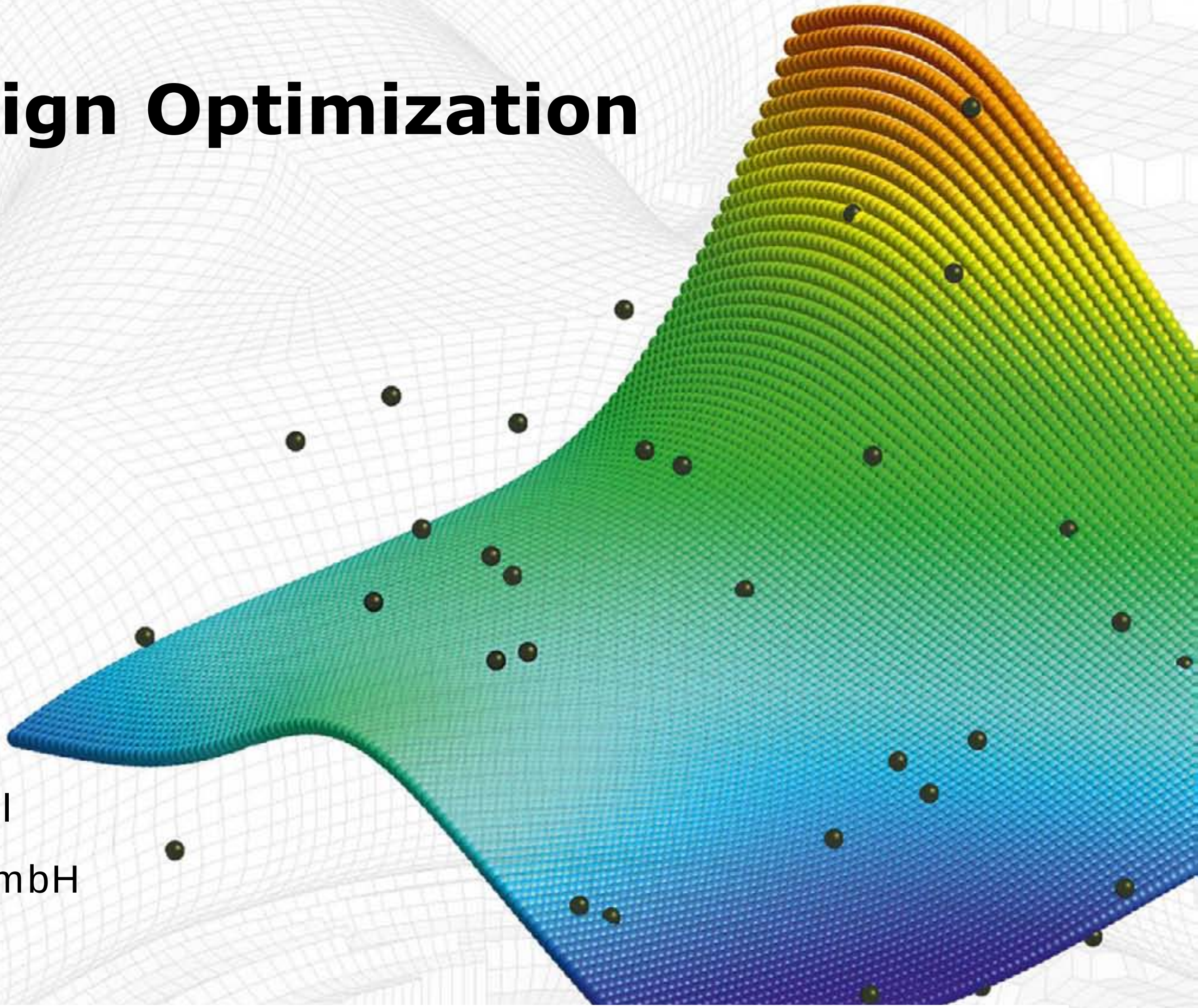
Robust Design Optimization

What ?
Why ?
How ?



Dr.-Ing. Johannes Will

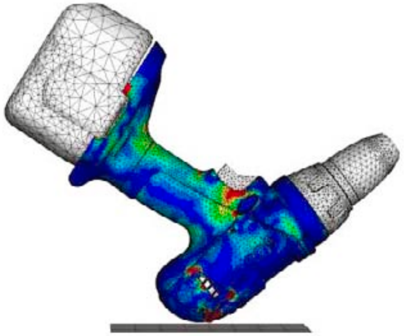
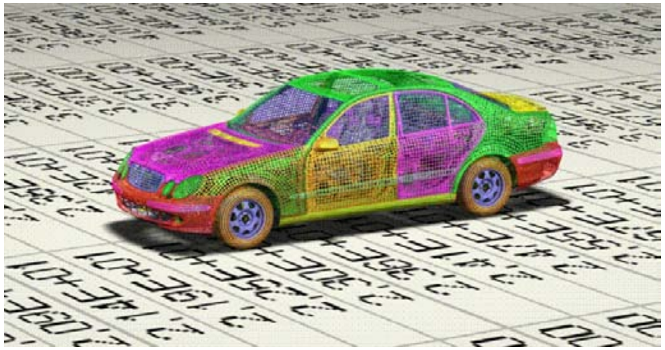
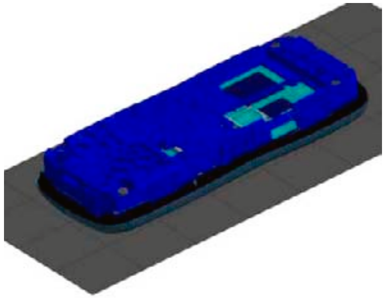
President Dynardo GmbH

dynardo

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 (reliability analysis) is the key methodology for safe, reliable and robust products
  - The combination of optimizations and robustness evaluation will lead to robust design optimization strategies

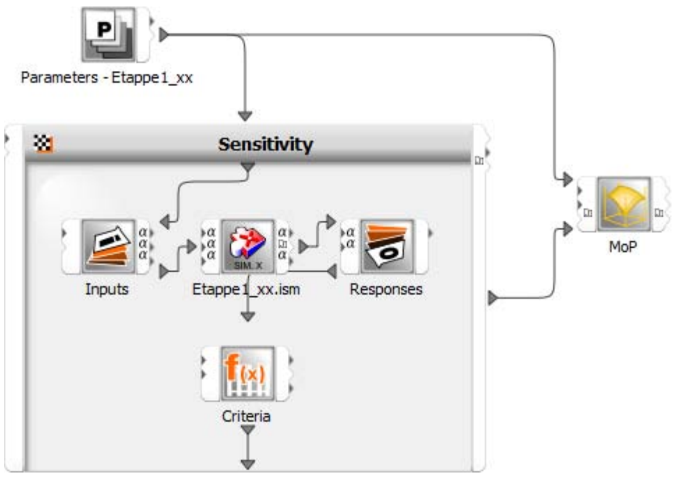
Premium Consultancy and Software Company for CAE-based Robustness Evaluation, Reliability Analysis and Robust Design Optimization using Stochastic Analysis

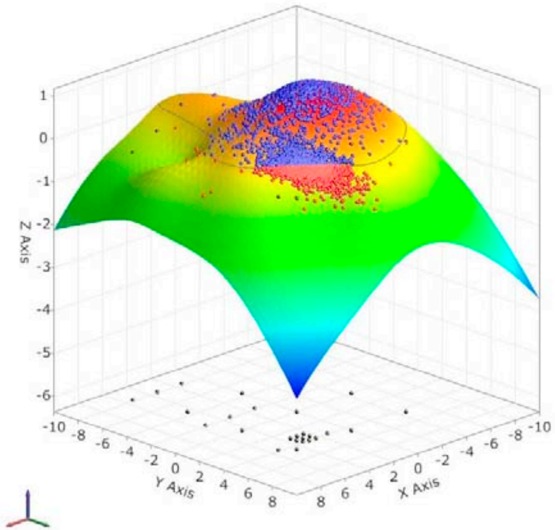




Dynardo is the consulting company which successfully introduced stochastic analysis into complex CAE-based virtual product development processes.
Recently, it is applied in the power generation industry, automotive industry, oil and gas or high-level consumer goods industry

