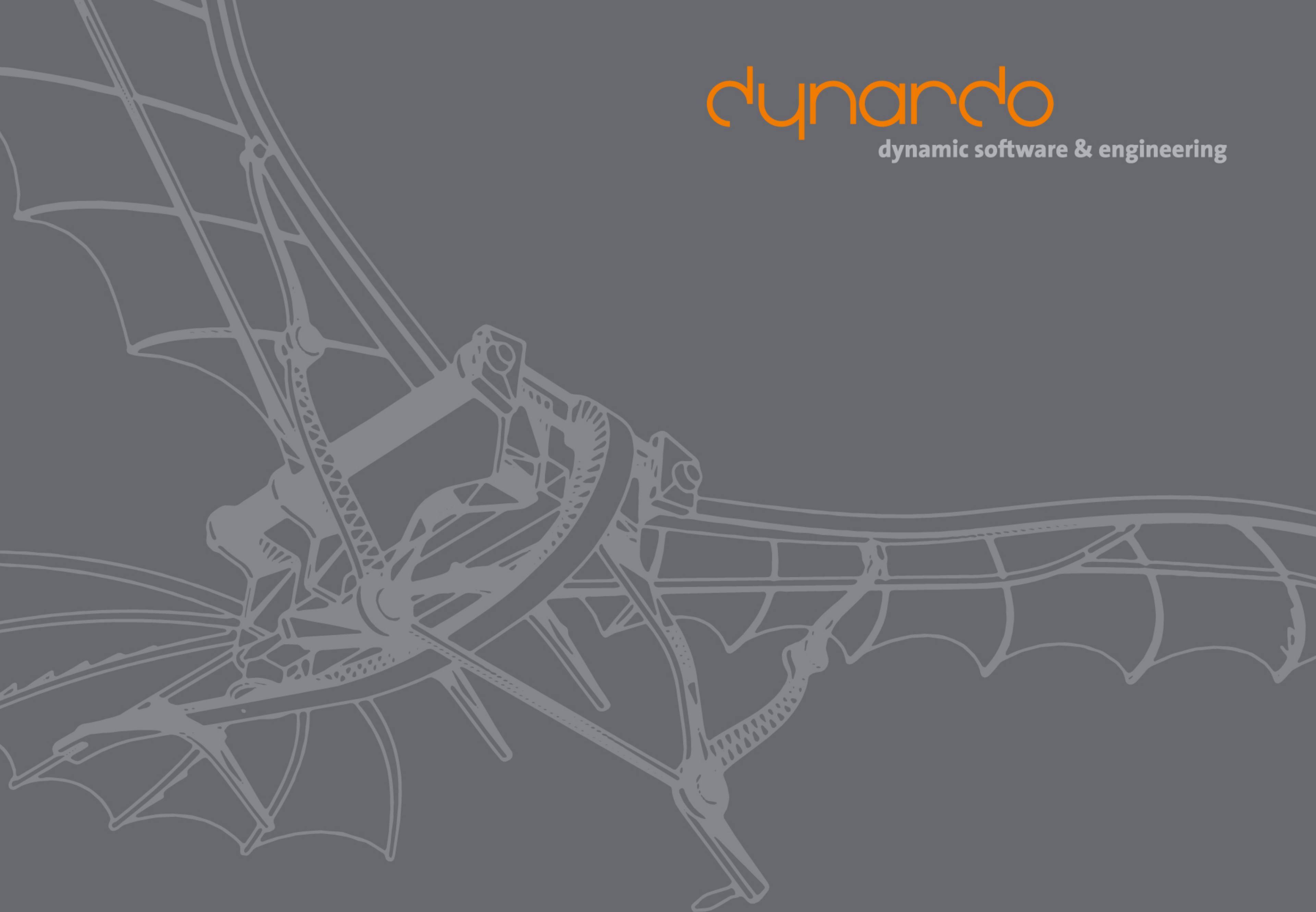
dynardo

dynamic software & engineering

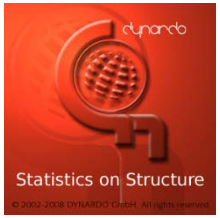


Founded: 2001 (Will, Bucher, CADFEM International)

More than 35 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

Challenges in Virtual Prototyping

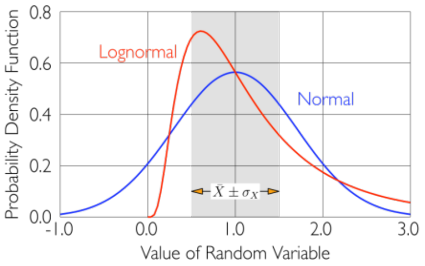
- Virtual prototyping is necessary for cost efficiency
- Test cycles are reduced and placed late in the product development
- CAE-based optimization and CAE-based robustness evaluation becomes more and more important in virtual prototyping
  - Optimization is introduced into virtual prototyping
  - Robustness 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

Challenge of RDO – reliable input

Successful RDO needs a balance between

- Reliable input = know how and definition of input uncertainties
- Reliable analysis = reliable stochastic analysis methodology
- Reliable post processing = use of stochastic/statistic results in the design process

Let's derive the functionality of an RDO process/package to support real world industrial RDO tasks



Reliable input scatter definition

- all possible important input scatter sources have to be included to be able to estimate Robustness
  - ⇒ many scattering variables (in the beginning) of an RDO task
  - ⇒ for best translation of input scatter a suitable variety of distribution functions are necessary
  - ⇒ correlations between scattering inputs needs to be considered

Challenge of RDO - reliable analysis

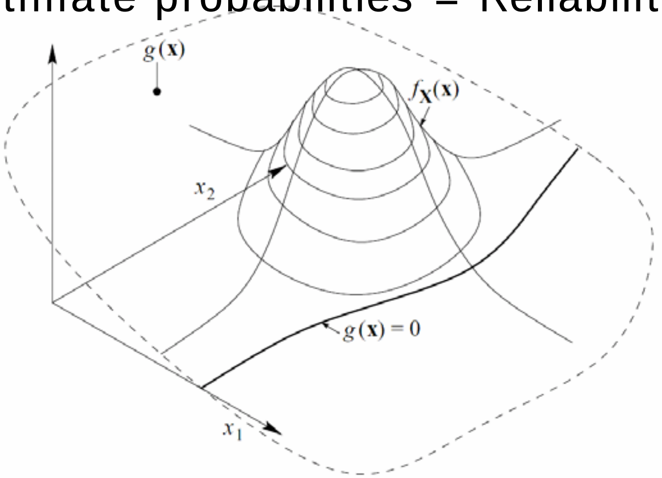
Reliable CAE-based stochastic analysis

- if single design evaluation needs significant CPU it is a challenge to balance between number of solver runs spend on Robustness Estimation and Reliability Analysis and the <u>reliability of the scatter measurements itself</u>

$\Rightarrow$ Efficient and reliable methodology to sort out important/unimportant input scatter and estimate variance based output scatter ranges (mean values, standard deviation)= Robustness Evaluation

$\Rightarrow$ 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!

$\Rightarrow$ Efficient and reliable methodology to estimate probabilities = Reliability Analysis

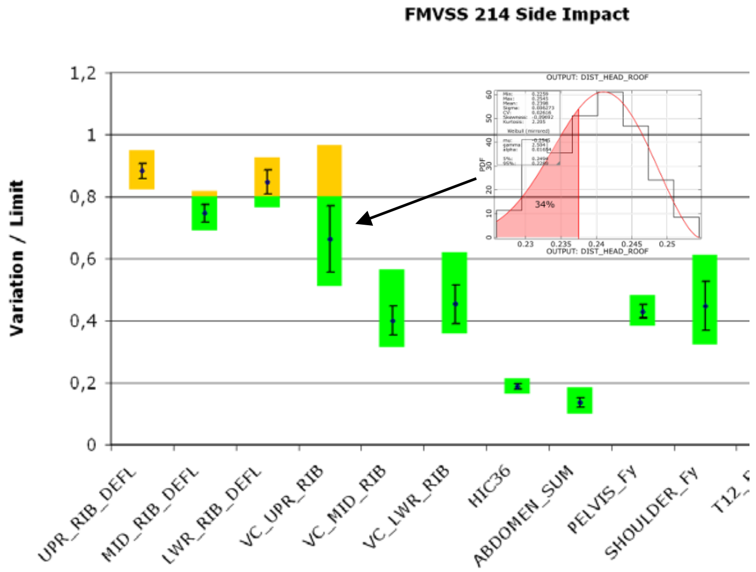


Challenge of RDO - reliable post processing

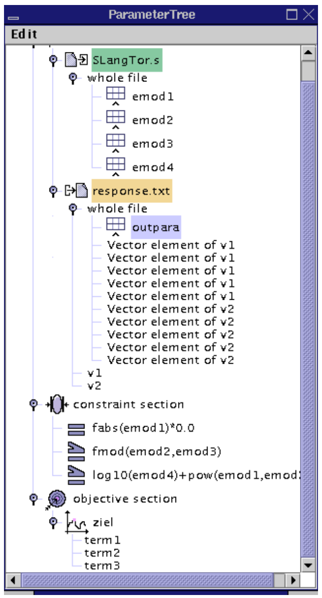
Reliable post processing

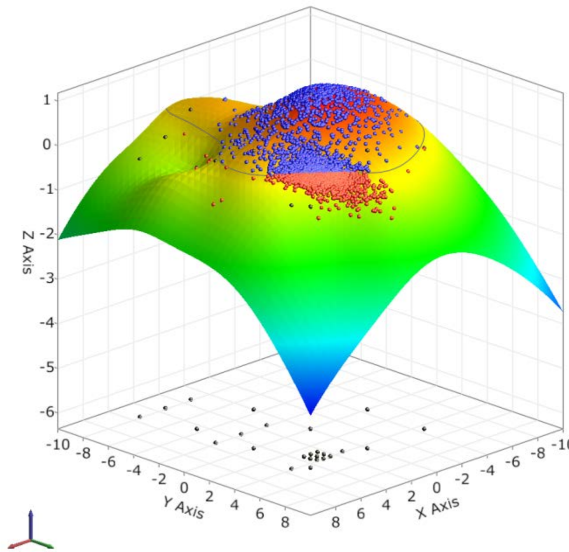
- Stochastic Analysis and statistical post processing estimates variation of response values
  - ⇒ Reliable quantification of input scatter variable importance
  - ⇒ Reliable estimation of variation using fit of distribution functions
  - ⇒ Provide error estimation of reliability measurements (probabilities)
  - ⇒ Filter of insignificant/unreliable results

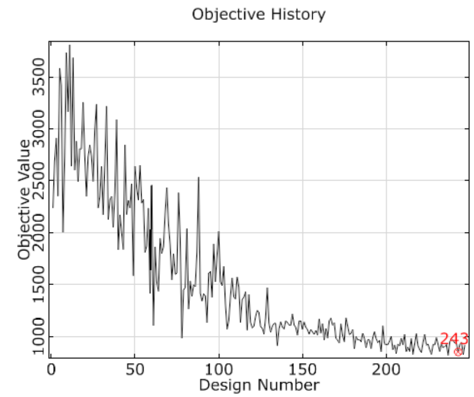
⇒ **Easy and safe to use**



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





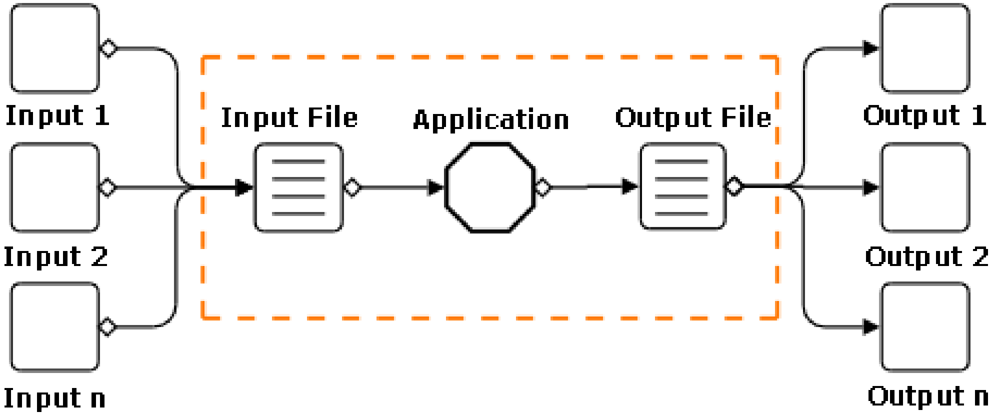


optiSLang is the commercial tool that has completed the necessary functionality of stochastic analysis to run real world industrial applications in CAE-based robust design optimizations.

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

optiSLang version 3 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,...

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Parametrize Editor

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

Input file:

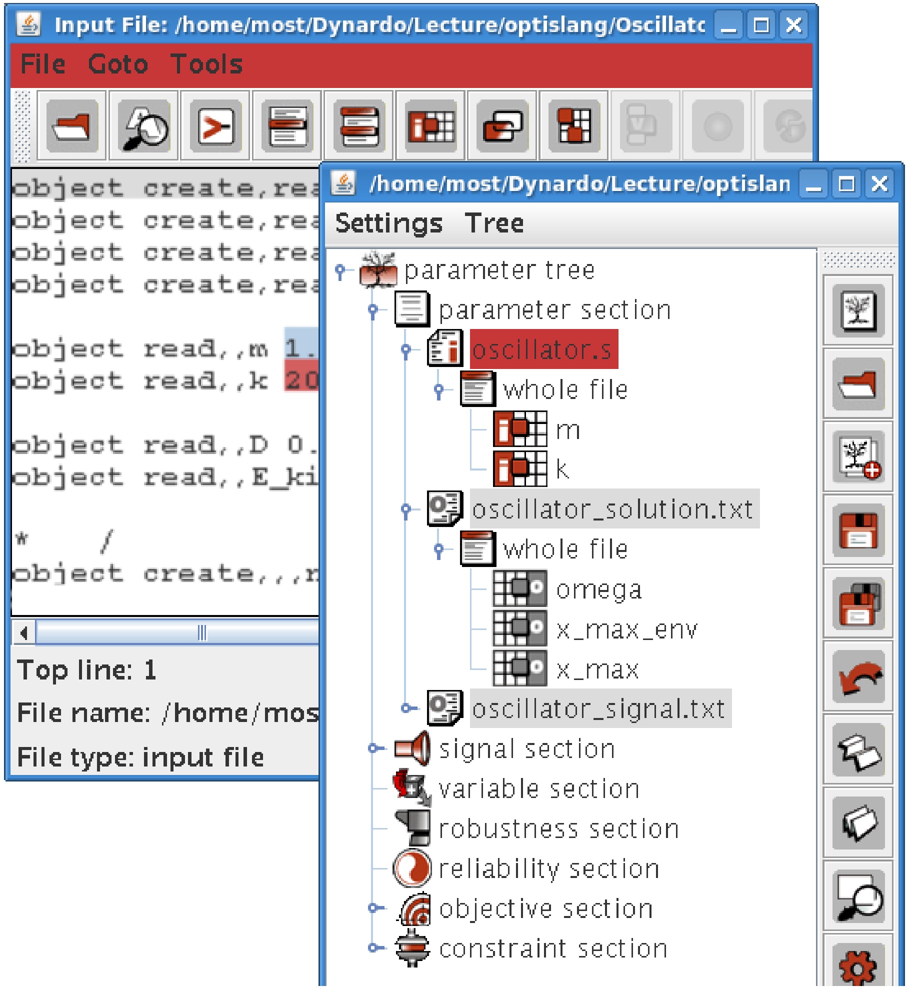
- Optimization parameter
- Robustness parameter
- RDO variable
- Dependent parameter and variables

Output file:

