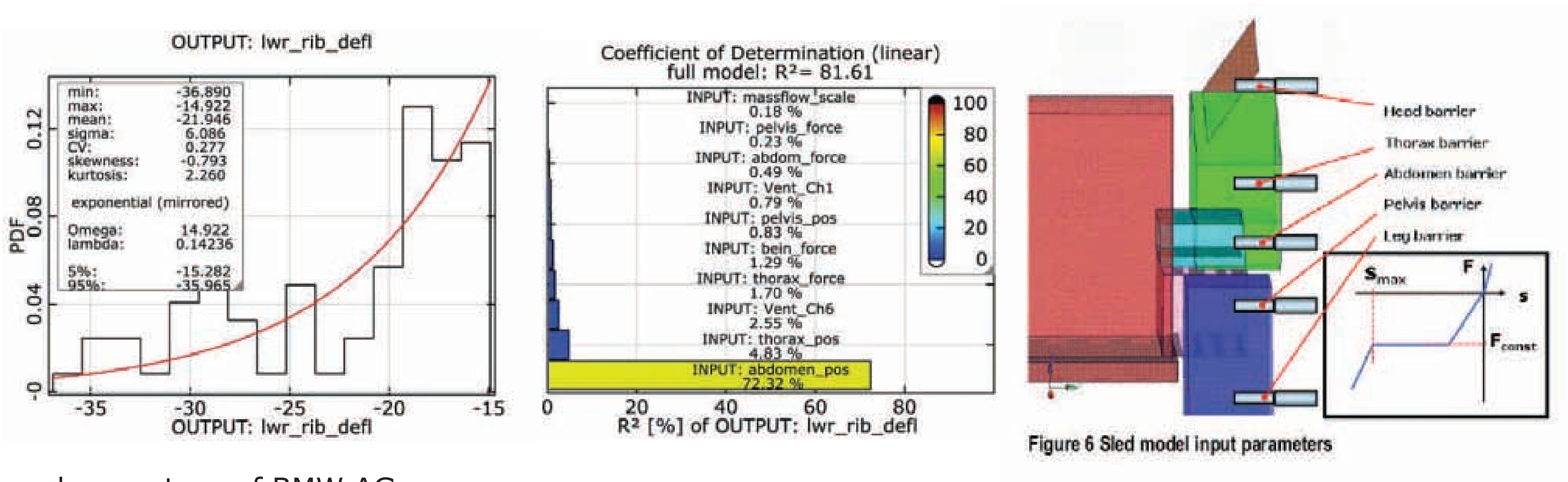


Figure 6 Sled model input parameters

by courtesy of BMW AG

Optimization of Passive Safety Systems

In small parameter dimensions ARSM is used for optimization:

- After understanding the sensitivities, an optimization task can be defined
- Adaptive Response Surface Methodology is used to optimize the subsystem
- Based on that information, further optimization on more detailed sled and side crash models will follow

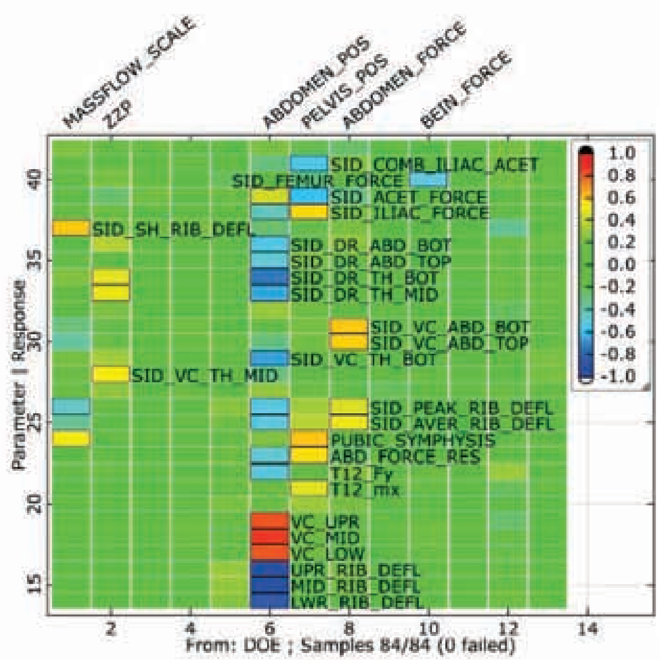
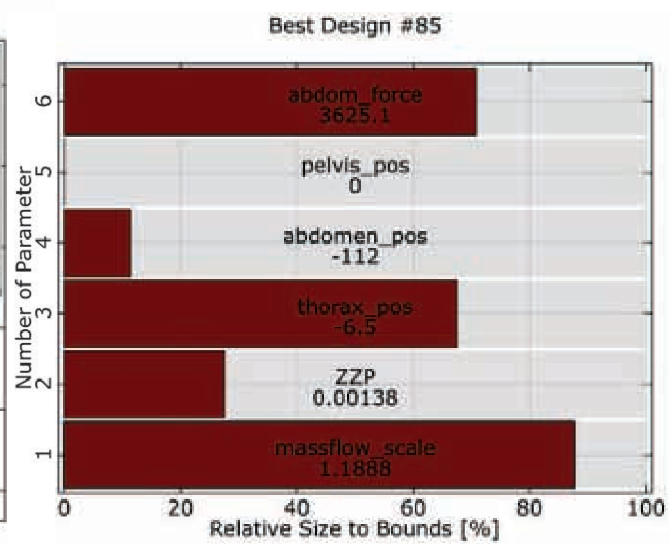
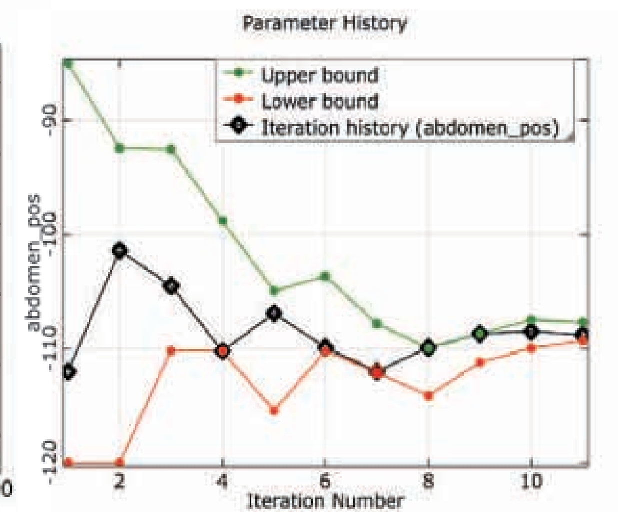