Excellence of optiSLang

- optiSLang is an algorithmic toolbox for
  - sensitivity analysis,
  - optimization,
  - robustness evaluation,
  - reliability analysis
  - robust design optimization (RDO)
- functionality of stochastic analysis to run real world industrial applications
- **<u>easy and safe</u>** to use
  - Powerful automation and integration environment
  - predefined workflows
  - algorithmic wizards
  - robust default settings





dynardo

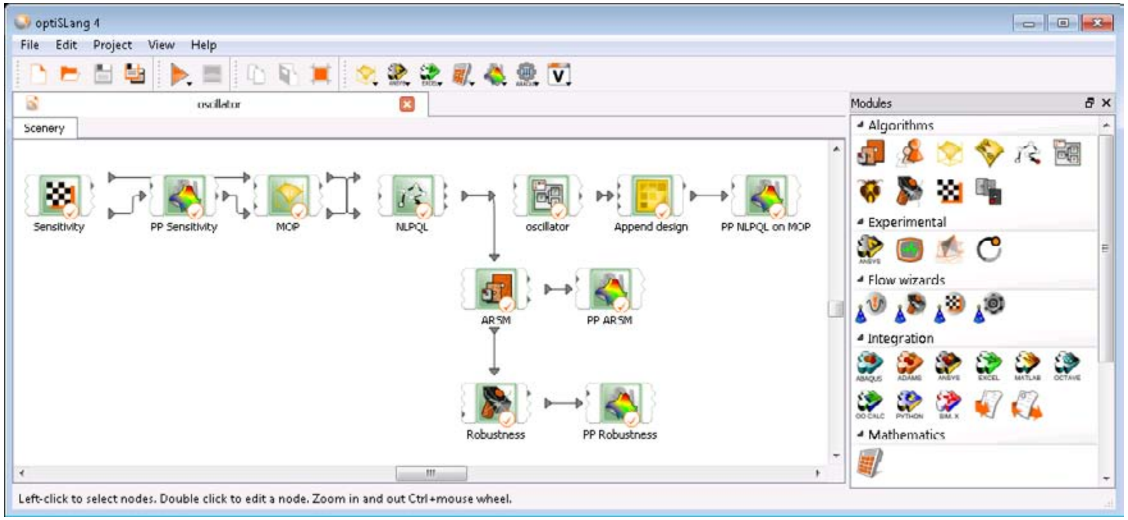
Customers expectation

- **Understand your design** using Sensitivity Analysis
  - Easy and safe to use workflow for engineers and designers to get a maximum understanding for the relations of parameterized properties with a minimum number of FE-calculations
- **Improve your Design** using Optimization Analy
  - Easy and safe to use workflow transfer learning's and suggest optimization strategy
- **Proof Robustness of your Designs** using Stochastic Analysis
  - Easy and safe to use workflow for 2-,3- or even a 6-sigma design

optiSLang v4

"Robust Design Optimization - easy and flexible to use"

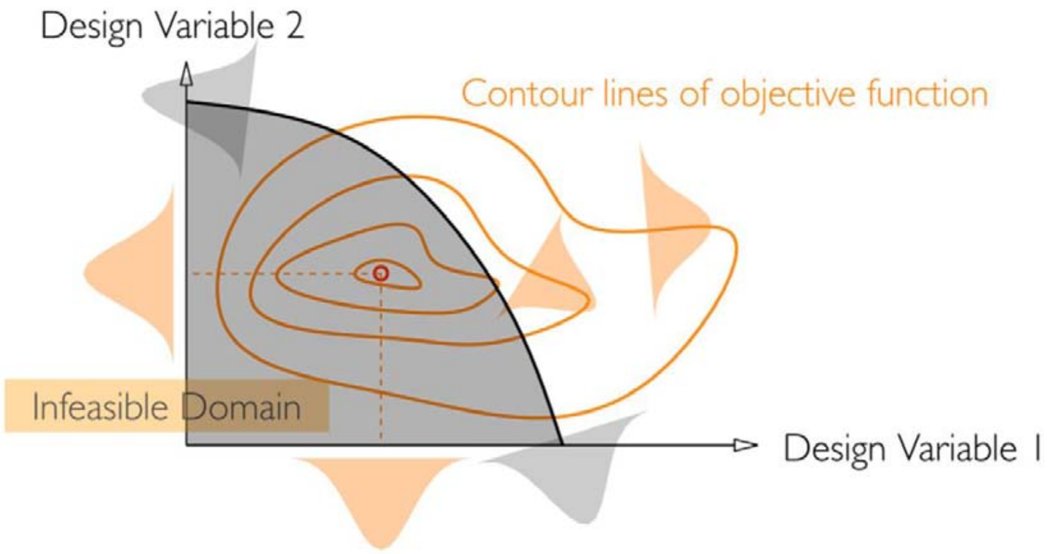
- automated generation of an interactive process chain using the **CAE-based modules of sensitivity analysis, optimization and robustness evaluation**
- minimum of user input required
- automated best practice management for algorithmic defaults
- flexible process integration and post-processing defaults



Robust Design Optimization

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.

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 (Loop in Loop) RDO** strategies estimating variance based or probability based measurements of variation for every candidate in the optimization space

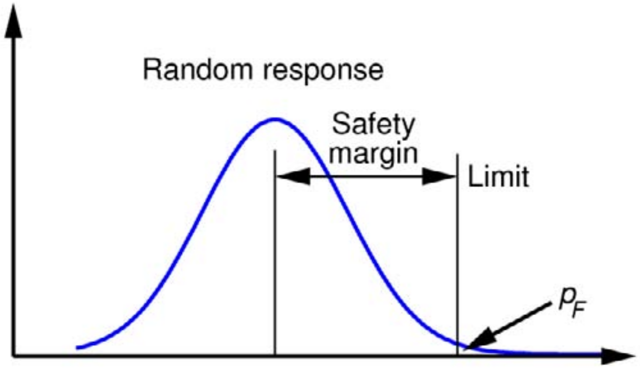
are possible RDO strategies.

Which Robustness measure we should use?

Variance based RDO

- Safety margins of all critical responses are larger than a specified sigma level (e.g. **Design for Six Sigma**)

$$y_{limit} - y_{mean} \leq a \cdot \sigma_y$$



Reliability based RDO

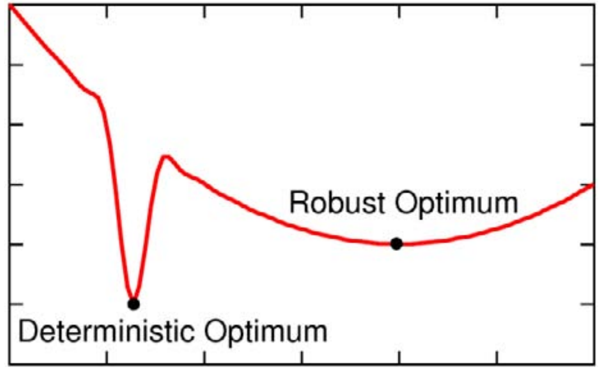
- Failure probability with respect to given limit states is smaller as required value