- Response variable
- Response vector
- Signals

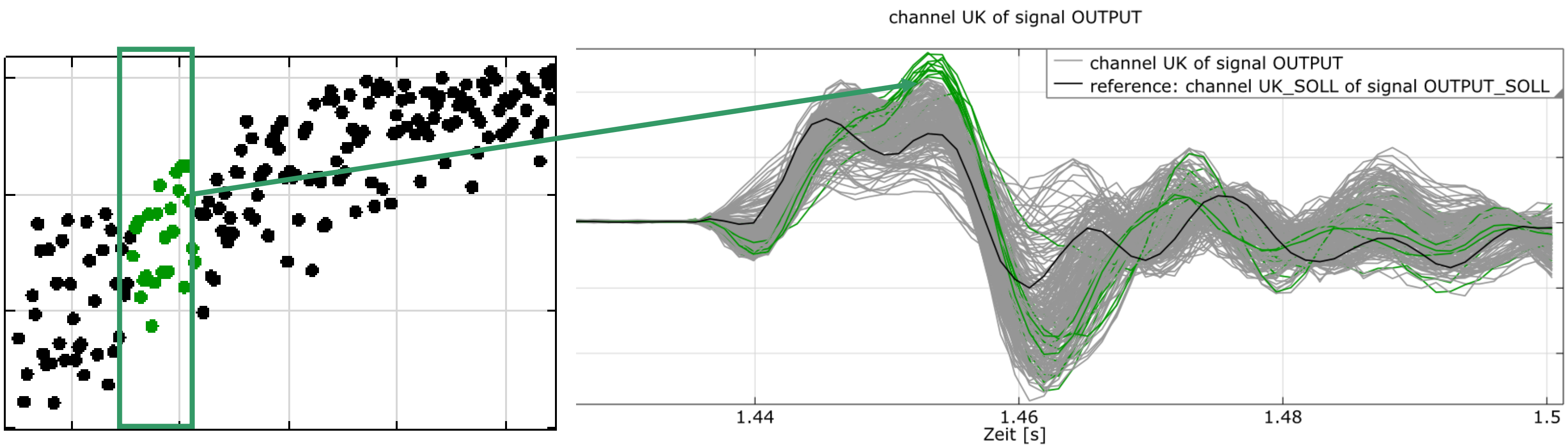
Problem definition section

- 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

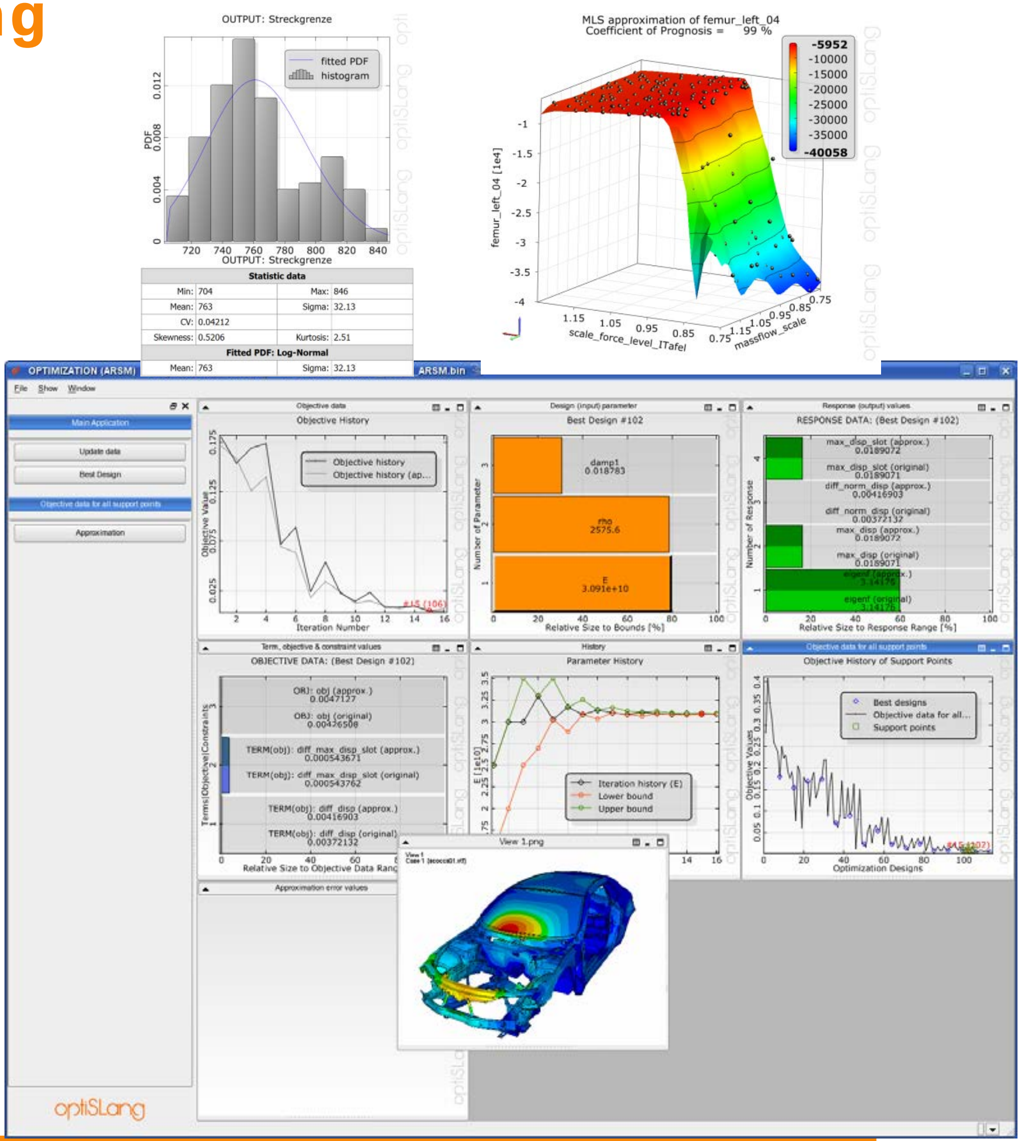


Pre and Post Processing

- 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



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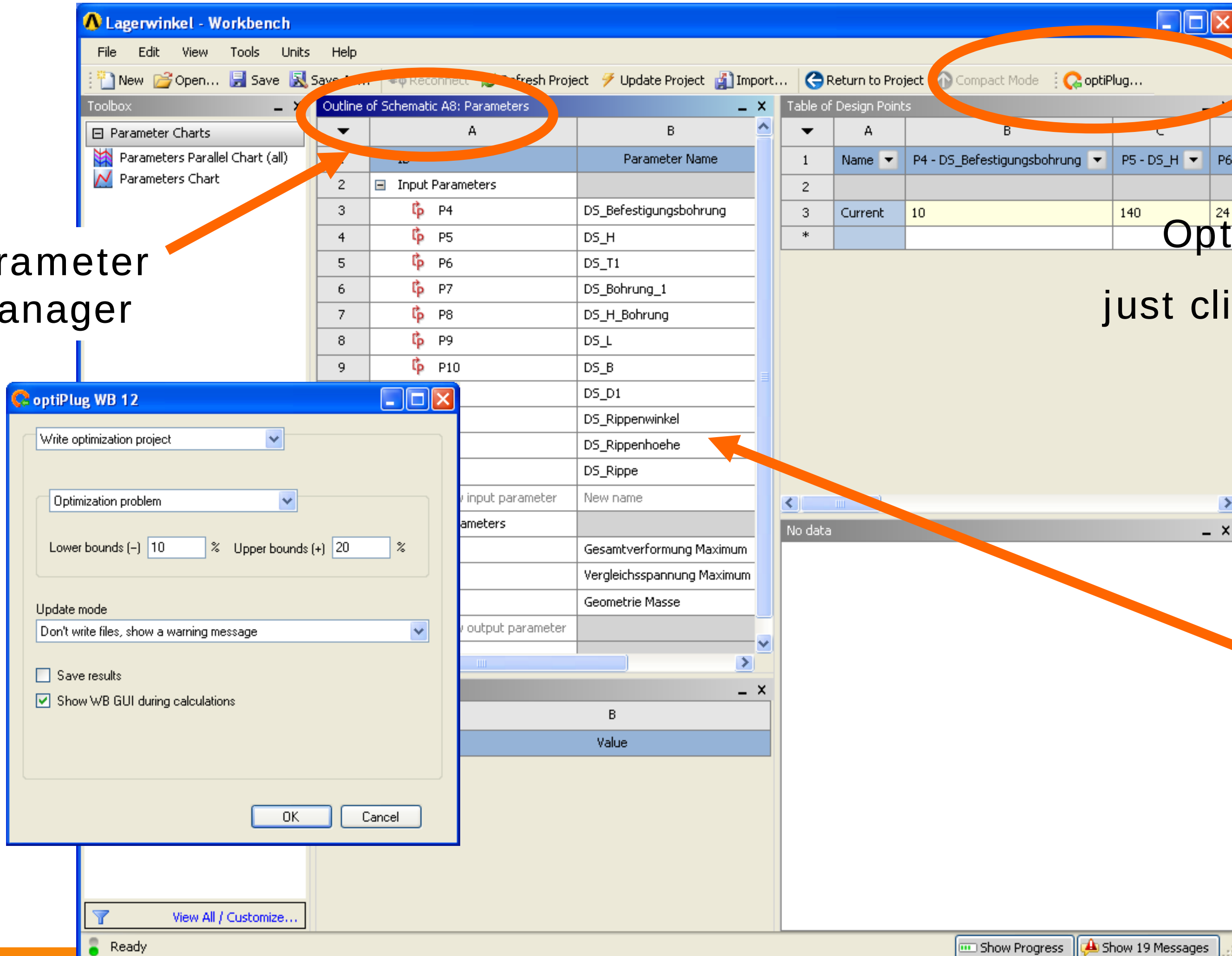
optiPlug - ANSYS Workbench optiSLang Interface

Parameter Manager

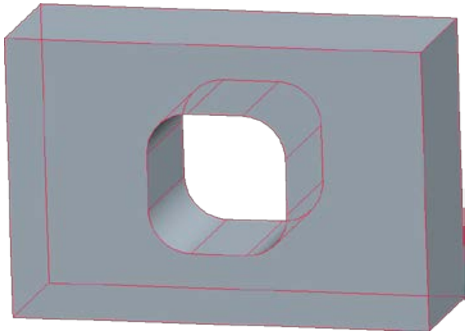


OptiSLang-Plugin:

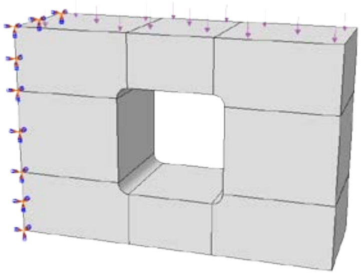
just click to integrate workbench in optiSLang

Parameter & Responses

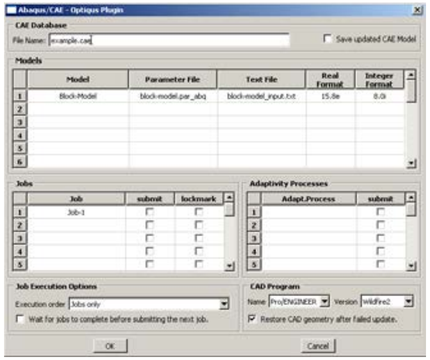
Plugins in ABAQUS

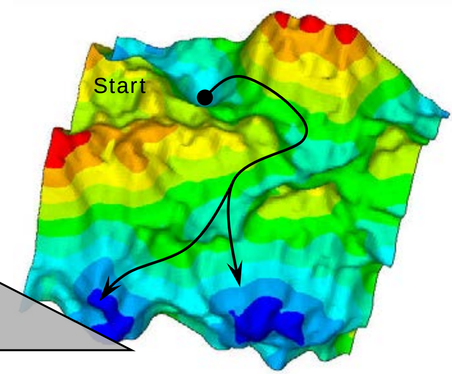


- Optiqus -Abaqus – Pro/E plug in
- Abaqus – Catia plug in
    - creates a command script which can be executed by the optimization program
        - uses associative interfaces to update the geometry in Abaqus/CAE
        - creates Abaqus input files for the CAE models



- Additional in Abaqus – Catia plugin (beta-version)
    - uses Catia design table for input parameters
    - input parameters are automatically parsed
    - creates the basic structure for optiSLang including runscript, and DoE workflow





Robust Design Optimization

Robust Design

Variance based Robustness Evaluation

Probability based Robustness Evaluation, (Reliability analysis)

Optimization

Sensitivity Study

Single & Multi objective (Pareto) optimization

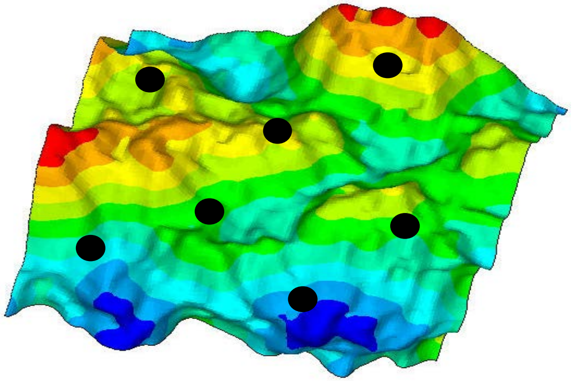
CAE process (FEM, CFD, MBD, Excel, Matlab, etc.)

Sensitivity Analysis

(Design Exploration)

optiSLang Sensitivity Analysis

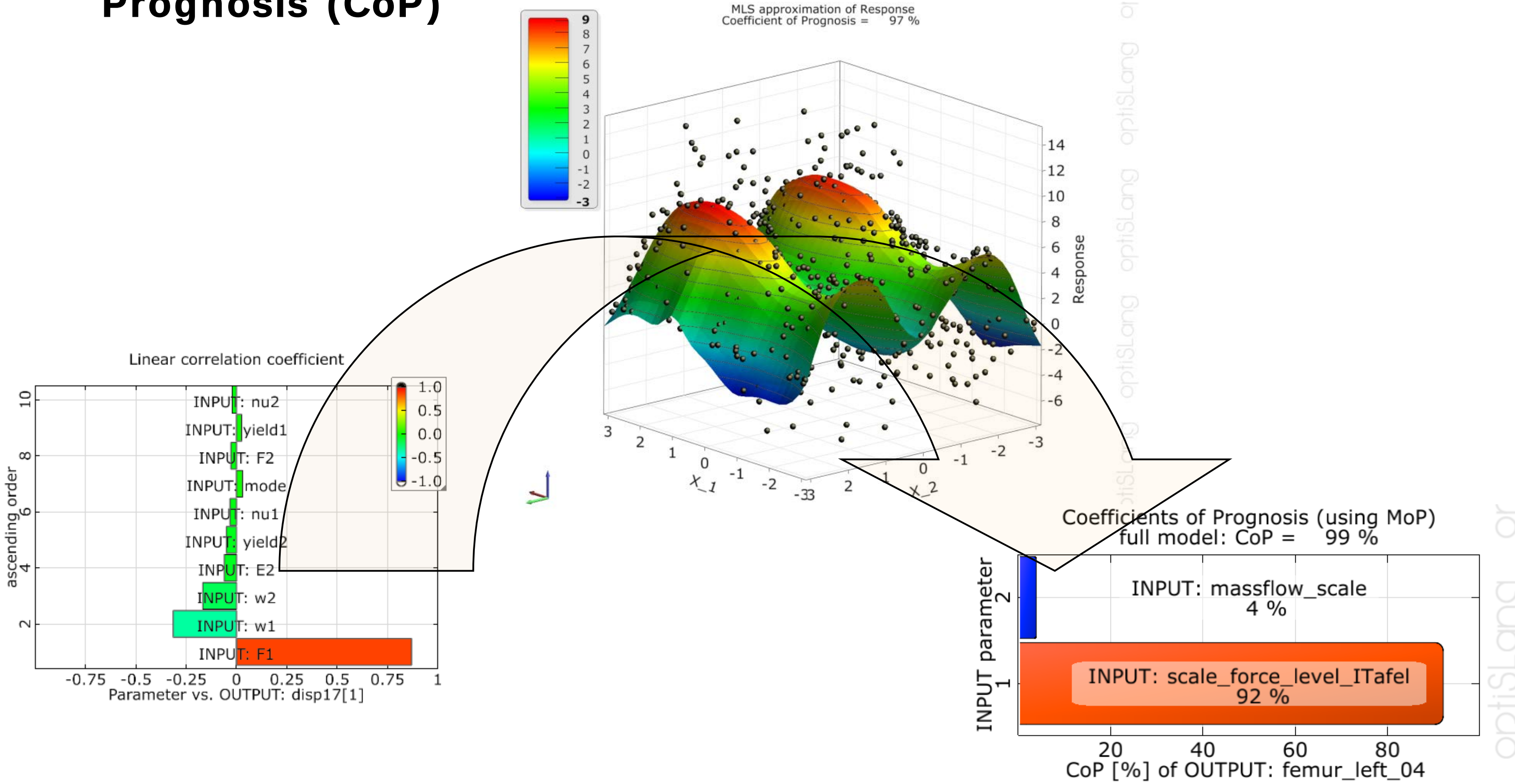
- optiSLang scans the design space with Latin Hypercube sampling and measures the sensitivity with statistic measurements



- Results of a global sensitivity study are:
  - **Global sensitivities** of the variables due to important responses
  - **Identification** of reduced sets of important variables which have the most significant influence on the responses
  - **Estimate** the variation of responses
  - **Estimate** the solver noise
  - **Better understanding** and verification of correlations between input parameter variation and design responses

Identifying important parameters

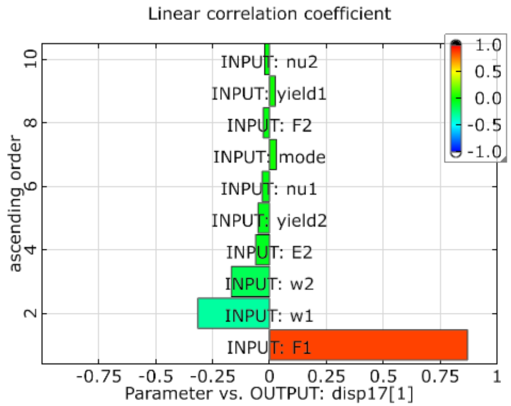
From tornado chart of linear correlations to the Coefficient of Prognosis (CoP)



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

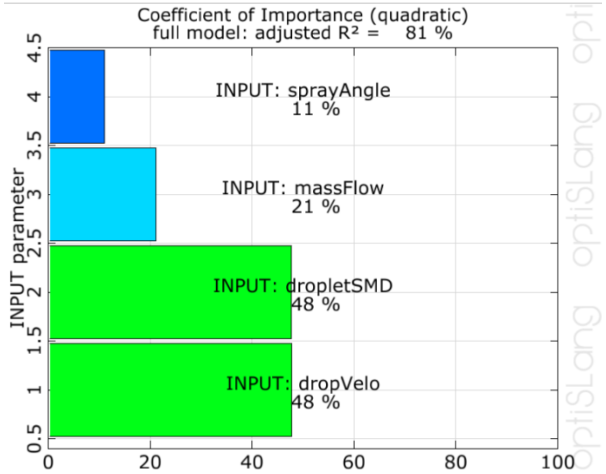
Statistical measurements

- Coefficients of linear/quadratic correlation is the simplest correlation measurement
- Spearmann correlation includes monotonic nonlinear correlations
- Multi-dimensional non-linear correlation