Figure 8. Linear correlation structure





Large Scale Multidisciplinary Optimization

Multidisciplinary Car Concept Optimization I

- **Objective:** weight reduction
- **Performance constraints:** stiffness constraints, eigenfrequency and eigenmode constraints, eigenfrequency distances, NHV constraints limiting acceleration and acoustic peaks, stress constraints)
- **Loading:** is defined with 8 static load cases (bending, torsion ,..) 3 quasi crash load cases, modal analysis and frequency analysis

The design space is defined with 1544 geometry variables.

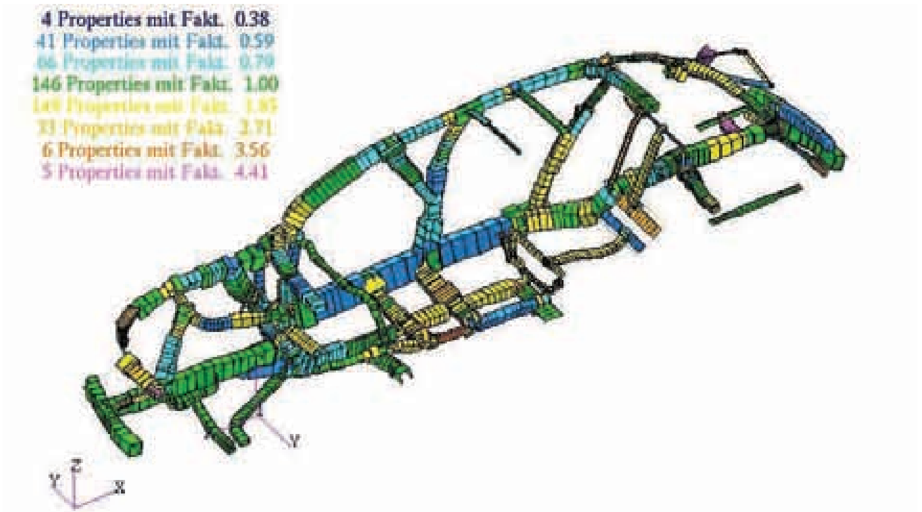
- **Difficulties:**
  - A large amount (99.99%) of the high dimensional design space is violating constraints
  - Very limited subspace has interesting weights
  - All best practice designs violate the constraints
  - Conflicting character of weight reduction and performance conditions

by courtesy of BMW

Large Scale Multi disciplinary Optimization

Multidisciplinary Car Concept Optimization II

- **Result in weight reduction:** 5.4 % compared with state of the art gradient based optimization strategy
- **Summary of successful hybrid multidisciplinary strategy:**
  - Sampling using parameter hierarchy and best practice design know-how
  - Global optimization (island search) using genetic algorithms in optiSLang
  - Cluster analysis
  - Local optimization using gradient based optimization