$$p_F \leq p_F^{target}$$

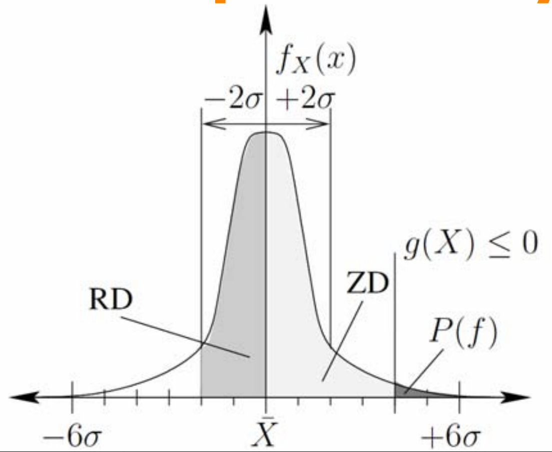
Taguchi based RDO

- Taguchi loss functions
- Modified objective function

$$f(y) = \frac{k}{N} \sum y_i^2 = k(\bar{y}^2 + \sigma_y^2)$$



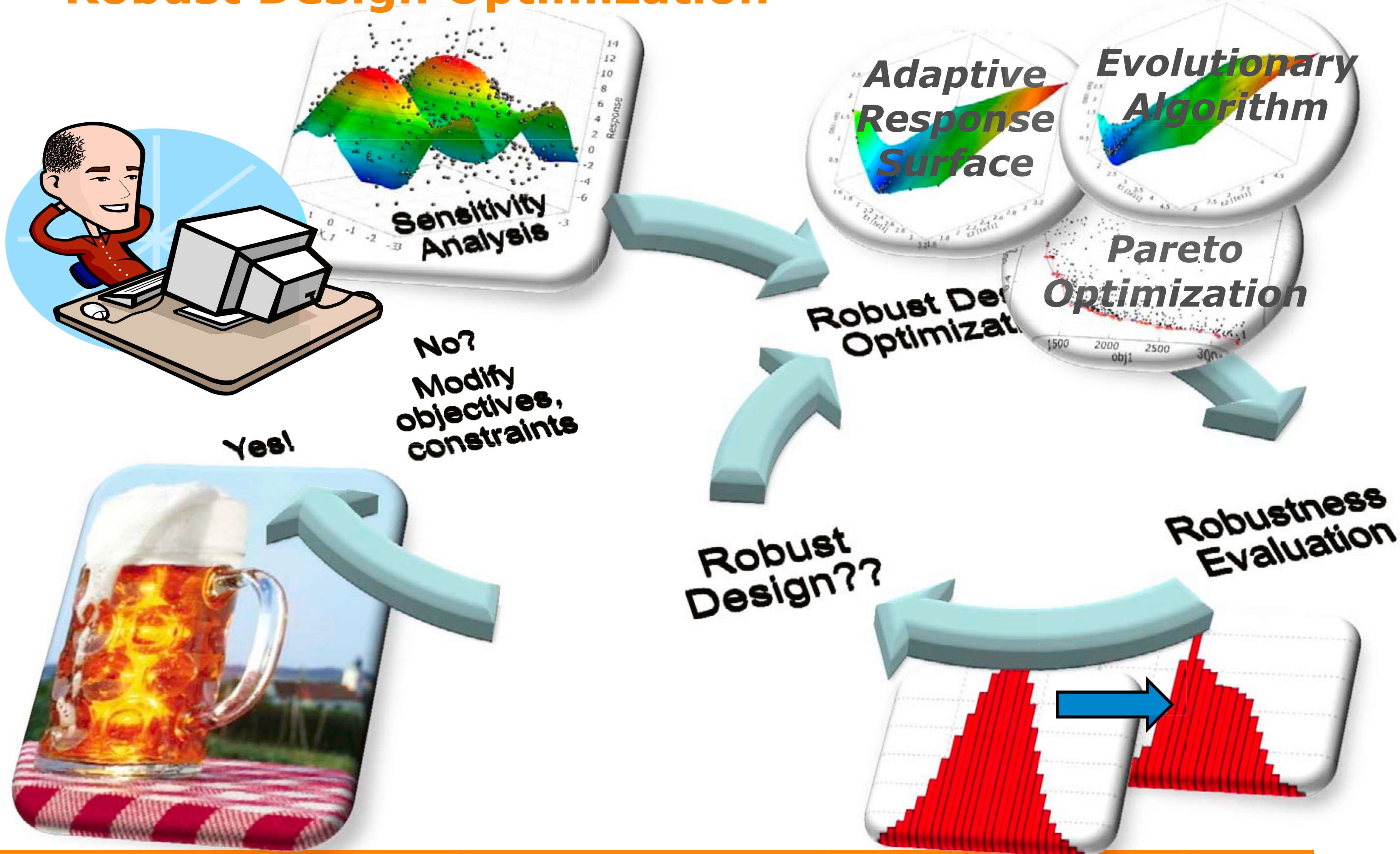
Failure probability for Six Sigma design



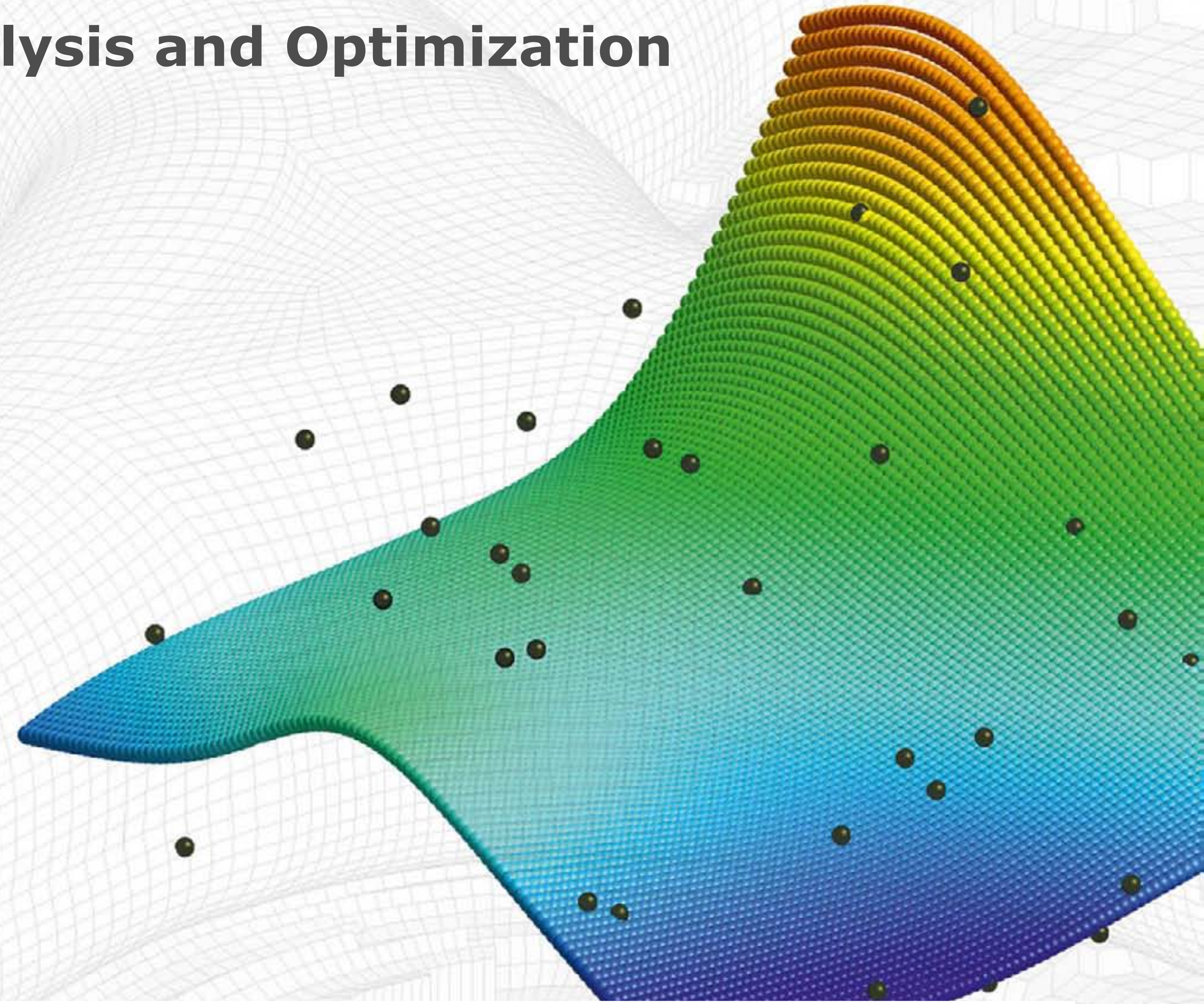
The statement six sigma results in 3.4 defects out of a million introduces a "safety distance" of 1.5 sigma shift for long term effects!
Therefore the target of virtual prototyping is a **6-1.5=4.5 Sigma design proof.**