- Coefficient of Determination (CoD) summarize pair wise correlations

- Coefficient of Importance (CoI) improve to single input parameter importance including mixed terms (mechanisms)

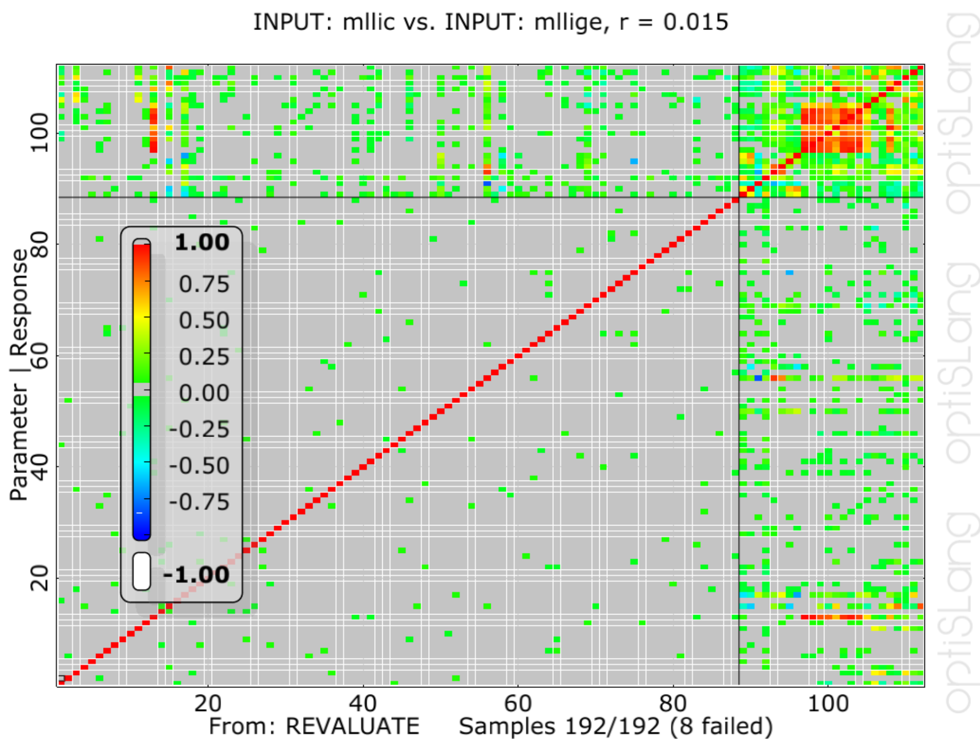


But how to solve the tradeoff between dimensionality and number of sample?

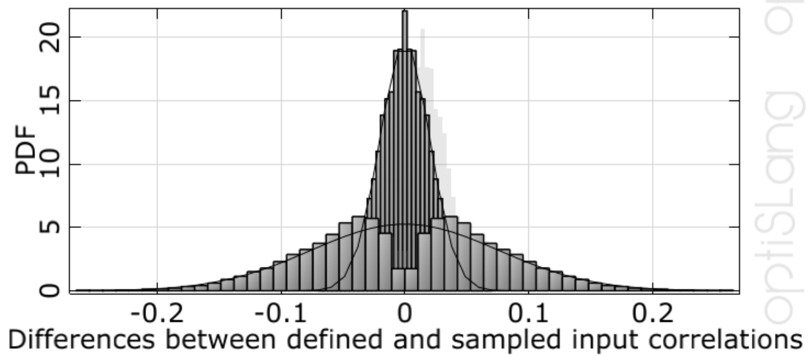
For 100 variables thousands of samples are needed to check non linear correlations!

Searching for important variables

- In large dimensions, the necessary number of solver runs for correlation analysis increase
- But in reality, often only a small number of variables is important
- Therefore, optiSLang includes **filter technology** to estimate significant correlation (significance, importance & correlation filter)



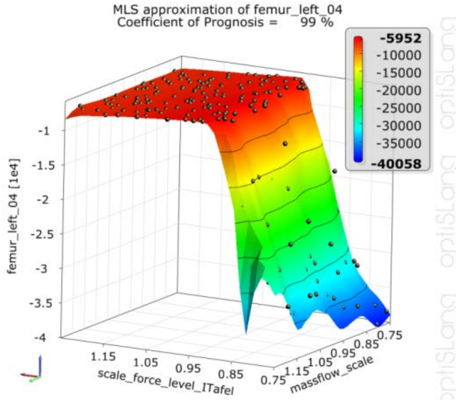
- significance level for linear & quadratic correlation coefficient



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



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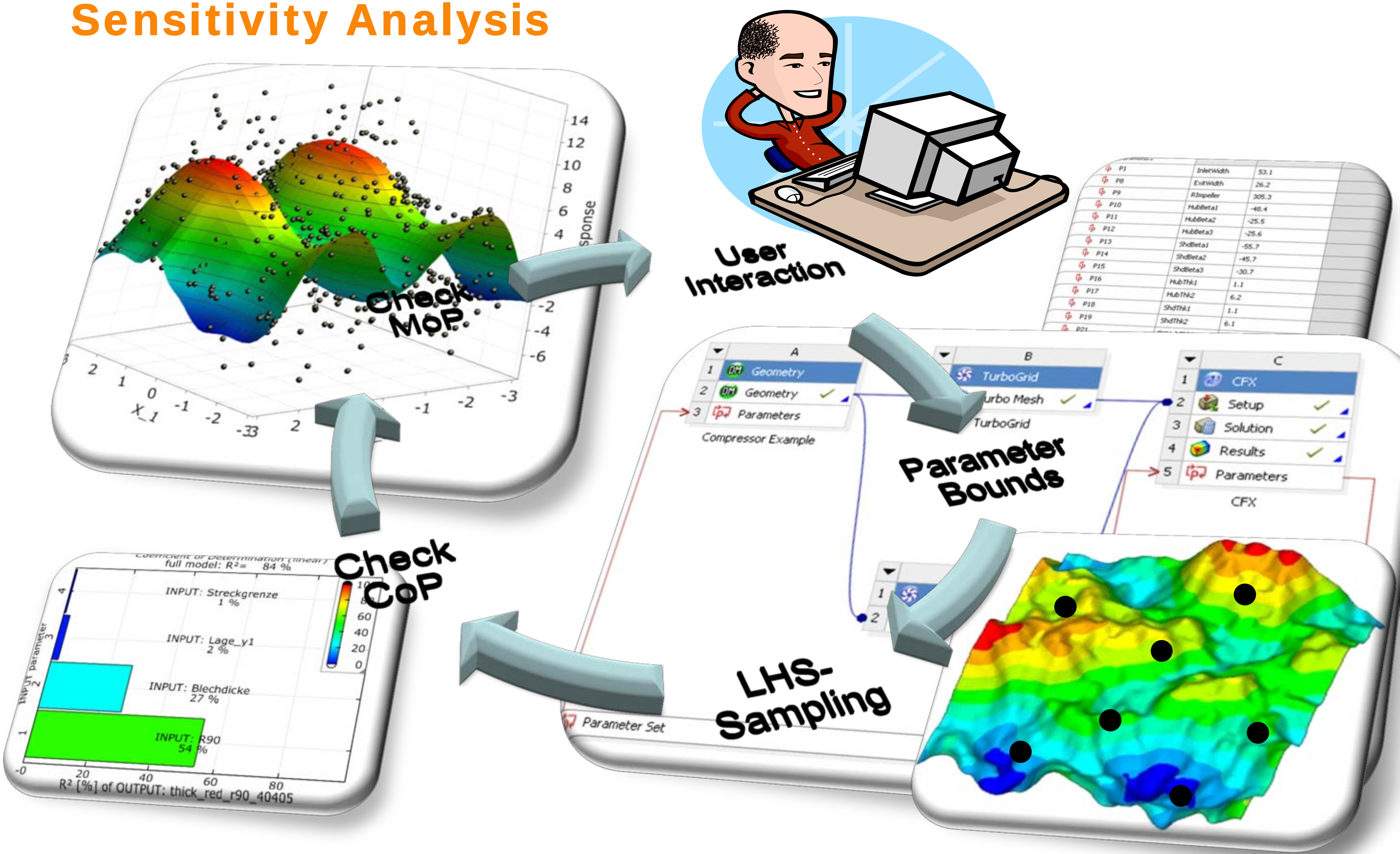
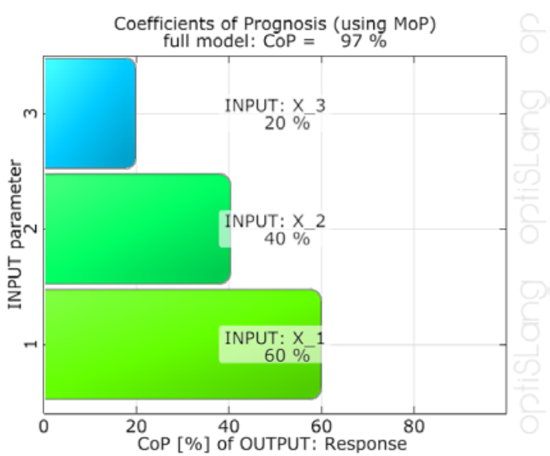
Sensitivity Analysis

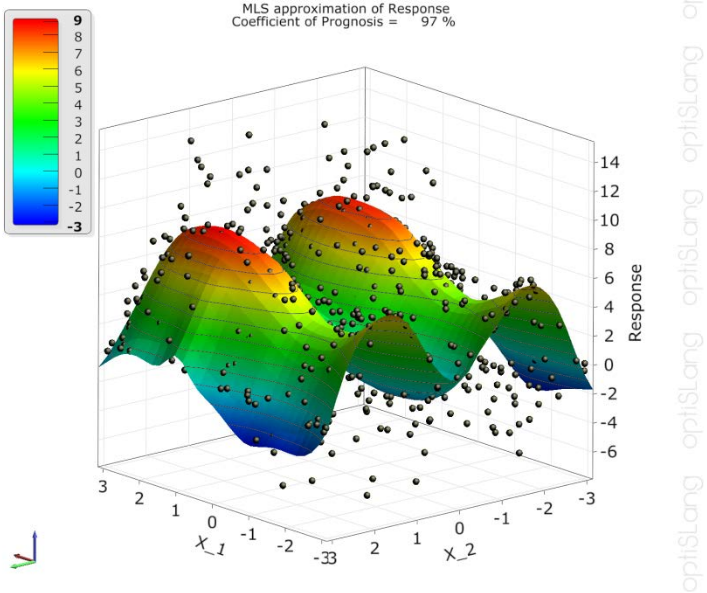


MOP allows "No Run to Much"

With MOP functionality we can start to check after 30..50 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)

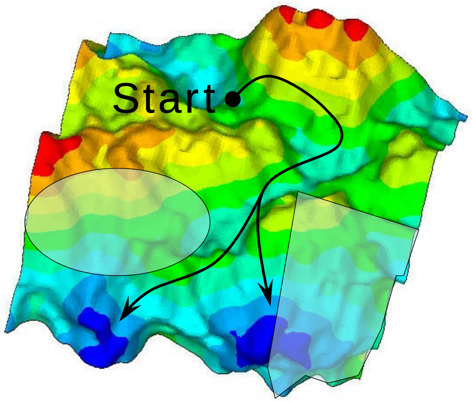




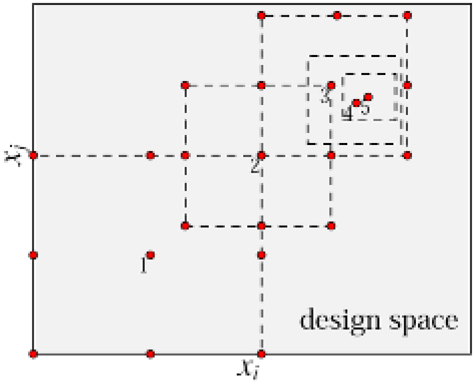
Multidisciplinary Optimization

Optimization Algorithms

Gradient-based algorithms



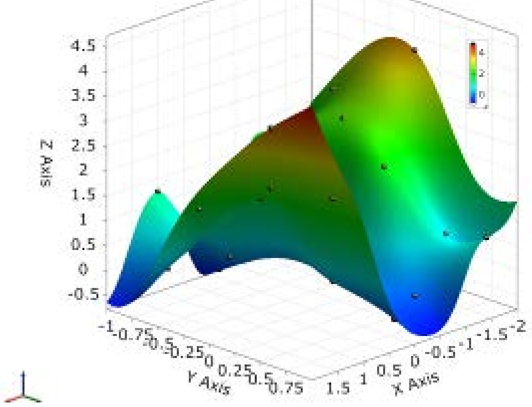
Local adaptive RSM



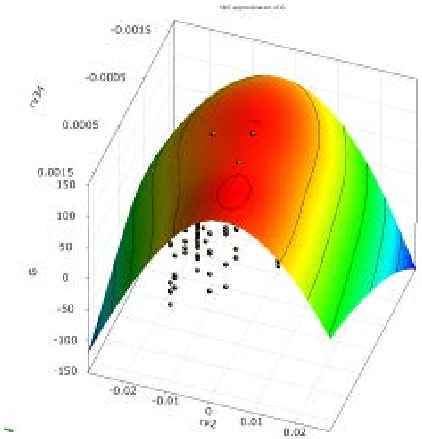
Natural Inspired Optimization

Genetic algorithms,
Evolutionary strategies &
Particle Swarm Optimization

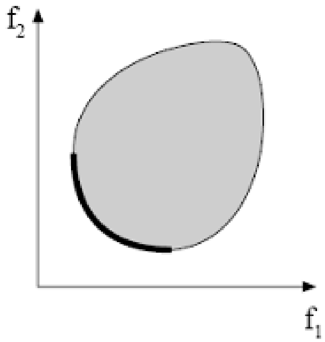
Meta model of optimal Prognosis (MOP)



Global adaptive RSM



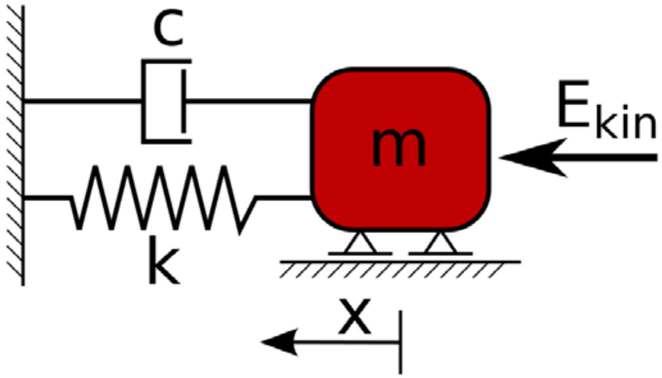
Multi objective (Pareto) Optimization



Example: damped oscillator

- Time-dependent displacement function

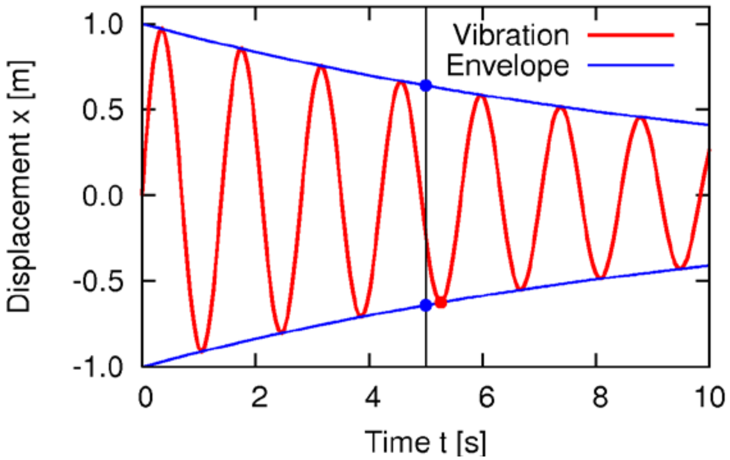
$$x(t) = e^{-D\omega_0 t}\frac{v_0}{\omega}\sin(\omega t),$$



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

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

- Optimization constraint: $w \leq 8\frac{1}{\mathrm{s}}$

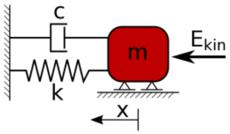


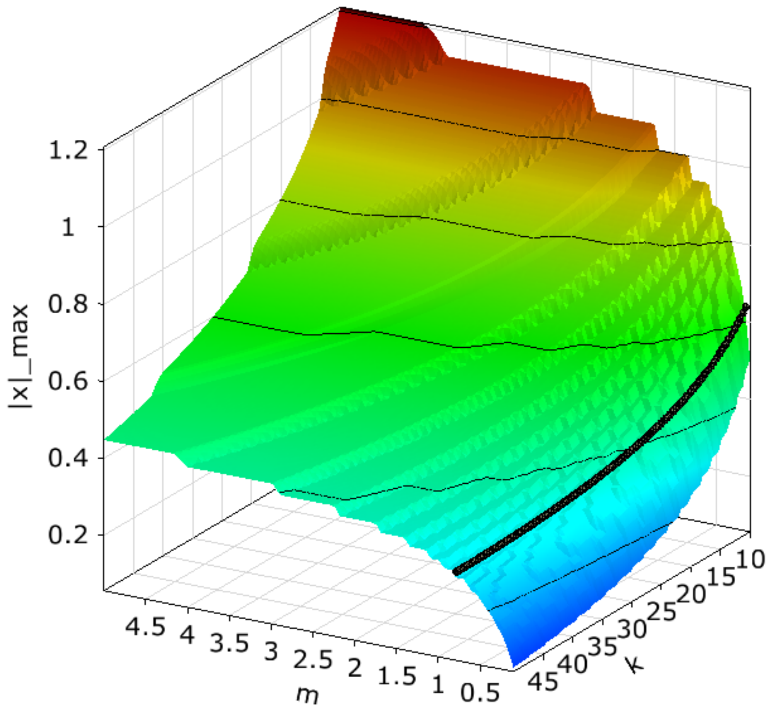
- Optimization parameter bounds & constant parameters:

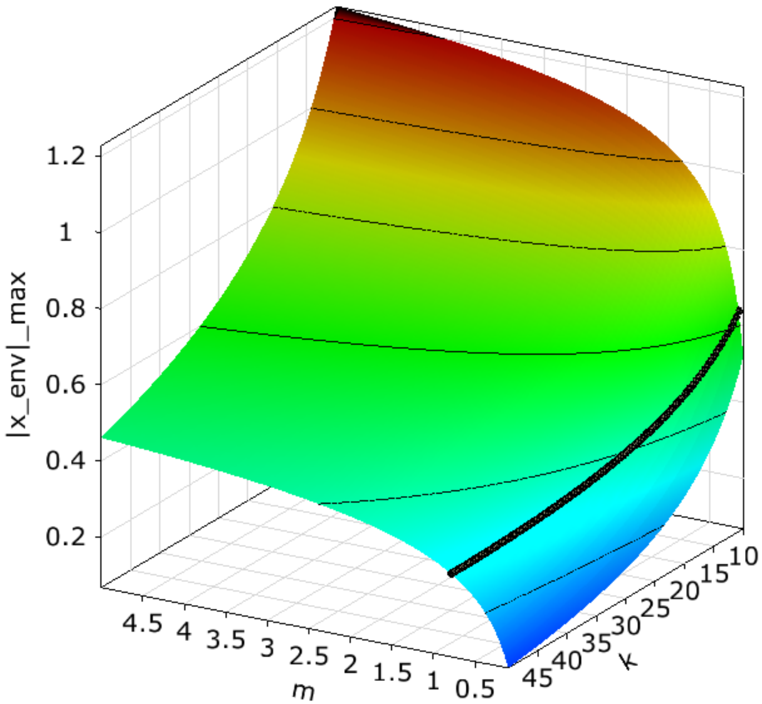
$$m \in [0.1, 5.0\ \mathrm{kg}] \qquad D = 0.02$$

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

Objective function







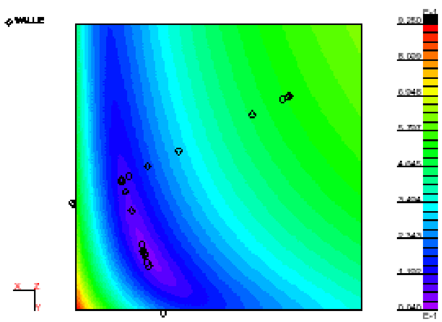
- Stepped objective function by using maximum elongation
- Smooth objective if amplitude is approximated with envelope

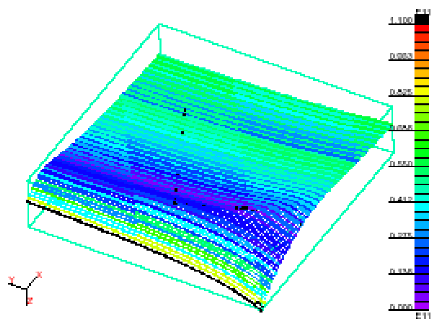
Gradient based Optimization

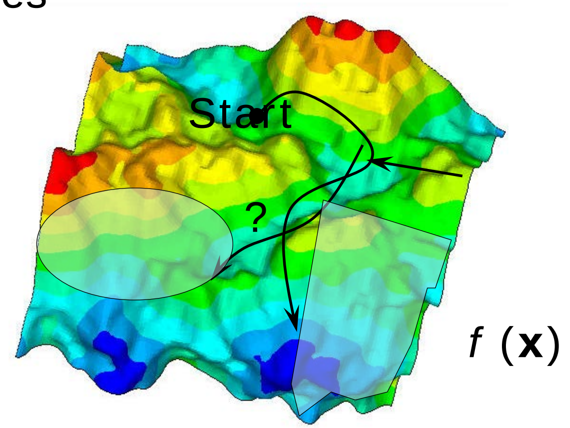
- NLPQL (Nonlinear Programming Quadratic Line Search – Prof. Schittkowski)
- Recommended area of application: reasonable smooth problems

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

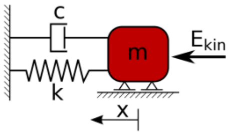
\- Local optima, expensive gradients
- Use with care for binary/discrete variables

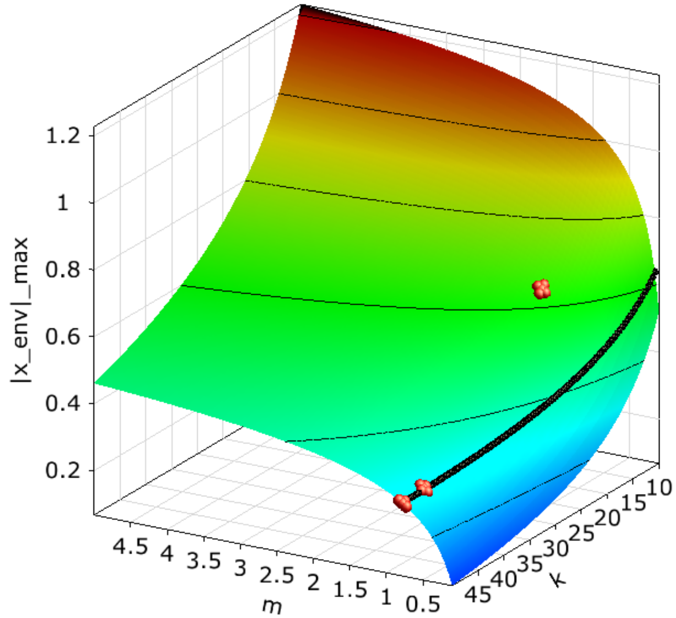






NLPQL on original and approximated objective function





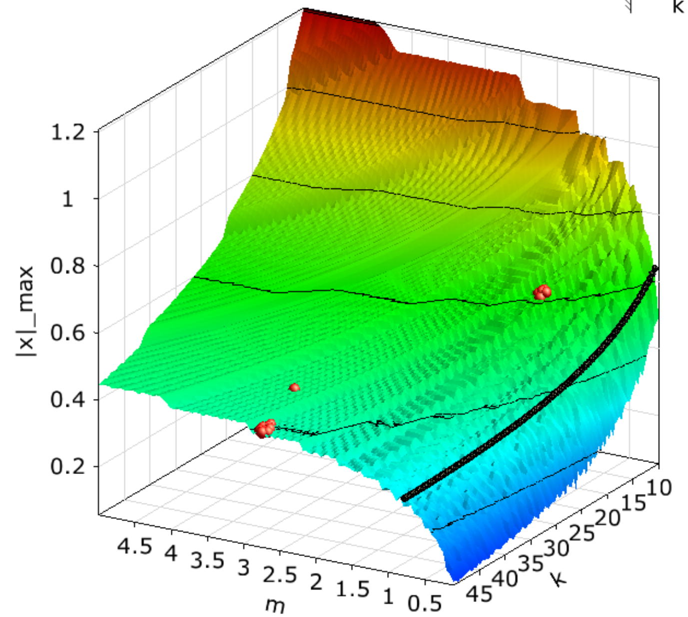
Envelope (18 solver calls)

$$m_{opt} = 0.78 \text{ kg}$$

$$k_{opt} = 50.0 \text{ N/m}$$

$$\omega_{opt} = 8.00 \text{ 1/s}$$

$$|\hat{x}|_{max}^{opt} = 0.28 \text{ m}$$



Direct, 100 time steps (29 calls)

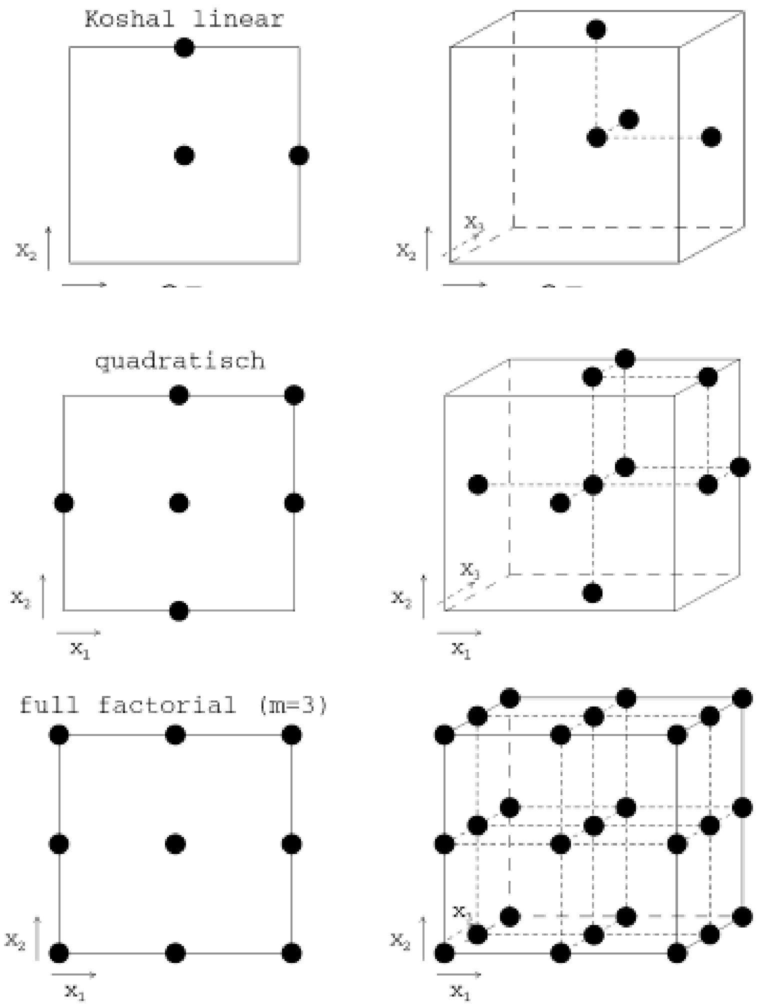
$$m_{opt} = 2.77 \text{ kg}$$

$$k_{opt} = 48.9 \text{ N/m}$$

$$\omega_{opt} = 4.20 \text{ 1/s}$$

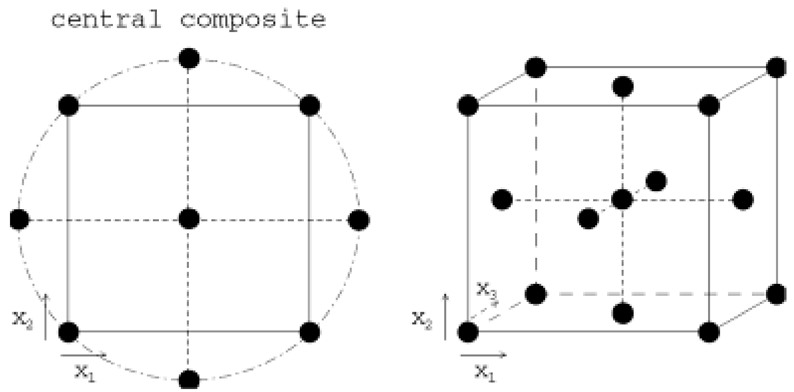
$$|x|_{max}^{opt} = 0.39 \text{ m}$$

Design of Experiment



Method principles & properties:

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

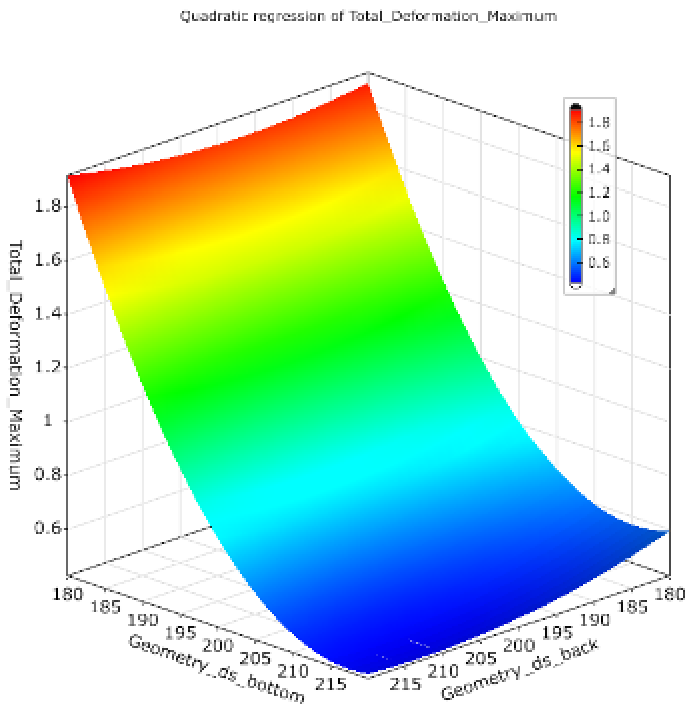


Global Response Surface Methods

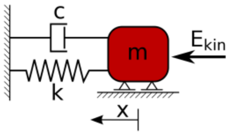
+ Global polynomial response surface approximation is effective for a small set of variables $n \leq 5$ .. 7

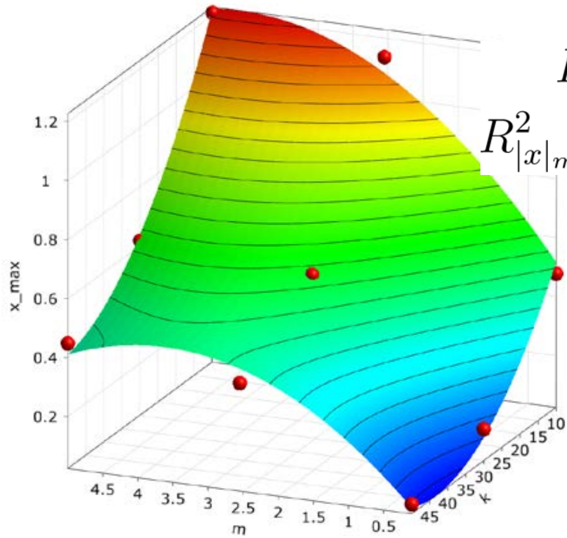
- Number of necessary support points for reasonably precise RS becomes very high in dimensions > 10

	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



Quadratic polynomial regression, D-optimal and LHS DOE

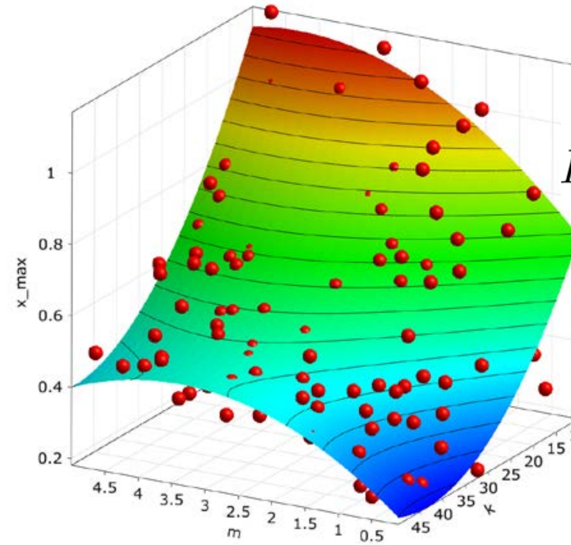




$$R^2_\omega = 80\%$$
$$R^2_{|x|_{max}} = 90\%$$

D-optimal (9 solver calls)

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



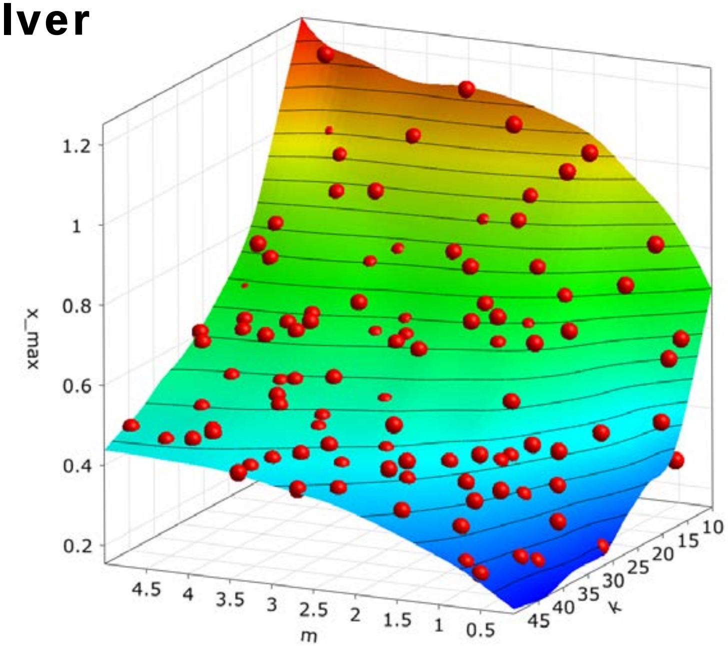
$$R^2_\omega = 86\%$$
$$R^2_{|x|_{max}} = 96\%$$

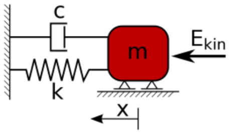
LHS (100 solver calls)

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

Always verify best design with solver!