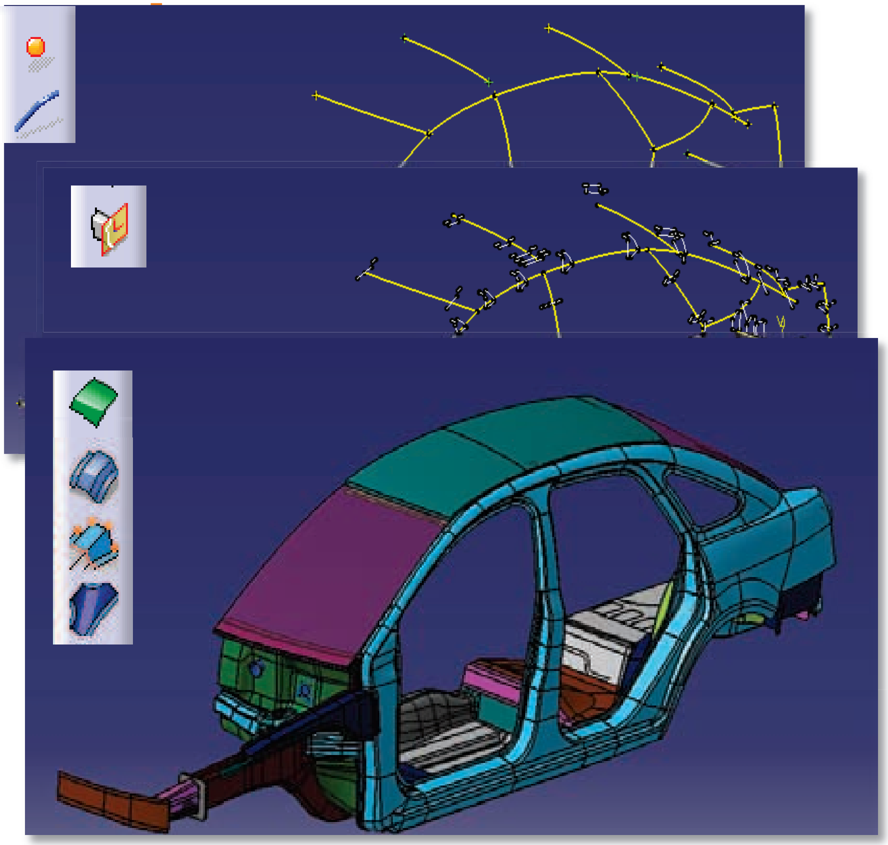


Picture: Weight difference of best design cluster 1 and reference solution

J. Will, C. Bucher, J. Riedel, I. Raasch: Search for alternative car concepts with OptiSLang, Proceedings 22. CAD-FEM Users Meeting 2004, Dresden, Germany, www.dynardo.de

FCM Parametric Modeller

Create concept models fast and easy with surfaces ready to



➔The result is a parametric CAD model with high-quality surfaces that are ready to mesh.

Step 1: Wireframe

Use design data, CAD-data or meshes as inputs or create something new and revolutionary from your mind

Intuitively position points by drag and drop with compass

Step 2: Cross Sections

Take CrossSections from a company-wide library

Use FCM to create sections through *any* existing geometry or meshes

Use CATIA's sketcher functionality

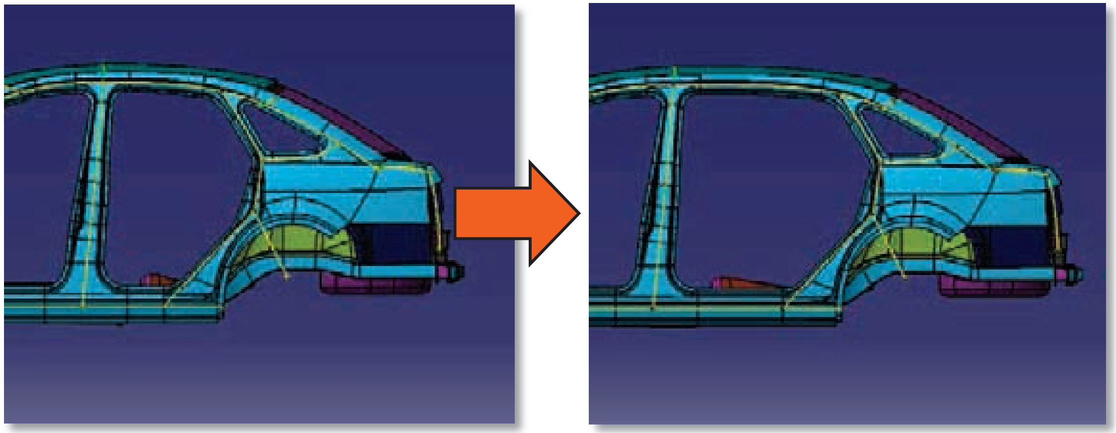
Step 3: Water-tight Surfaces

Create frame-like structures with FCM Beam, Junction and Map features from Cross Section to Cross Section

Create Surfaces without gaps or overlaps

FCM Parametric Modeller and Analysis Pre processor

Fundamental design changes can be performed without update errors



Flat FCM parametric allow stable changes

Modifications can be easily performed also for non-CAD-experts. Model remains water-tight all the time.

Example for stable FCM parametrics: stretching the whole rear of the vehicle

Create optimal design by using FCM in the loop with optimization software:

FCM parameters can be manually changed from within CATIA or from outside.

Optimizers as OptiSLang access geometry and CAE parameters

For each new design, shell meshes can be created automatically through Batchmeshing.

Source: Schmid; FCM - Fast Concept Modeller; Optimization of full vehicle concepts using Beam models; Weimar Optimization and Stochastic days 2010.