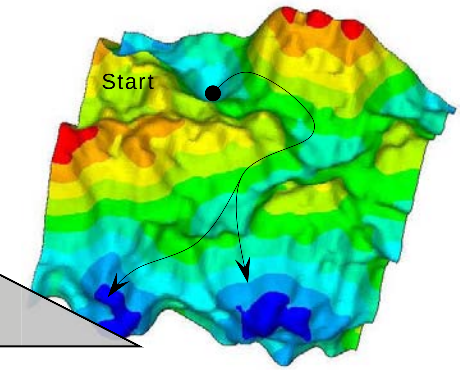
Sigma level	Variation	Probability of failure	Defects per million (short term)	Defects per million (long term – $\pm 1.5\sigma$ shift)
$\pm 1\sigma$	68.26	3.1 E-1	317,400	697,700
$\pm 2\sigma$	95.46	4.5 E-2	45,400	308,733
$\pm 3\sigma$	99.73	2.7 E-3	2,700	66,803
$\pm 4\sigma$	99.9937	6.3 E-5	63	6,200
$\pm 5\sigma$	99.999943	5.7 E-7	0.57	233
$\pm 6\sigma$	**99.9999998**	**2.0 E-9**	**0.002**	**3.4**

Robust Design Optimization



Sensitivity Analysis and Optimization





Robust Design Optimization

Robust Design

Variance based Robustness Evaluation

Probability based Robustness Evaluation, (Reliability analysis)

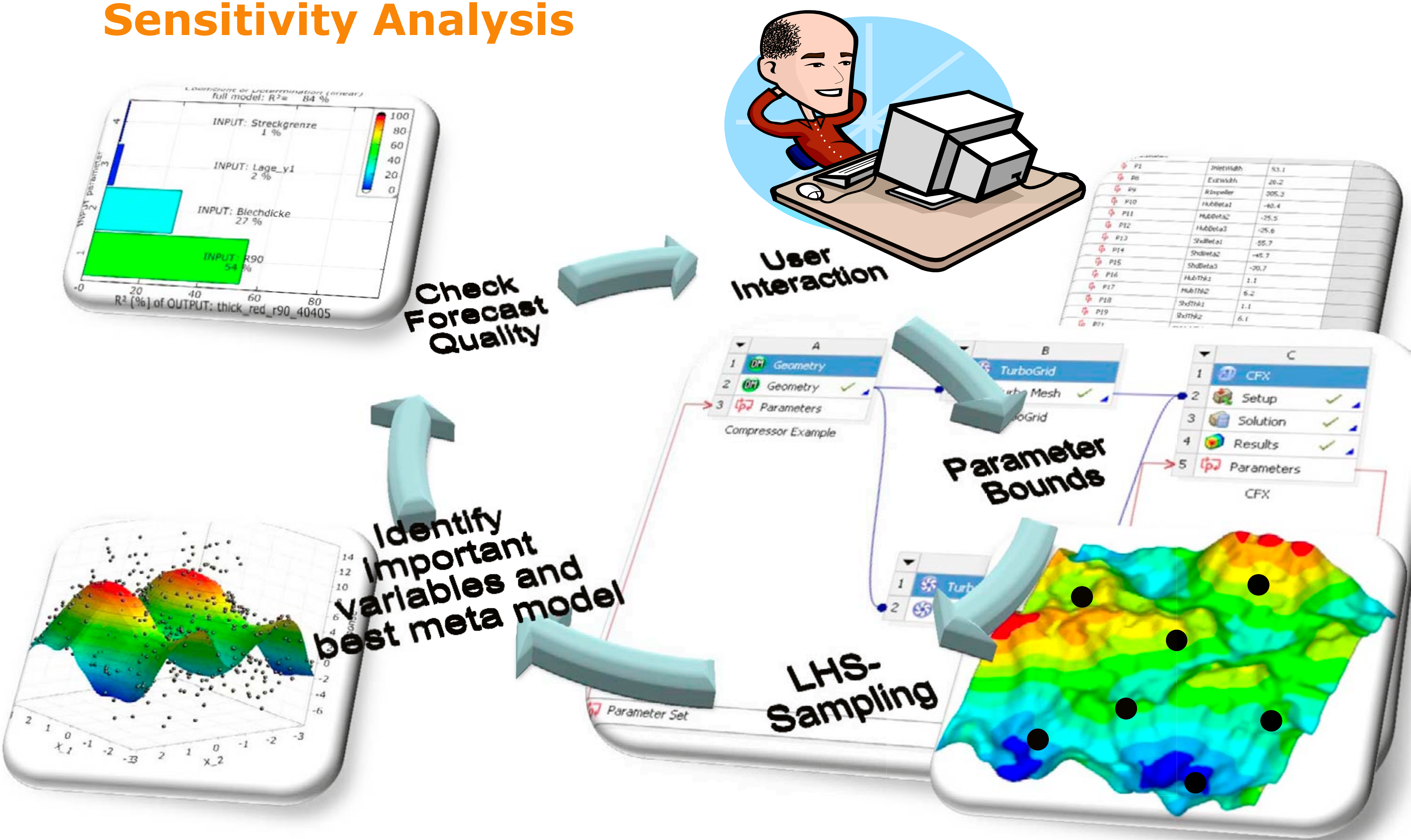
Optimization

Sensitivity Study

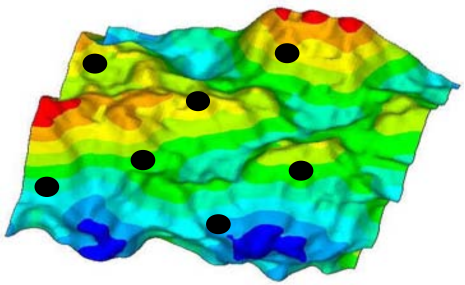
Single & Multi objective (Pareto) optimization

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

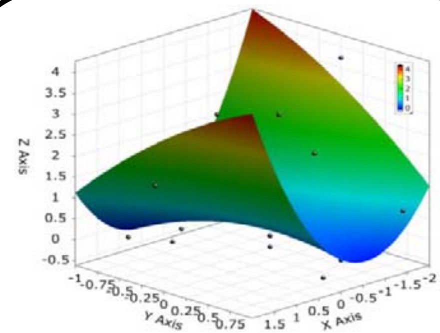
Sensitivity Analysis



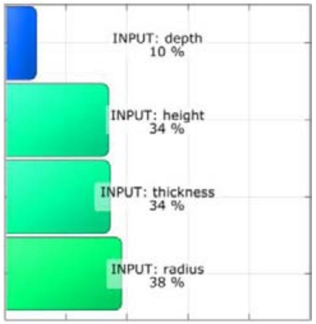
Flowchart and Methods of Sensitivity Analysis