Using MOP as solver





$$CoP_{\omega} = 98\%$$

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

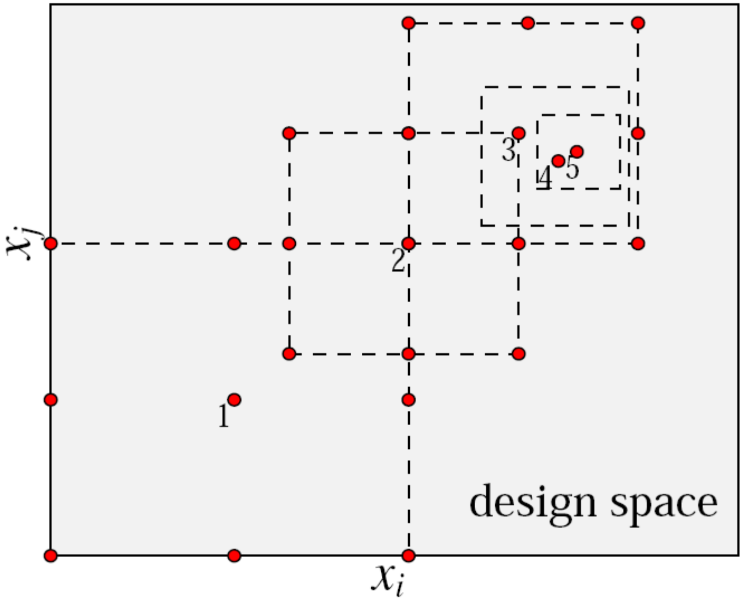
- Reuse of samples from sensitivity analysis
- Smoothing of noisy objective function
- High CoPs (≥90%) are required for objective **and** constraints
- **Always verify best design with solver!**

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

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

Adaptive Response Surface Methods (Local)

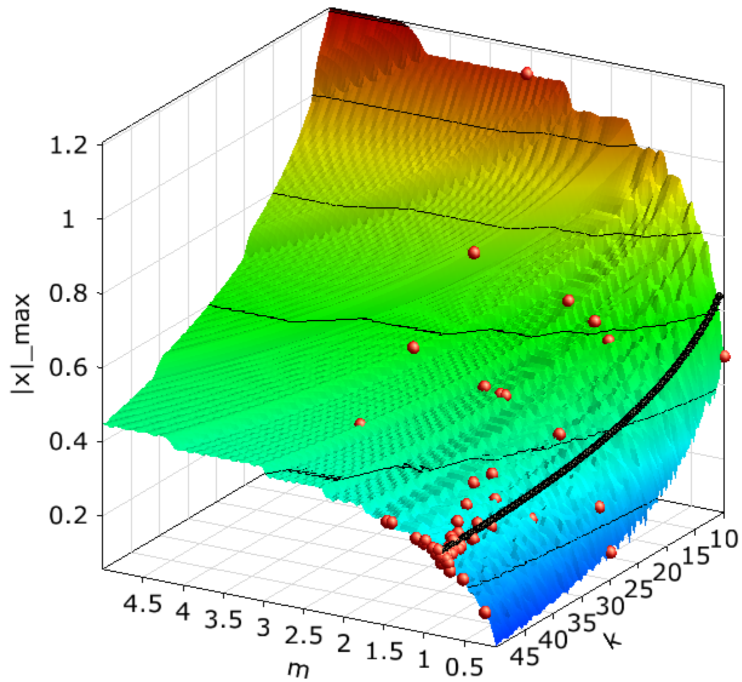
Adaptive design of experiment – design space

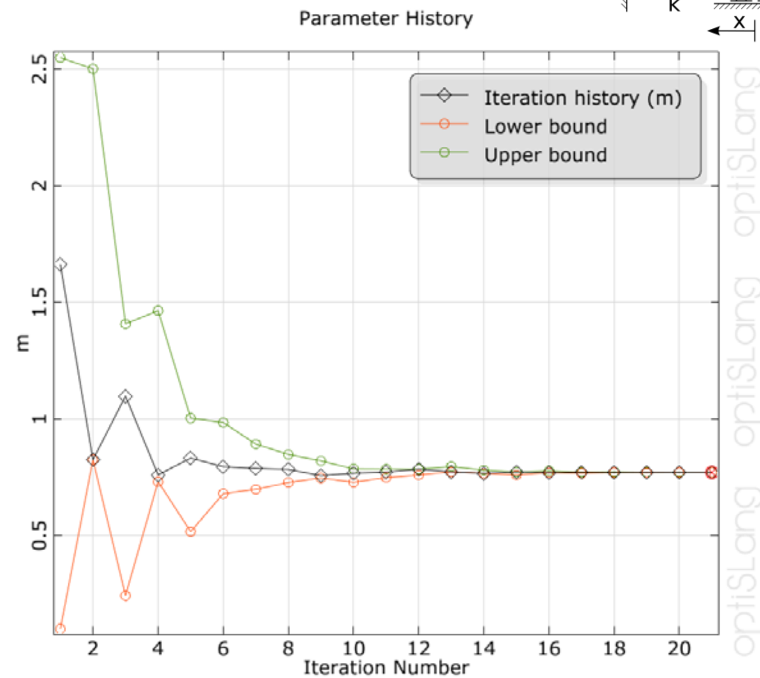


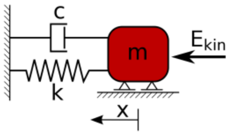
- Starting with a large subregion
- Iteration moves and shrinks the subspace till a solution converges to an optimum
- Approximation of the responses with low level trial function (e.g. linear and quadratic polynomial functions)

+ 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

Local ARSM with linear polynomial







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

$$m_{opt} = 0.77 \text{ kg}$$

$$k_{opt} = 49.3 \text{ N/m}$$

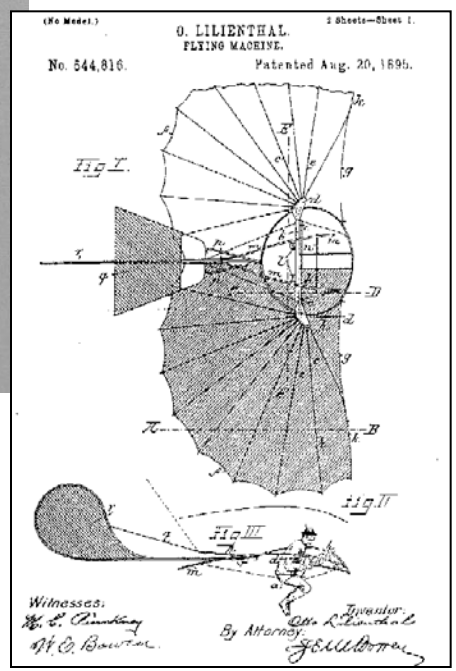
$$\omega_{opt} = 7.99 \text{ 1/s}$$

$$|x|^{opt}_{max} = 0.25 \text{ m}$$

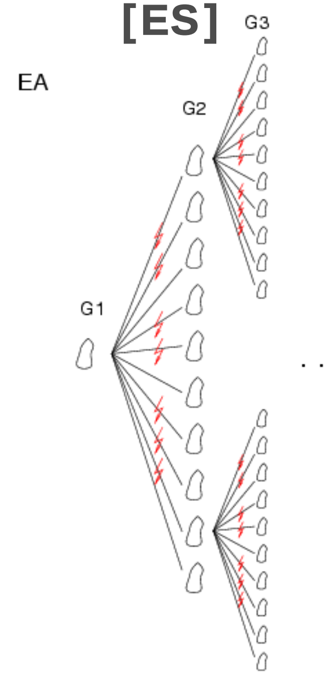
Evolutionary Algorithms (EA)

Imitates Evolution ("Optimization") in Nature:

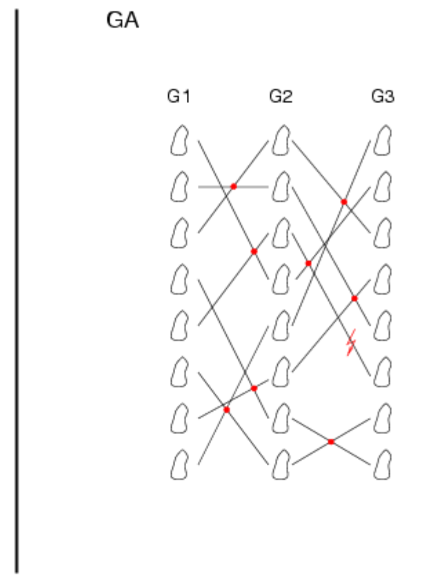
- Survival of the fittest
- Evolution due to mutation, recombination and selection
- Developed for optimization problems where no gradient information is available, like binary or discrete search spaces



Evolution Strategies [ES]



Genetic Algorithms [GA]



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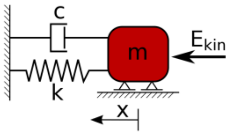
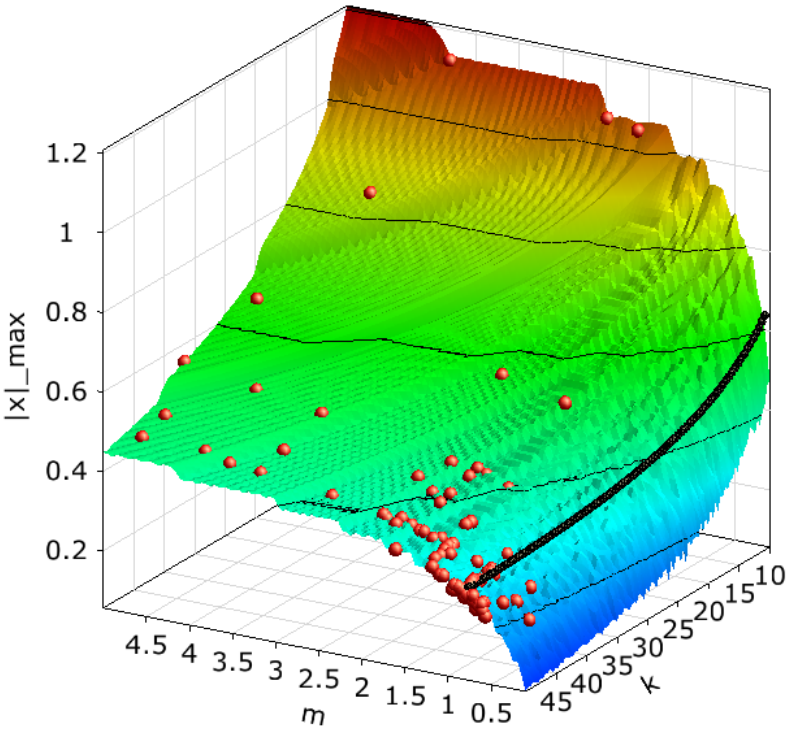
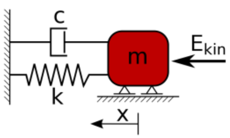
Genetic algorithm



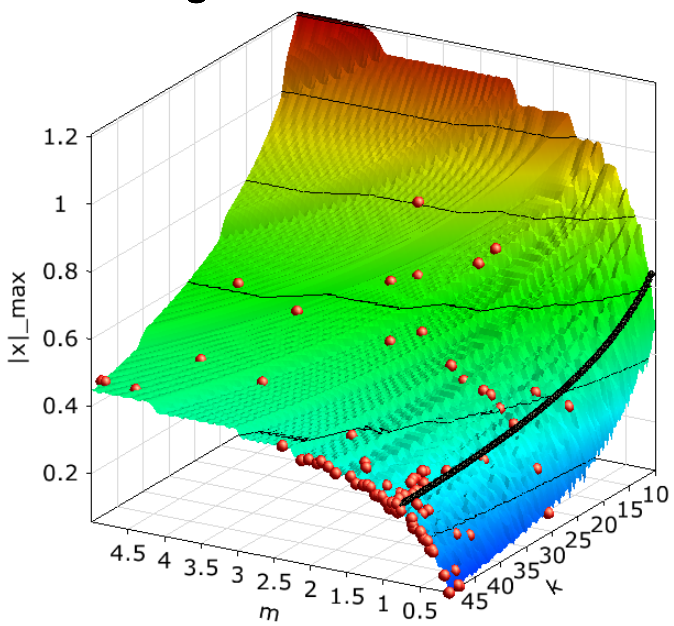


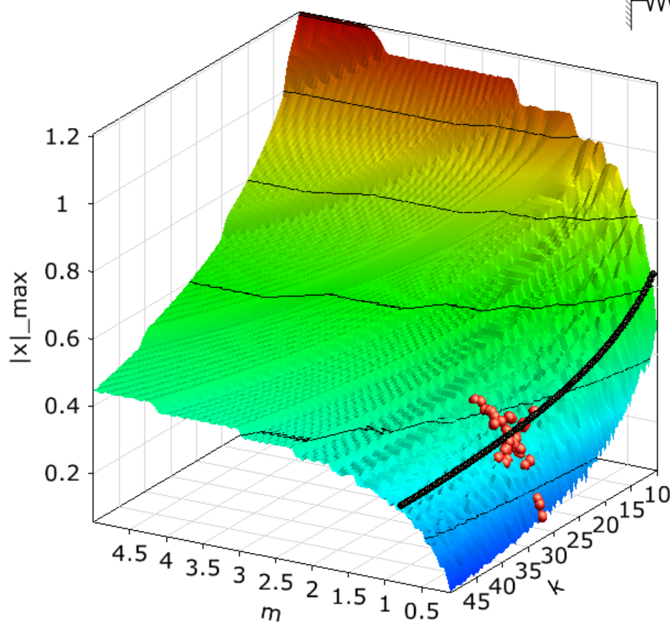
- 99 solver calls

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



EA with global and local search





Global search (102 solver calls)

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

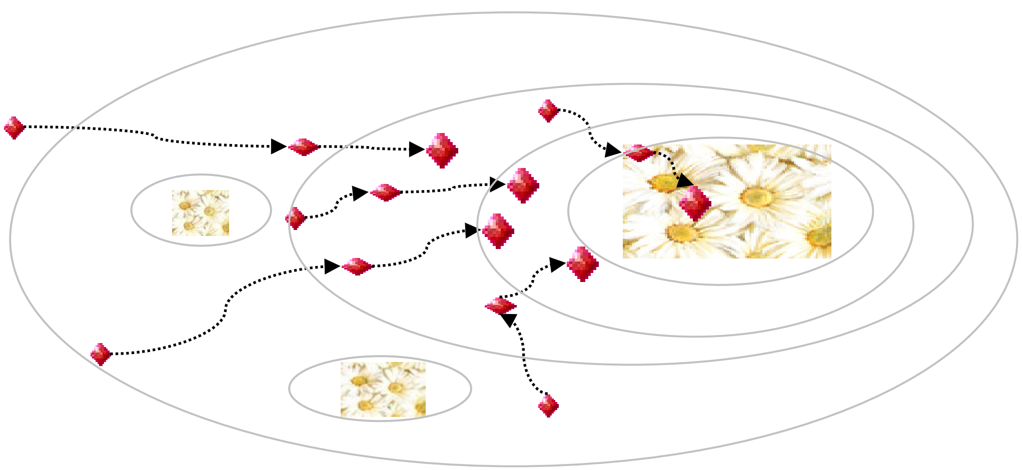
Local search (51 solver calls)

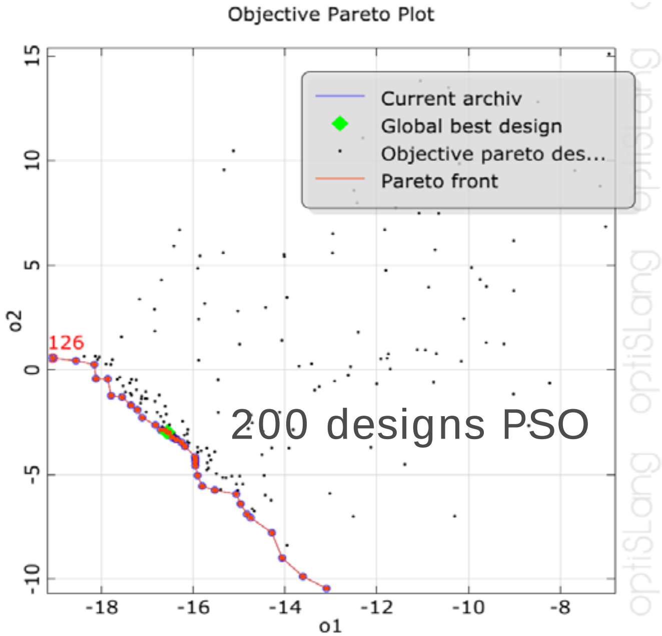
$$m_{opt} = 0.51 \text{ kg}$$
$$k_{opt} = 32.4 \text{ N/m}$$
$$\omega_{opt} = 7.99 \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.31 \text{ m}$$