Design of Experiments
- Deterministic
- advanced LHS

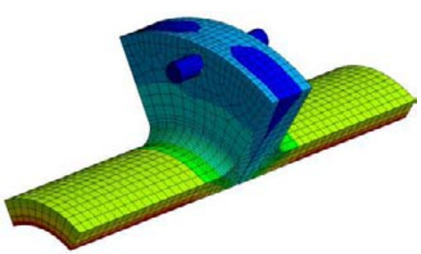


Regression Methods
- 1D regression
- nD polynomials
- Sophisticated meta models



Sensitivity Evaluation
- Correlations
- Reduced regression
- Variance-based

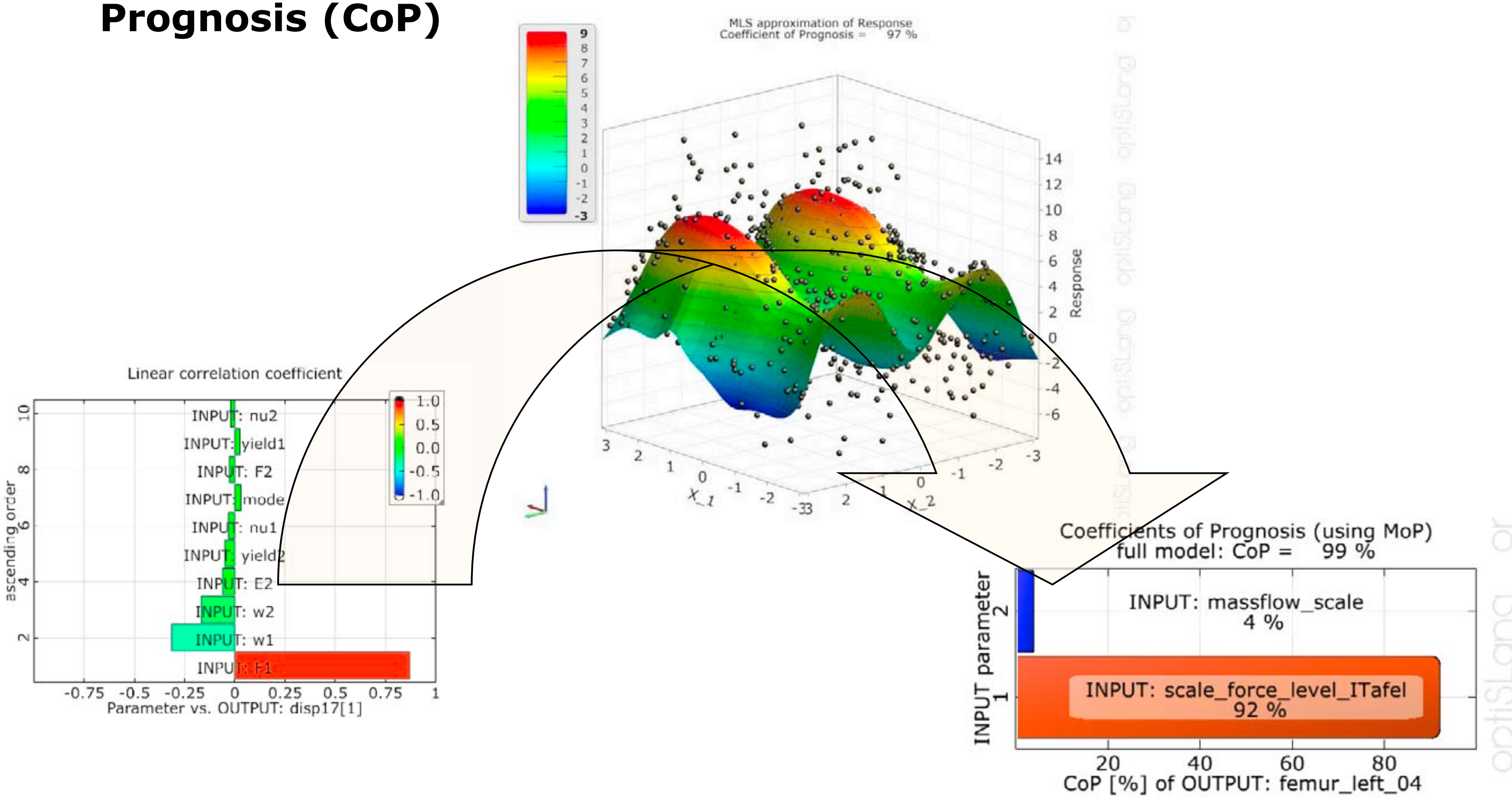
Solver



1. Design of Experiments generates a specific number of designs, which are all evaluated by the solver
2. Regression methods approximate the solver responses to understand its behavior
3. The variable influence is quantified using the approximation functions

Identifying important parameters

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

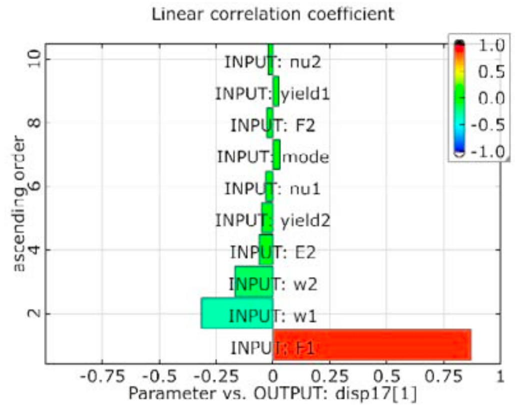


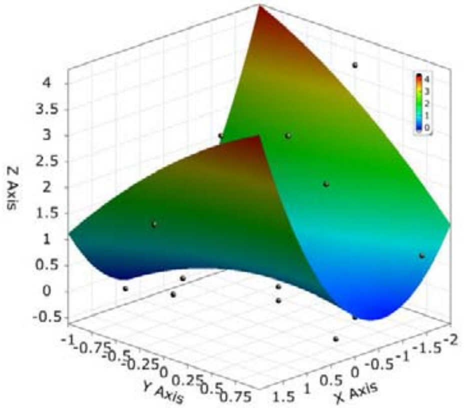
Will, J.; Most, T.: Metamodel of optimized Prognosis (MoP) – an automatic approach for user friendly design optimization; Proceedings ANSYS Conference 2009, Leipzig, Germany, www.dynardo.de

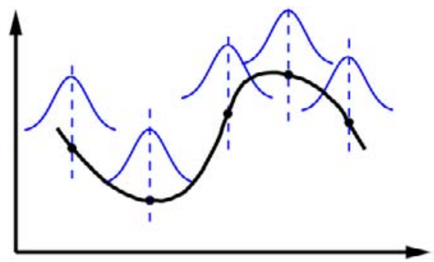
Statistical measurements

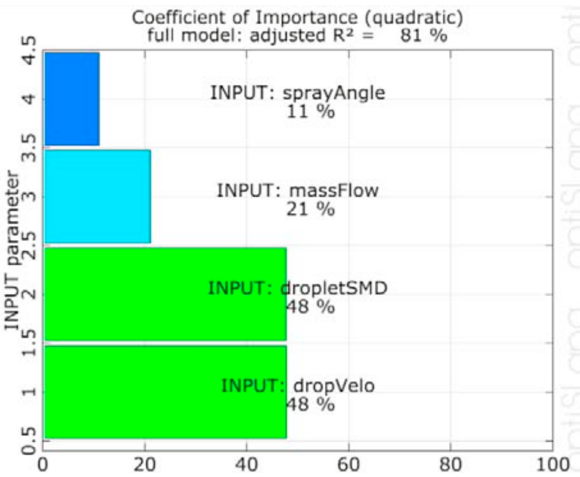
Correlation Measurements

- 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,..)