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**





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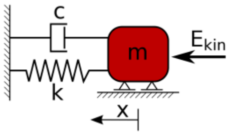
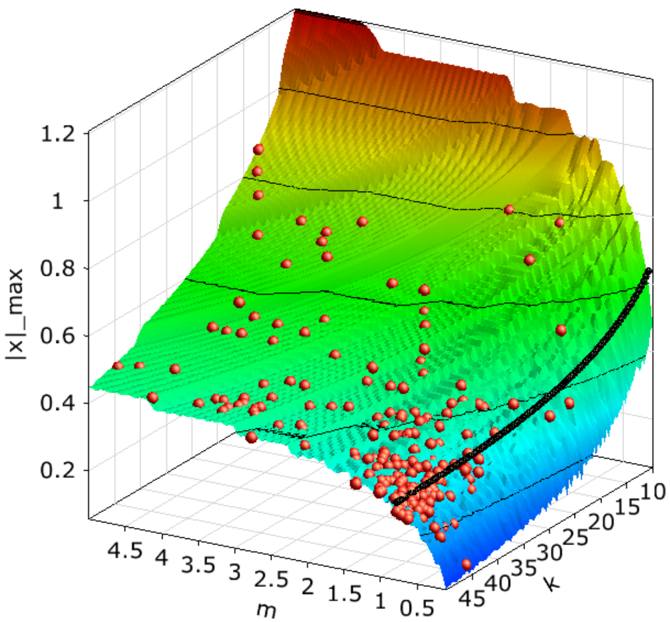
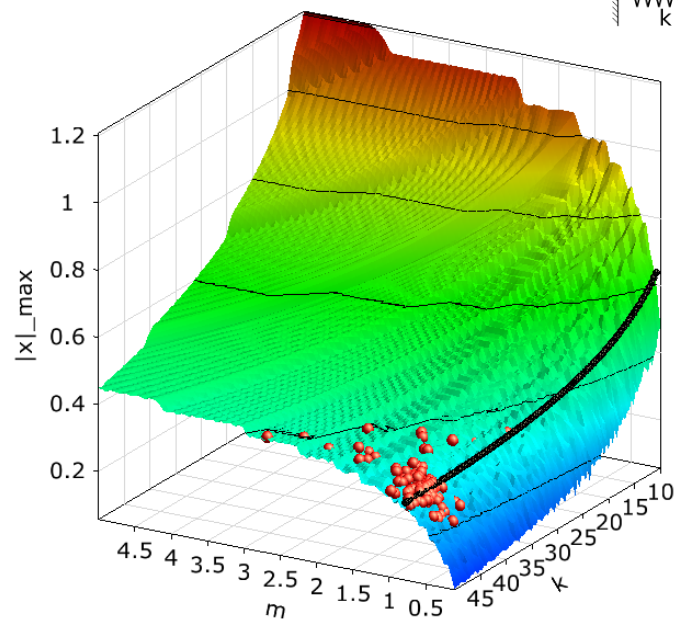


PSO with global and local search



PSO global (220 solver calls)

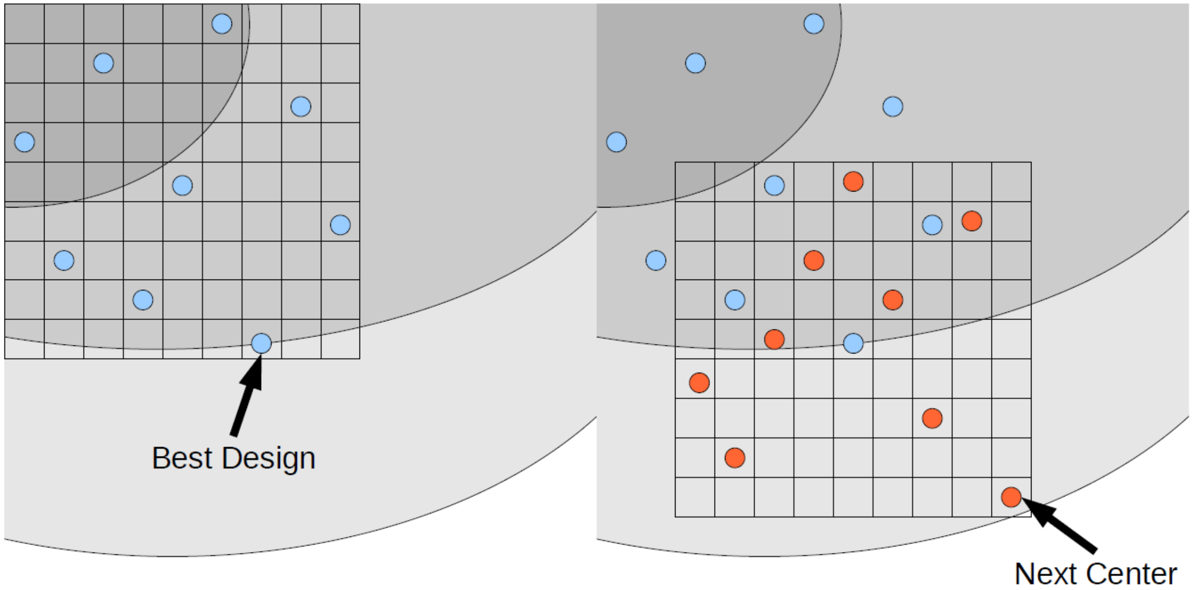
$$m_{opt} = 0.72 \text{ kg}$$
$$k_{opt} = 46.0 \text{ N/m}$$
$$\omega_{opt} = 8.00 \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.262 \text{ m}$$



PSO local (198 solver calls)

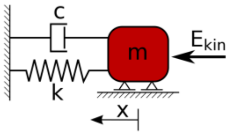
$$m_{opt} = 0.73 \text{ kg}$$
$$k_{opt} = 46.9 \text{ N/m}$$
$$\omega_{opt} = 7.99 \text{ 1/s}$$
$$|x|^{opt}_{max} = 0.258 \text{ m}$$

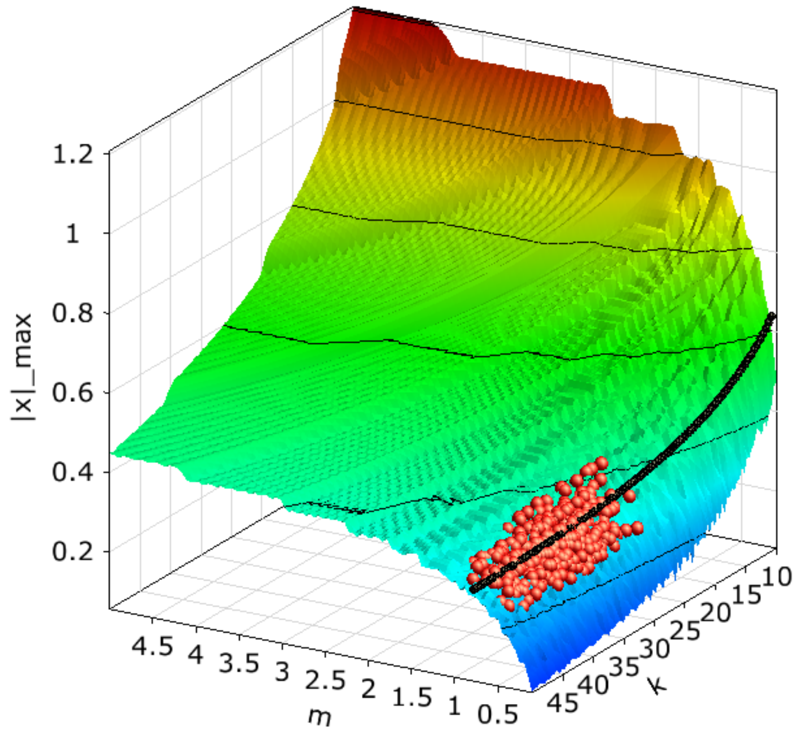
Simple Design Improvement



- 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



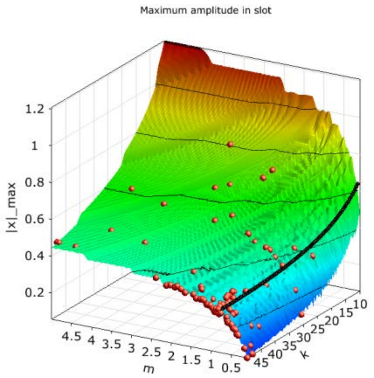


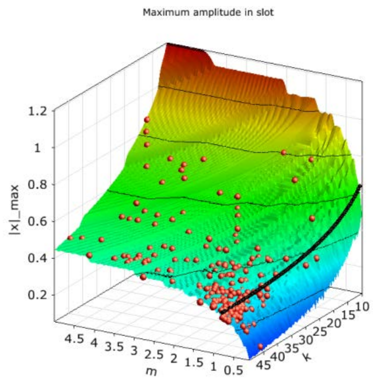
- 318 solver calls

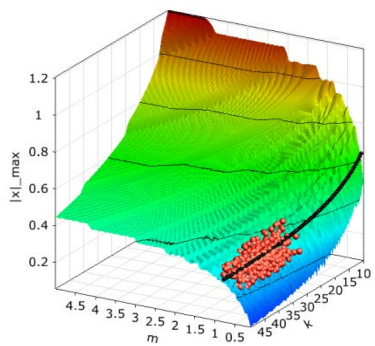
$$m_{opt} = 0.70 \text{ kg}, \qquad k_{opt} = 44.9 \text{ N/m}$$
$$\omega_{opt} = 8.00 \text{ 1/s}, \quad |x|_{max}^{opt} = 0.26 \text{ m}$$

Nature inspired Optimization

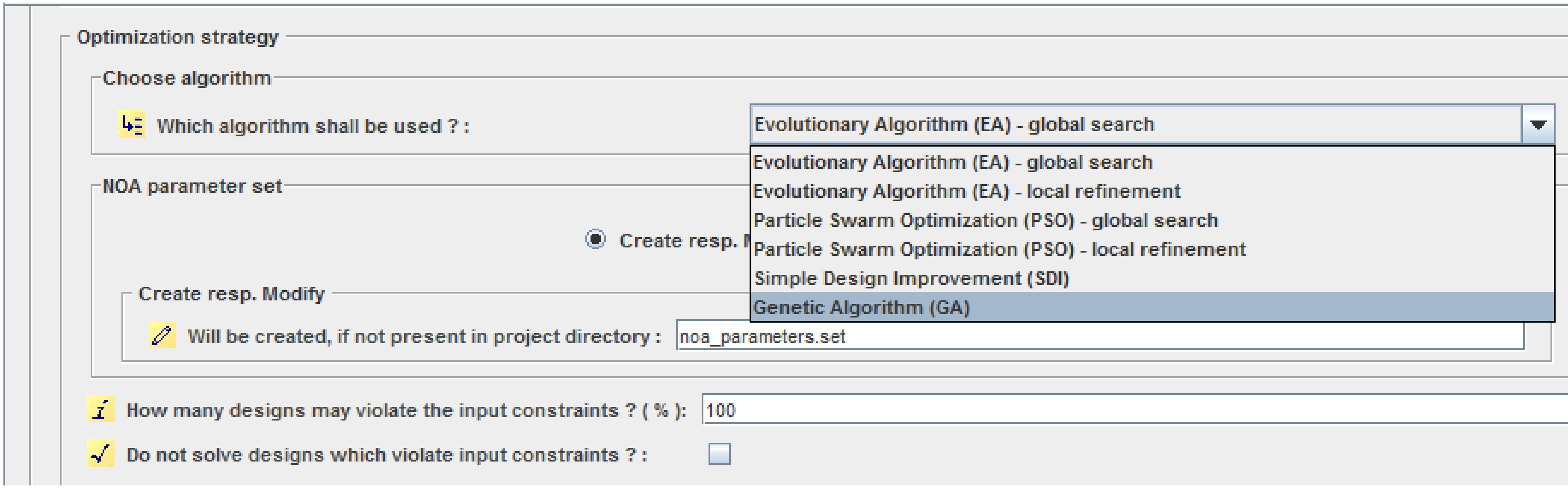
- Evolutionary algorithm
  - Suitable for global and local search
  - Search for new designs and evolutionary improvement of designs
- Genetic algorithm
  - Search for new designs
  - Search for feasible design islands with additional local optimization (e.g. NLPQL)
- Particle swarm optimization
  - 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



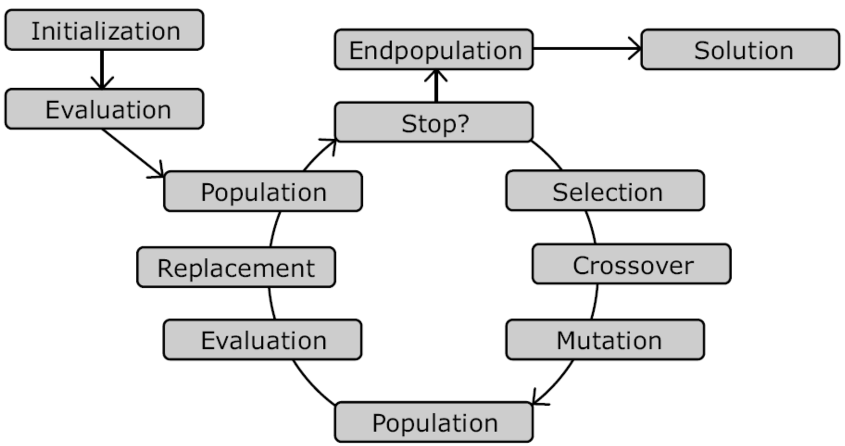




Toolbox for Natural inspired Optimization

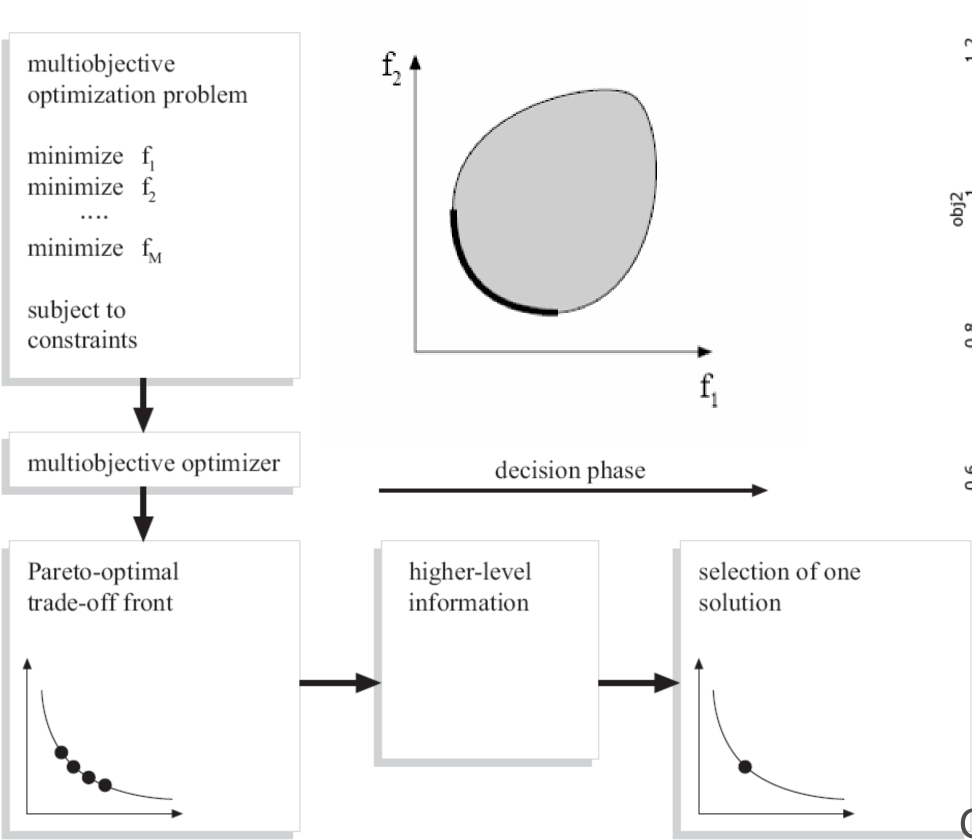


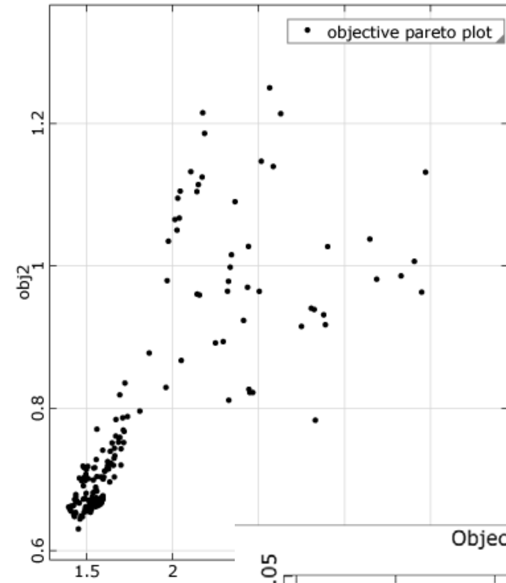
- Global and local search for EA
- Global and local search for PSO
- Simple design improvement (local search)
- Genetic algorithm (global search, adaptive mutation to reduce number of infeasible designs)



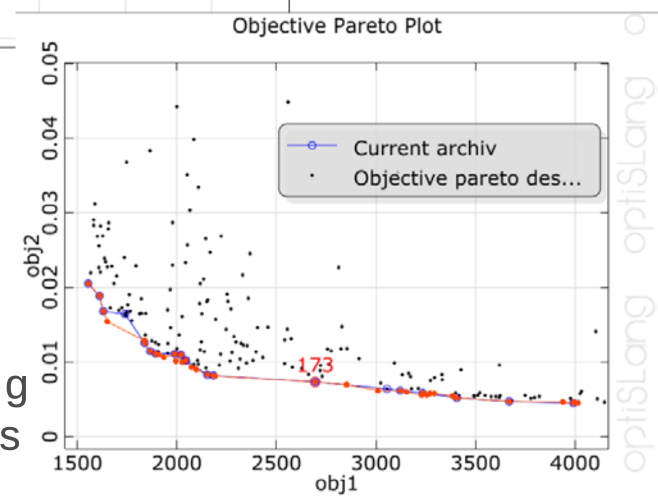
Multi Criteria Optimization Strategies

Pareto Optimization Strategies





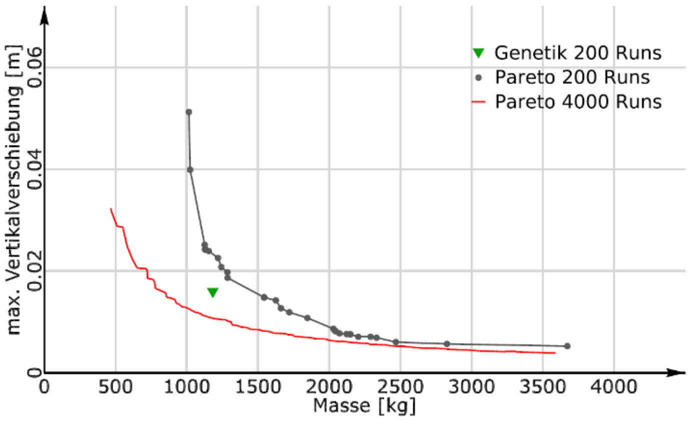
Correlated objectives

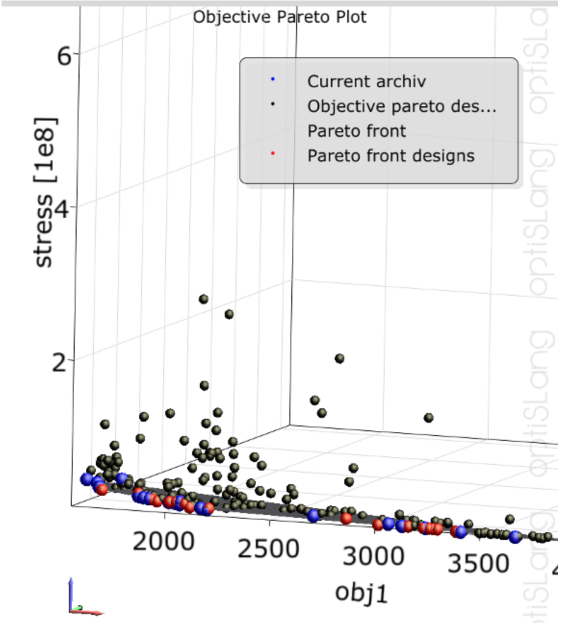


Conflicting objectives

Multi Criteria Optimization Strategies

Pareto Optimization using Evolutionary Algorithms (SPEA2)

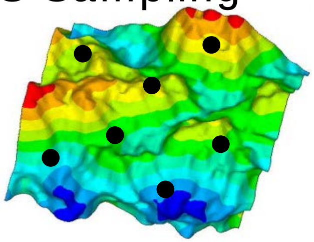




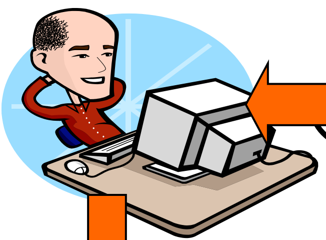
- Only in case of conflicting objectives, a Pareto frontier exists and Pareto optimization is recommended (optiSLang post processing supports 2 or 3 conflicting objectives)
- Effort to resolute Pareto frontier is higher than to optimize one weighted optimization function

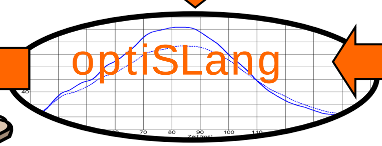
Sensitivity Analysis and Optimization

1) Start with a sensitivity study using the LHS Sampling



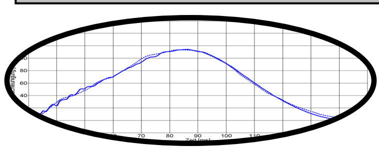
Scan the whole Design Space



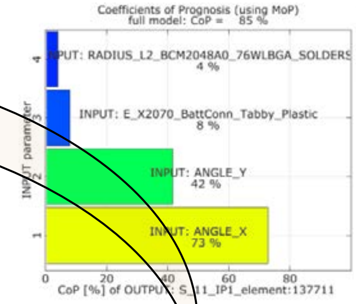


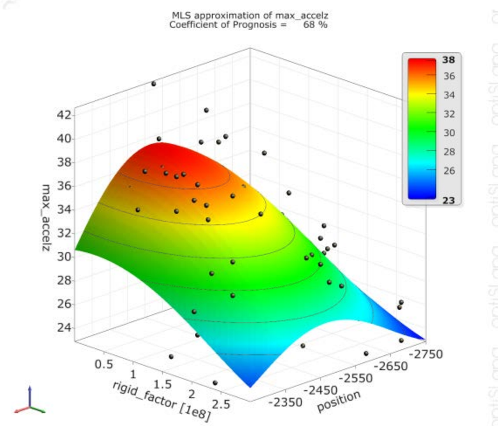
Understand the Problem using CoP/MoP

Search for Optima



2) Identify the important parameters and responses
- understand the problem
- reduce the problem





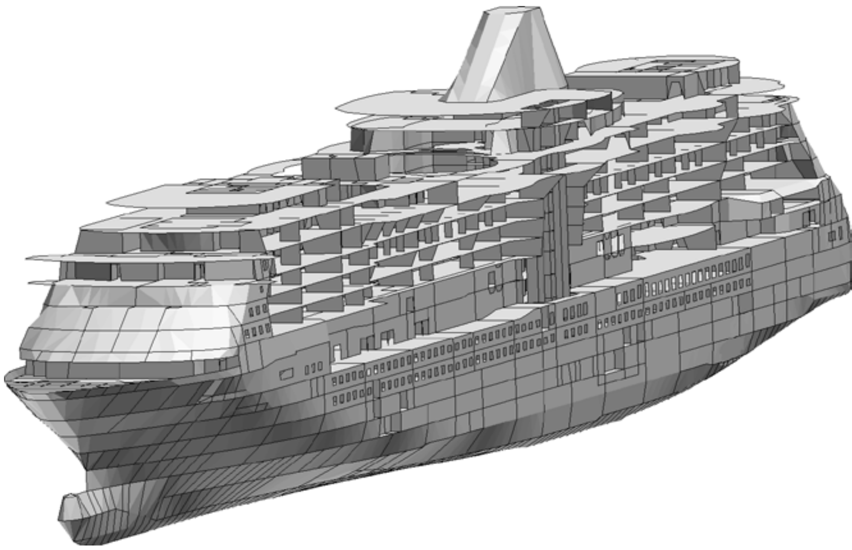
3) Run an ARSM, gradient based or biological based optimization Algorithms

4) Goal: user-friendly procedure needs as much automatism as possible

Optimization of a Large Ship Vessel

EVOLUTIONARY ALGORITHM

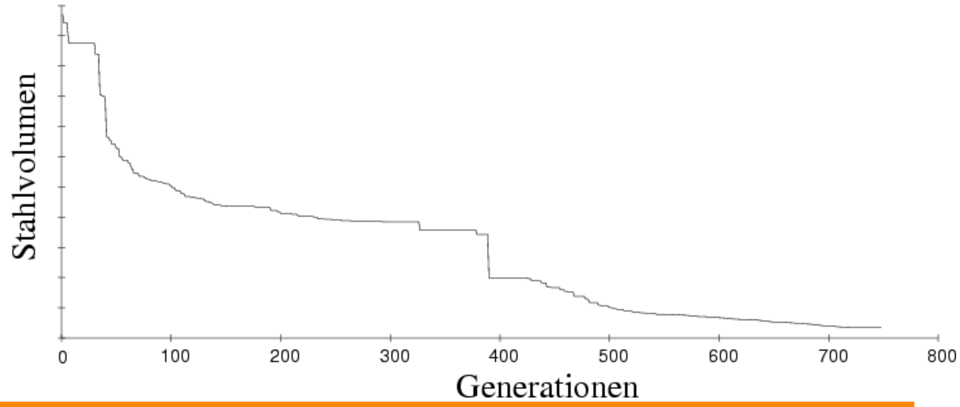
- Optimization of the total weight of two load cases with constrains (stresses)
- **30.000** discrete Variables
- Self regulating evolutionary strategy
- Population of 4, uniform crossover for reproduction
- Active search for dominant genes with different mutation rates



Solver: ANSYS

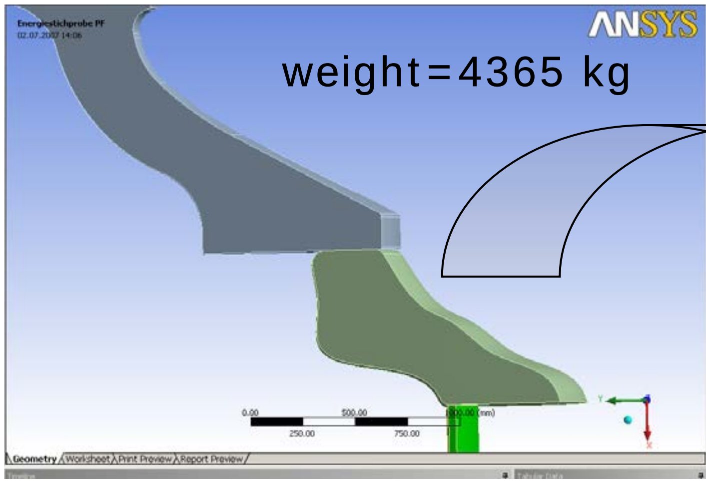
Design Evaluations: 3000

Design Improvement: > 10 % 0

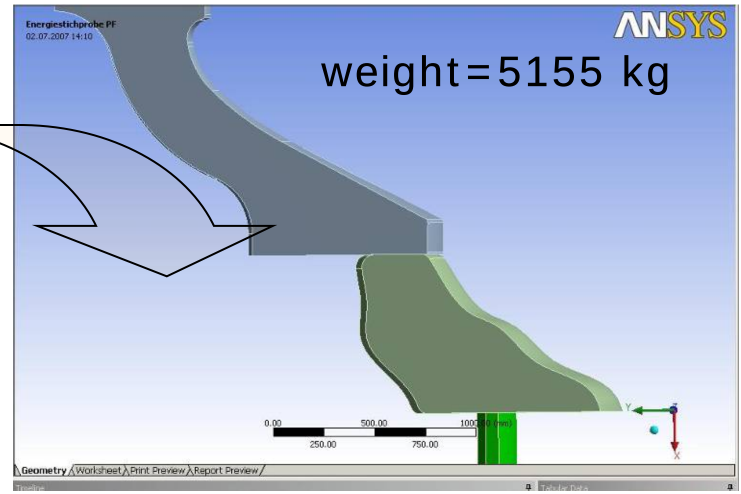


Optimization of see hammer

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

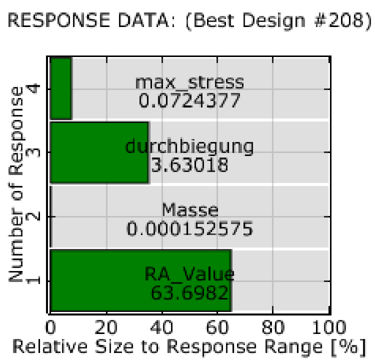
Design Evaluations: 200 times 4 loadcase
CAE: ANSYS workbench
CAD: ProEngineer

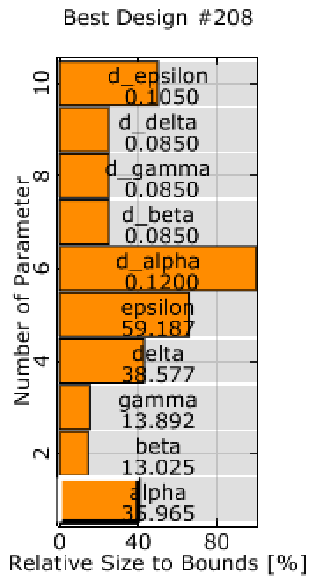
Optimization of Tennis Racket

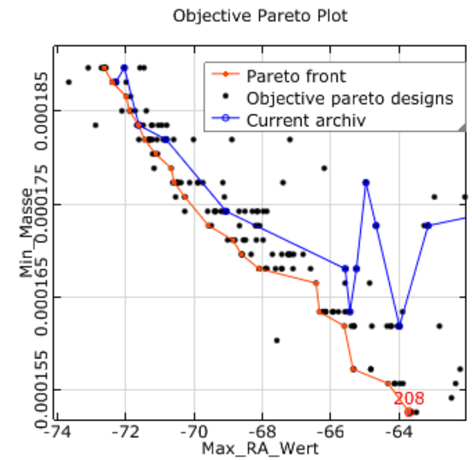
The challenge in tennis racket optimization is to find a optimal design of the composite structure.

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.







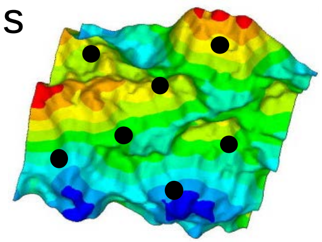
Design Parameter ≥10
Design Evaluations: 200
CAE: ANSYS Workbench

by courtesy of HEAD THE POWER OF YOU

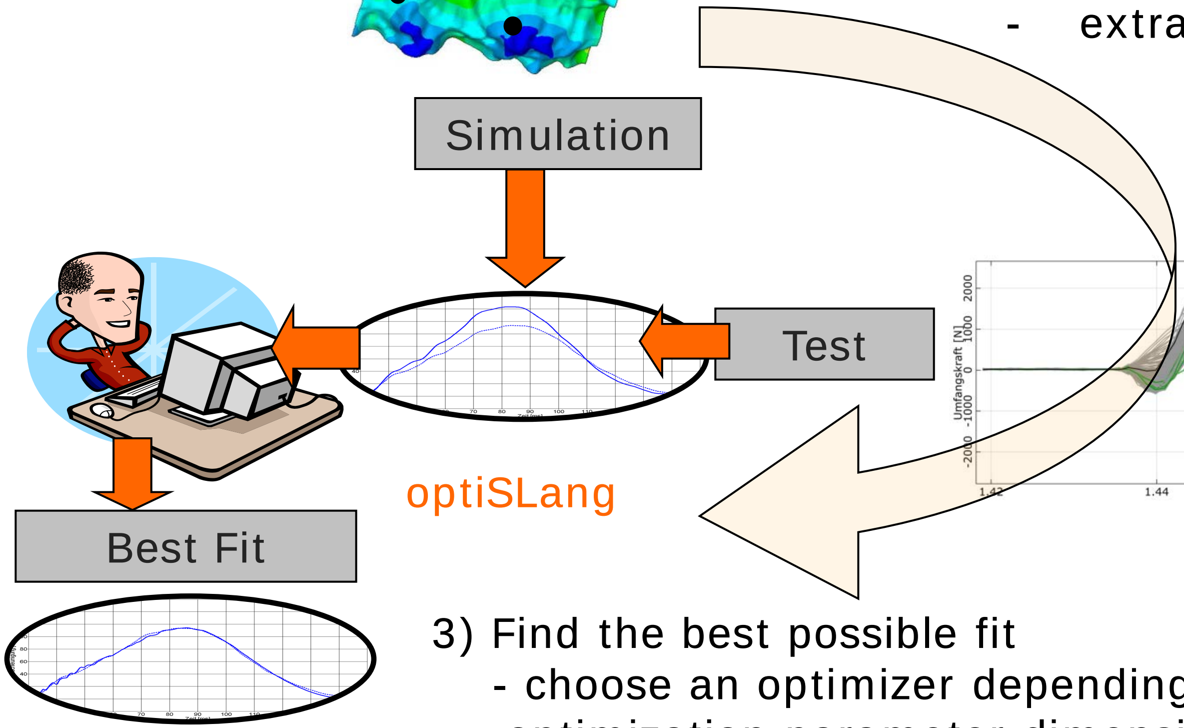
Parameter Update
and System Identification