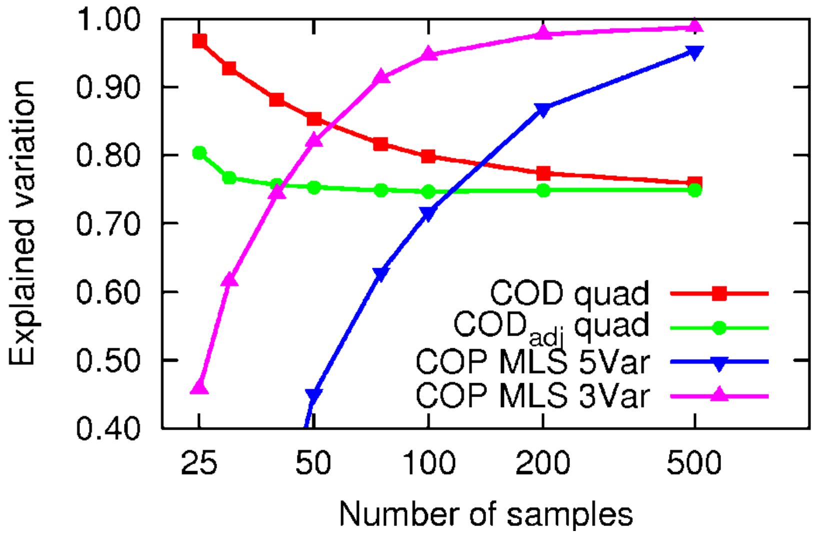


Goodness of fit Measurements (CoD)

- 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



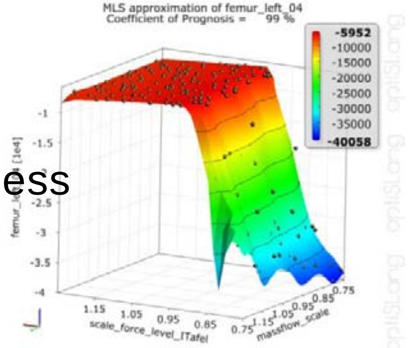
- Prediction quality is better if unimportant variables are removed from the approximation model

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 as approximation of the CAE process

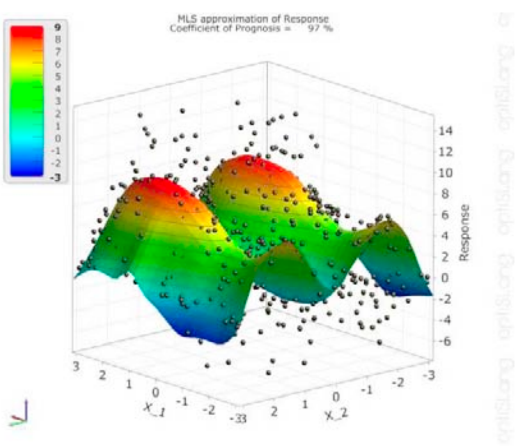


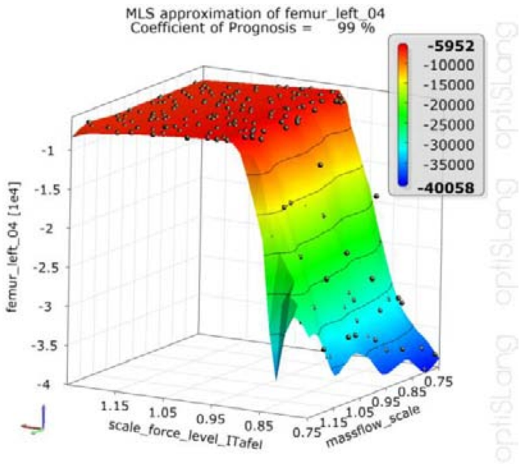
Easy and safe to use!

What do we mean with that?

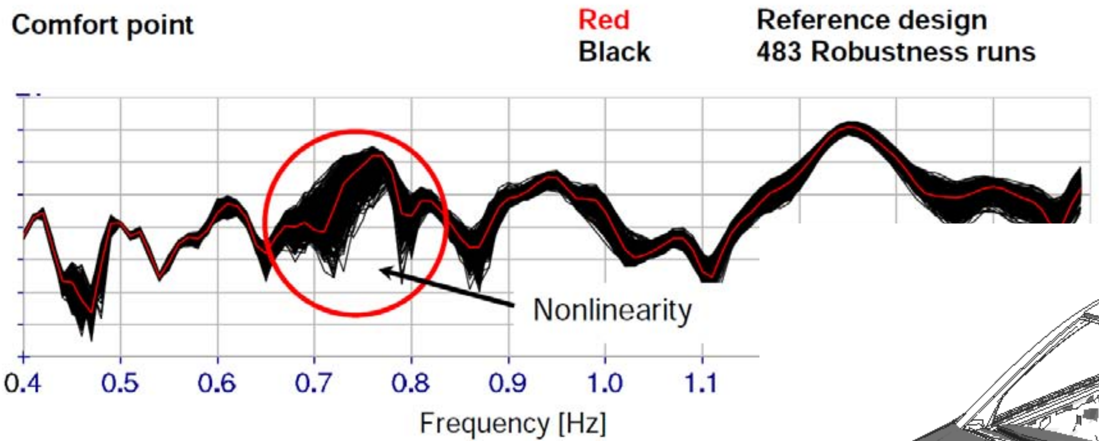
- “classic” DOE+RSM technology ask user to reduce number of variables, choose a suitable DOE with a suitable regression function and check the quality of the resulting response surface (RS) and the “optima” on the RS.

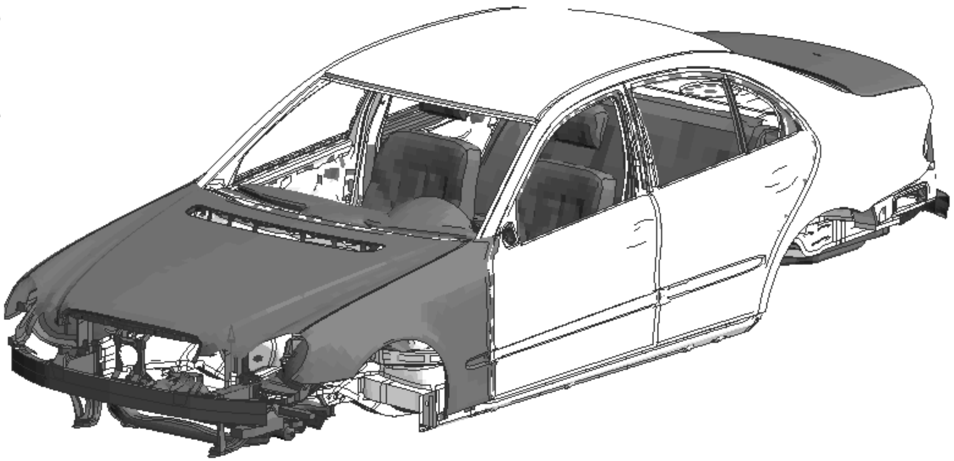
- optiSLang provides a automatic flow to reduce variables and generate the best possible response surface for every response with a given number of solver calls [Meta model of optimal Prognosis (MoP)] and checks MoP Prognosis quality and “optima” in real space.