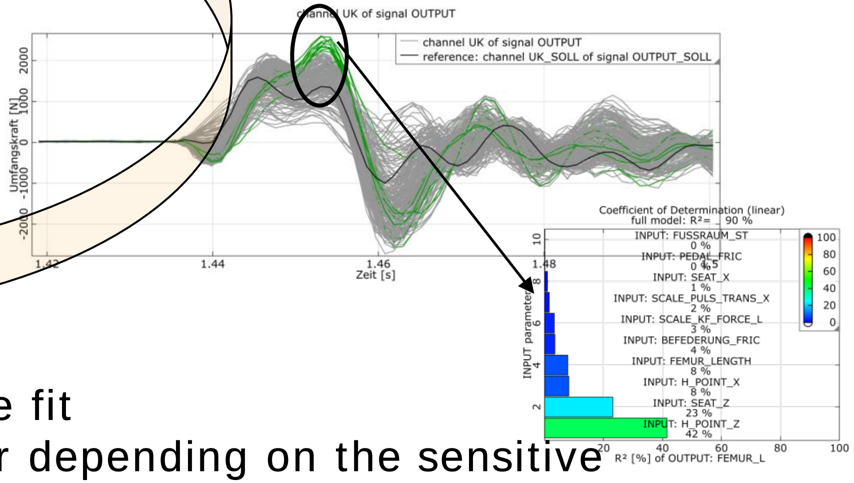
Calibration using optiSLang

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

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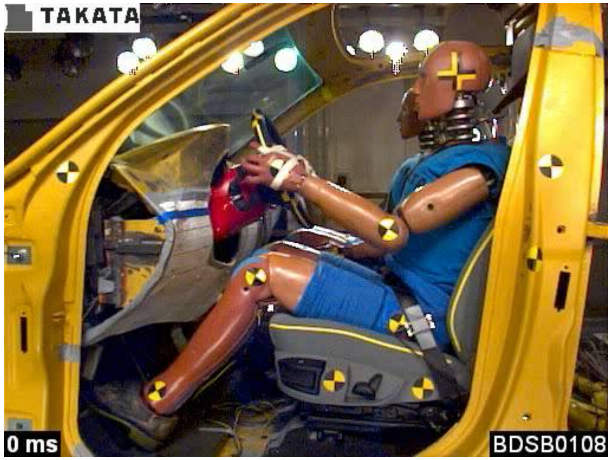
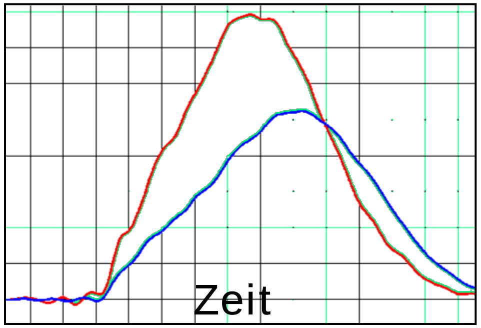
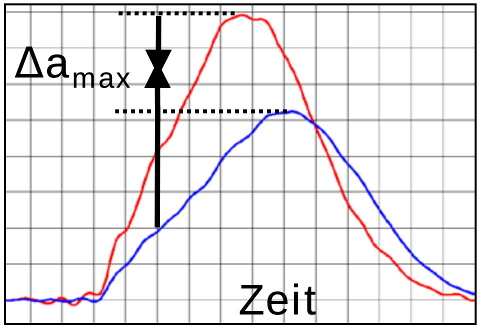
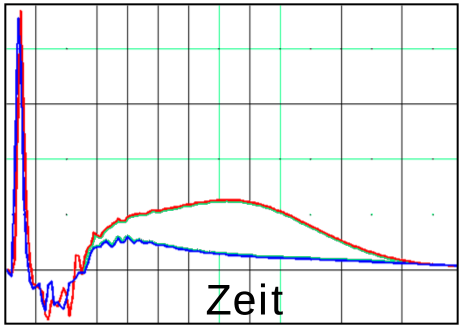
Validation of Airbag Test Results

- Validation of numerical models with test results (7 test configuration)
- Modelling with Madymo
- Sensitivity study to identify sensitive parameters and responses and to verify the design space
- Definition of the objective function





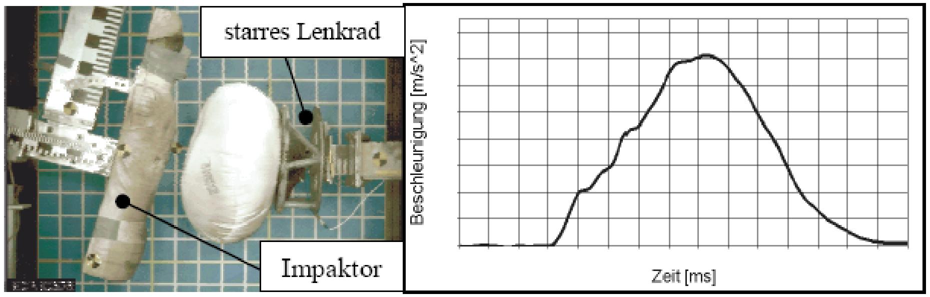


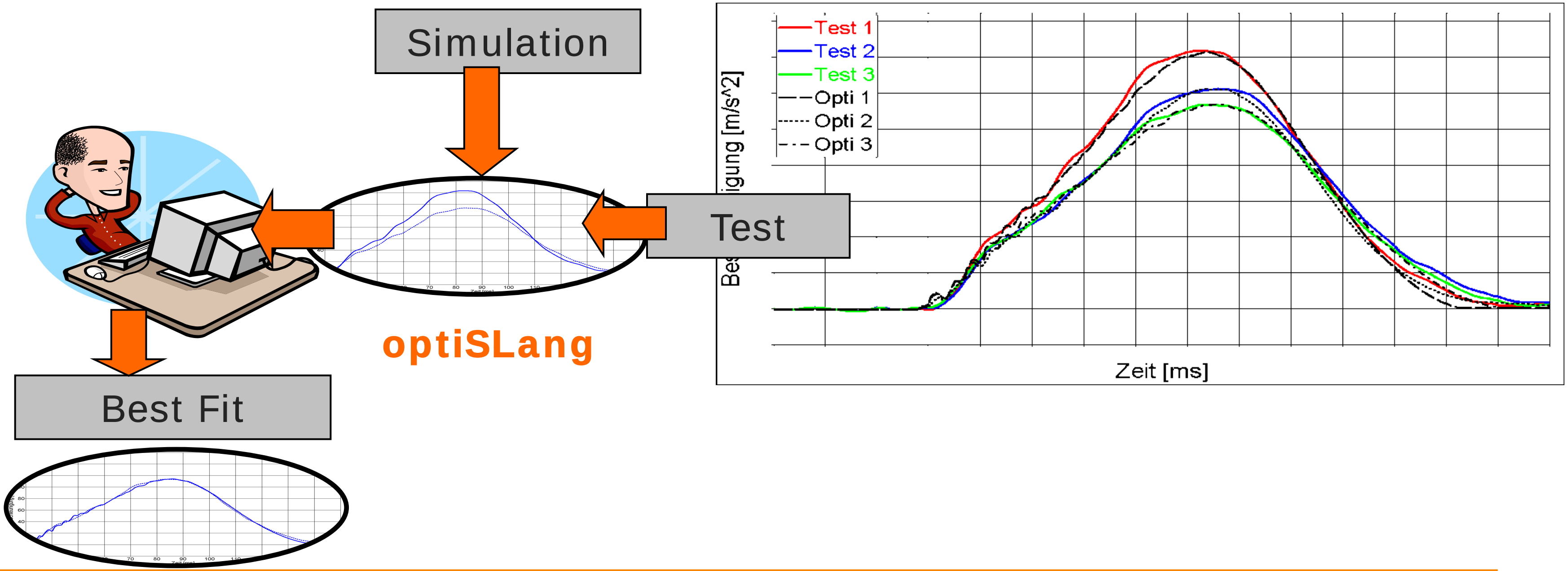


= α **acceleration integral** + β **acceleration peak** + γ **pressure integral**

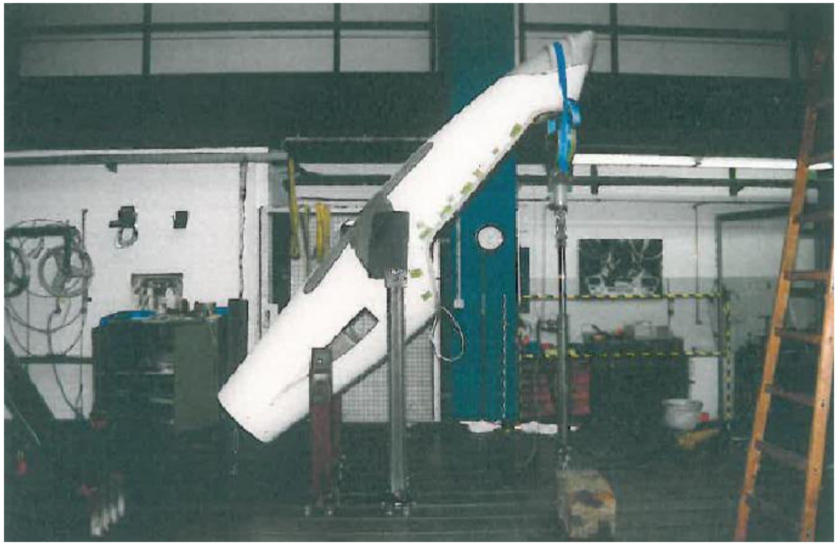
Validation of Airbag Test Results

- optiSLang’s genetic algorithm for global search
- 15 generation
  *10 individuals
  *7 test configuration
- (Total:11 h CPU)





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

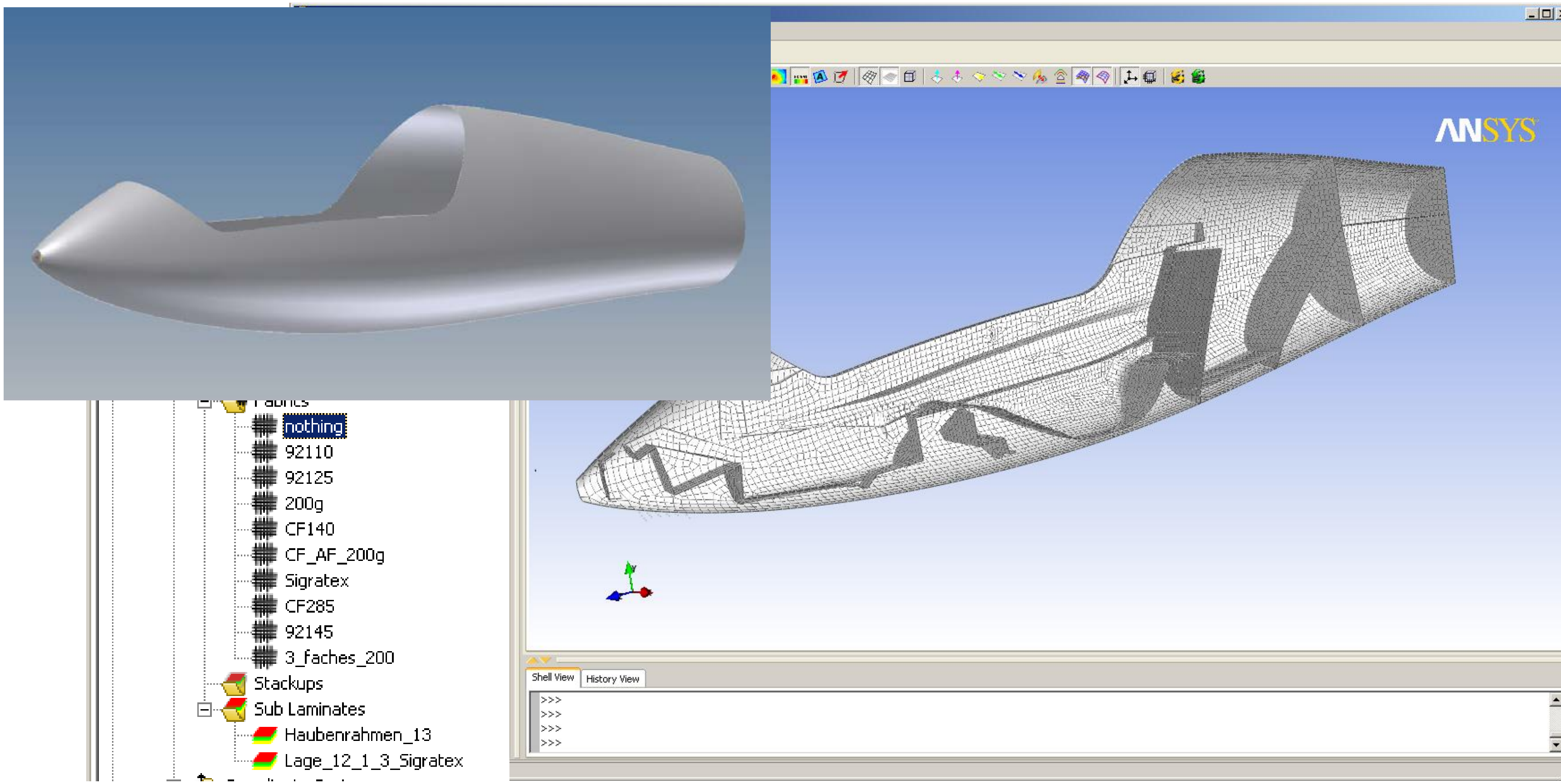


Body was tested regarding crash performance (German TÜV)

1. Calibration of test results

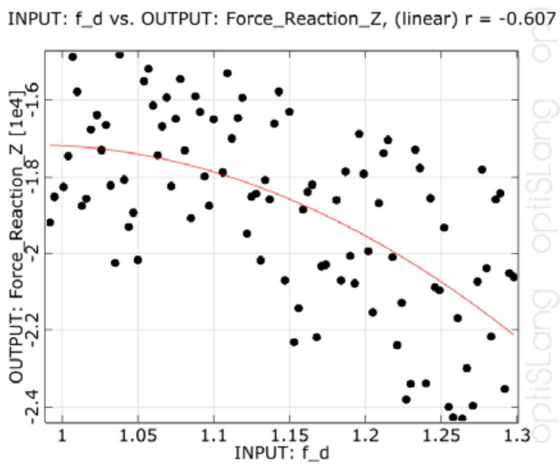
2. Optimization of Crash performance of the airplane cockpit carbon fiber body to withstand the next higher crash loading class

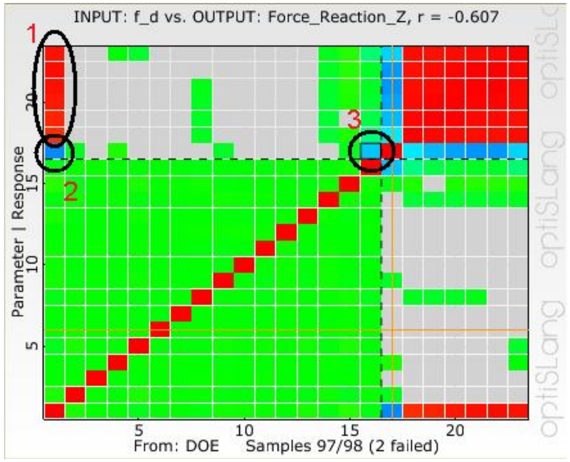
Parametrization of carbon body using ANSYS ACP



- 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:

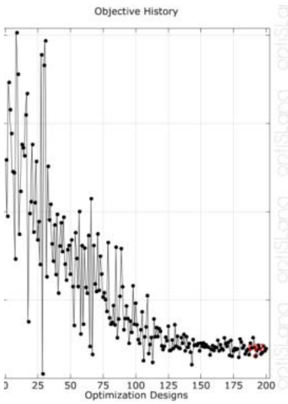
- very good fit of test results!
- identified model is qualified for optimization
- the safety margin of the calibrated model is large enough

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

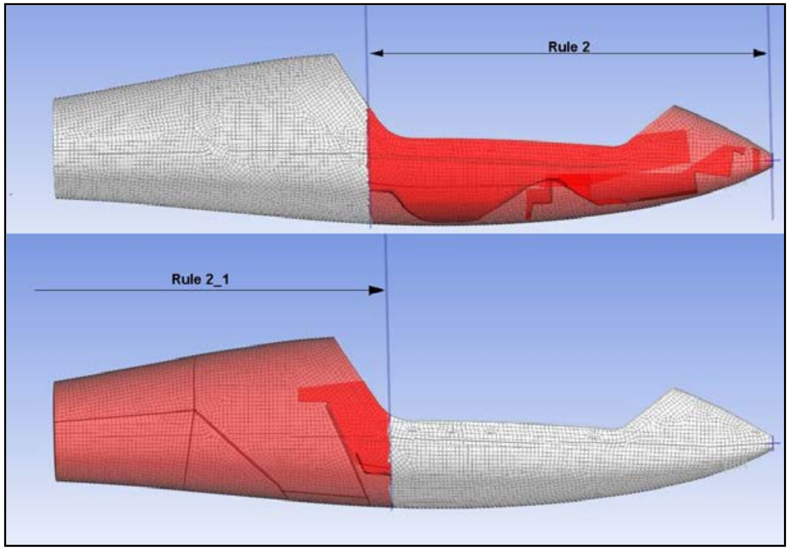
Optimization for higher crash loading

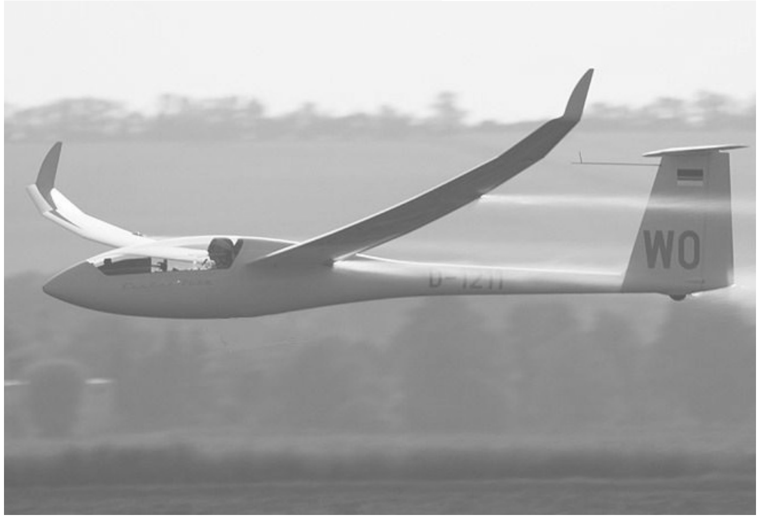


objective: minimum Mass
constraints: maximum load, no critical damage of structur (irf-values)

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