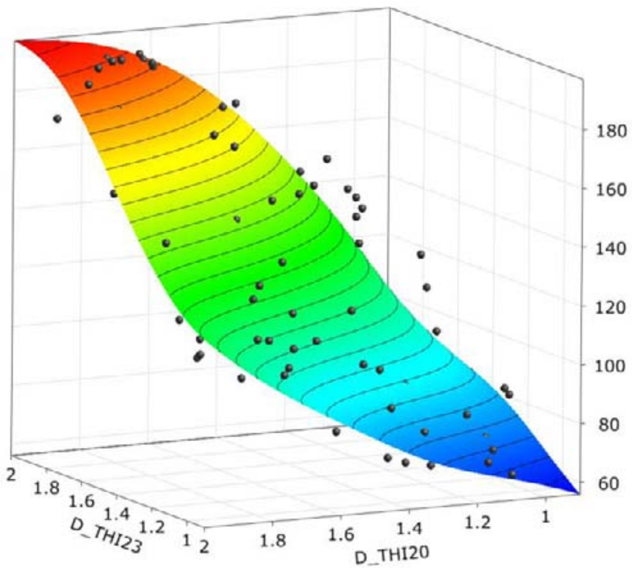
Application: Noise Vibration Harshness

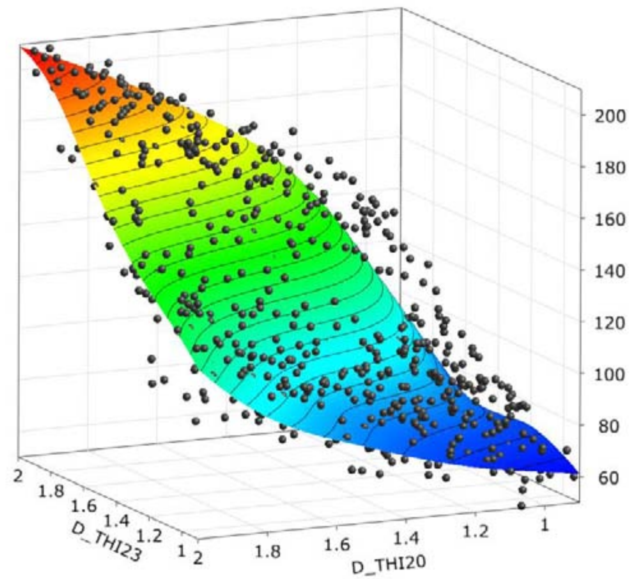




- Input parameters are 46 sheet thicknesses of a car body
- Variation of inputs within a +/- 20% interval
- Output values are sound pressure levels at certain frequencies
- One single solver run is already very time consuming

Application: Noise Vibration Harshness

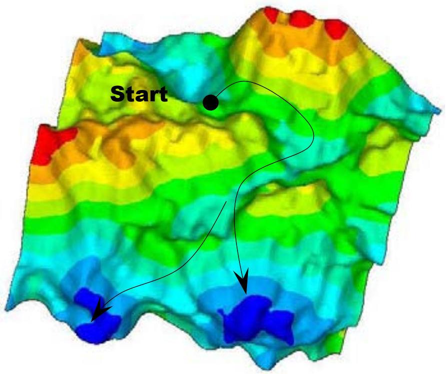




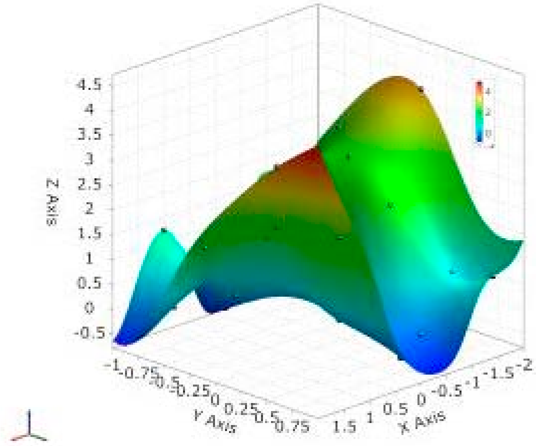
Samples	100	200	400	600	800
Full model CoP	90.9%	91.7%	95.7%	96.3%	96.9%
D_THI5	-	-	2.4%	2.3%	2.7%
D_THI6	6.0%	5.3%	8.2%	8.3%	8.7%
D_THI20	41.3%	42.7%	42.3%	43.4%	42.2%
D_THI23	49.1%	48.0%	50.7%	51.0%	53.8%

Optimization Algorithms

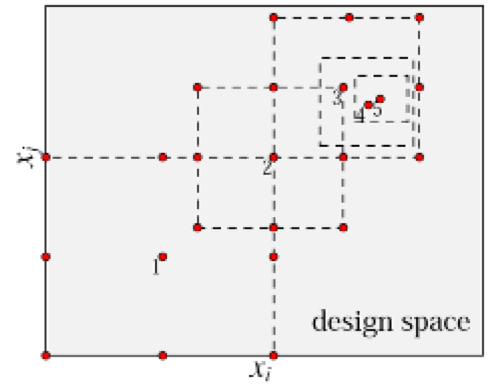
Gradient-based



Response surface method

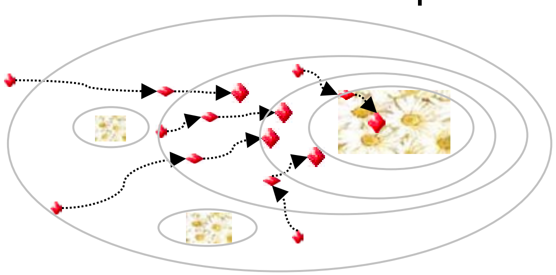


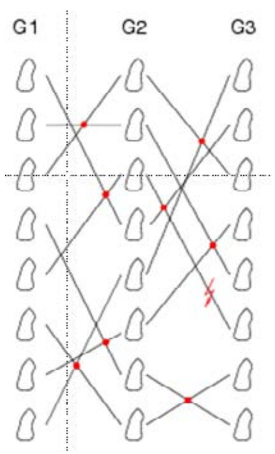
Adaptive RSM



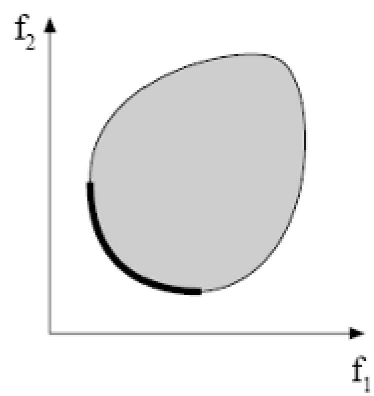
Biological Algorithms:

- Genetic algorithms,
- Evolutionary strategies
- Particle Swarm Optimization



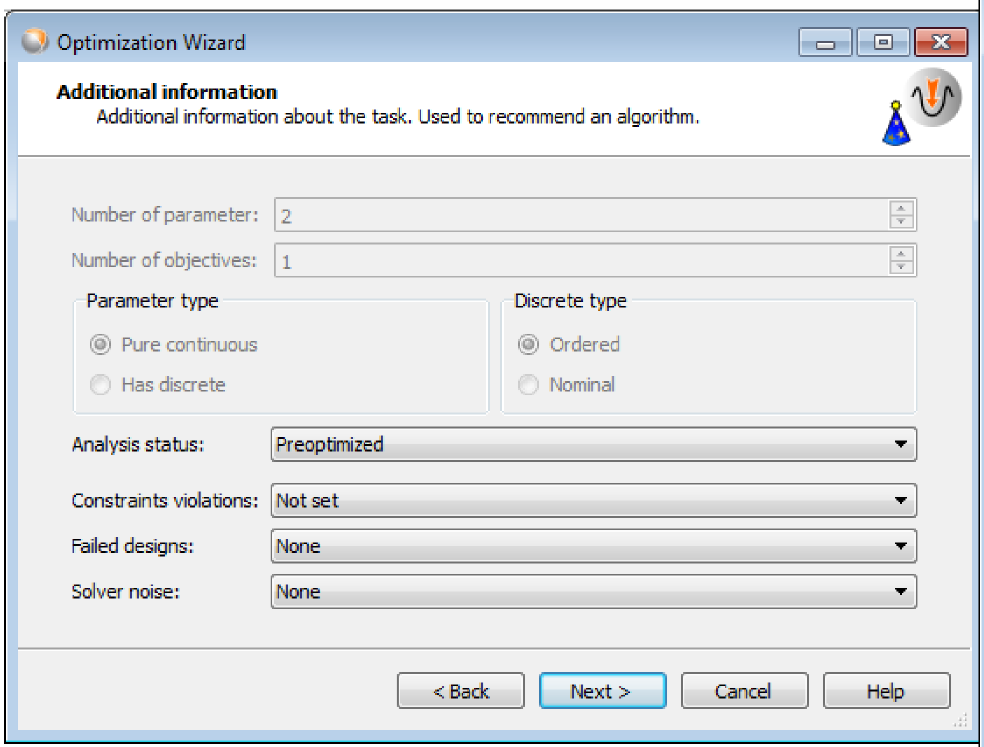


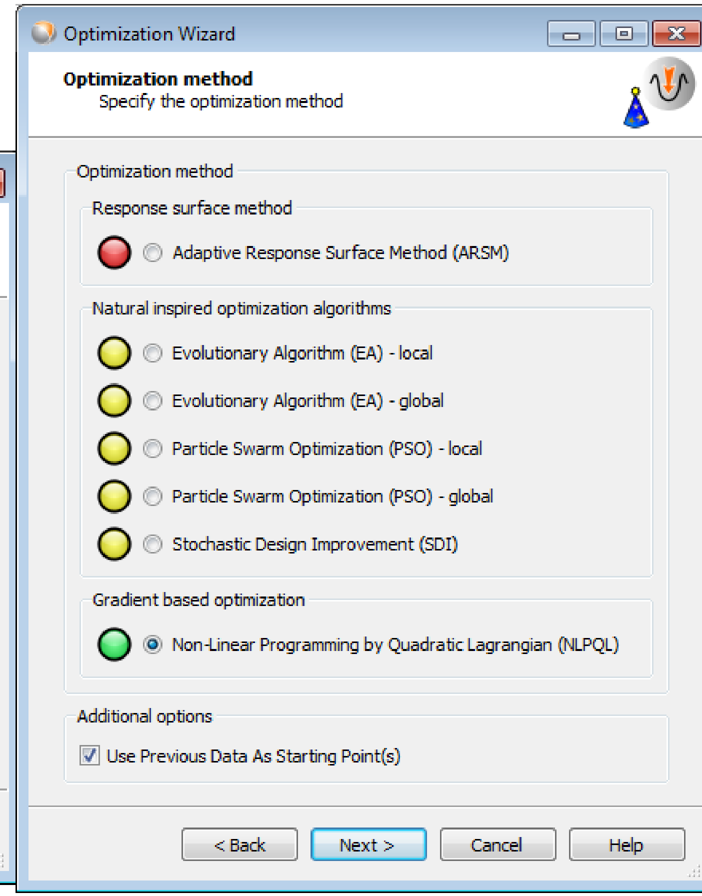
Pareto Optimization



Optimizer Selection Wizzard

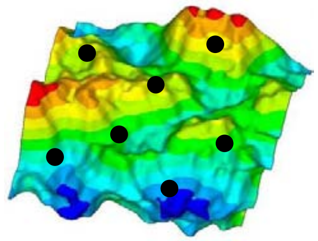
- An optimizer is automatically suggested depending on the parameter properties, the defined criteria as well as user specified settings



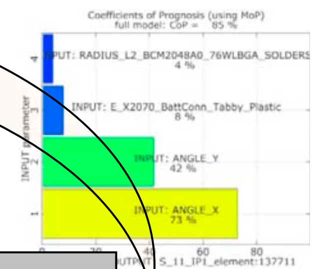


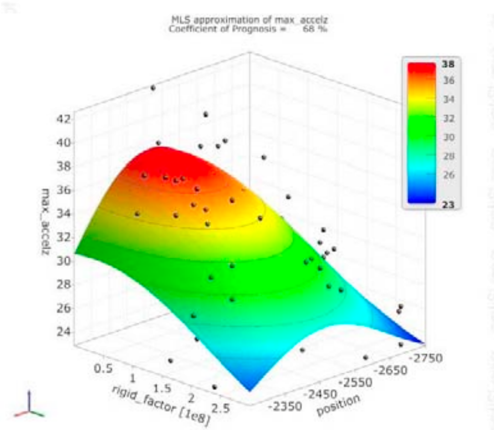
Workflow of Sensitivity Analysis and Optimization

1) Start with a sensitivity study

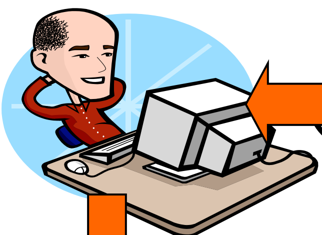


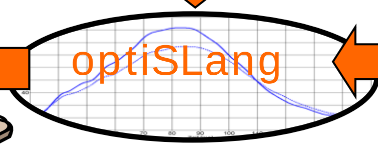
2) Identify the important parameters and responses using meta model technique
- understand the problem
- reduce the problem





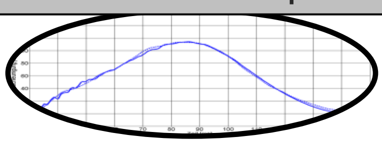
Scan the whole Design Space





Understand the Problem using CoP/MoP

Search for Optima

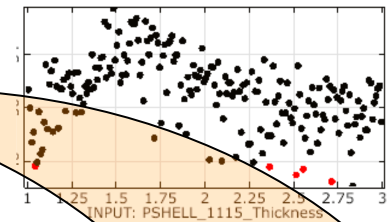


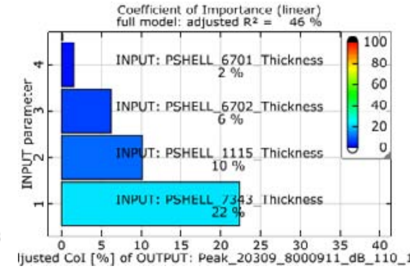
3) Run gradient based or biological based optimization algorithms at optimal meta model (MOP)

4) Run an RSM based, gradient based or biological based optimization algorithms using additional CAE solver runs

Iterative process optimizing NVH Comfort

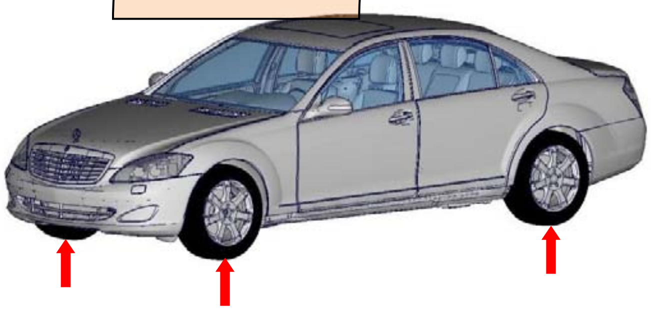
Reduction of Noise and Vibration for roadway excitation

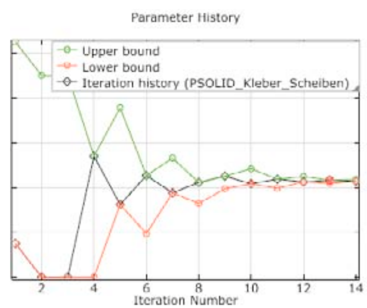


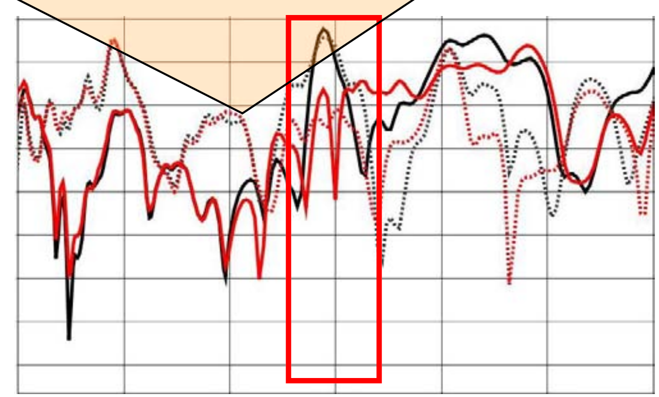


First sensitivity study using >400 optimization variables leads to very low explainability of variation CoP's <30%)

Second sensitivity study using <40 most important variables shows CoP's > 40..60% preserving most of the optimization potential.



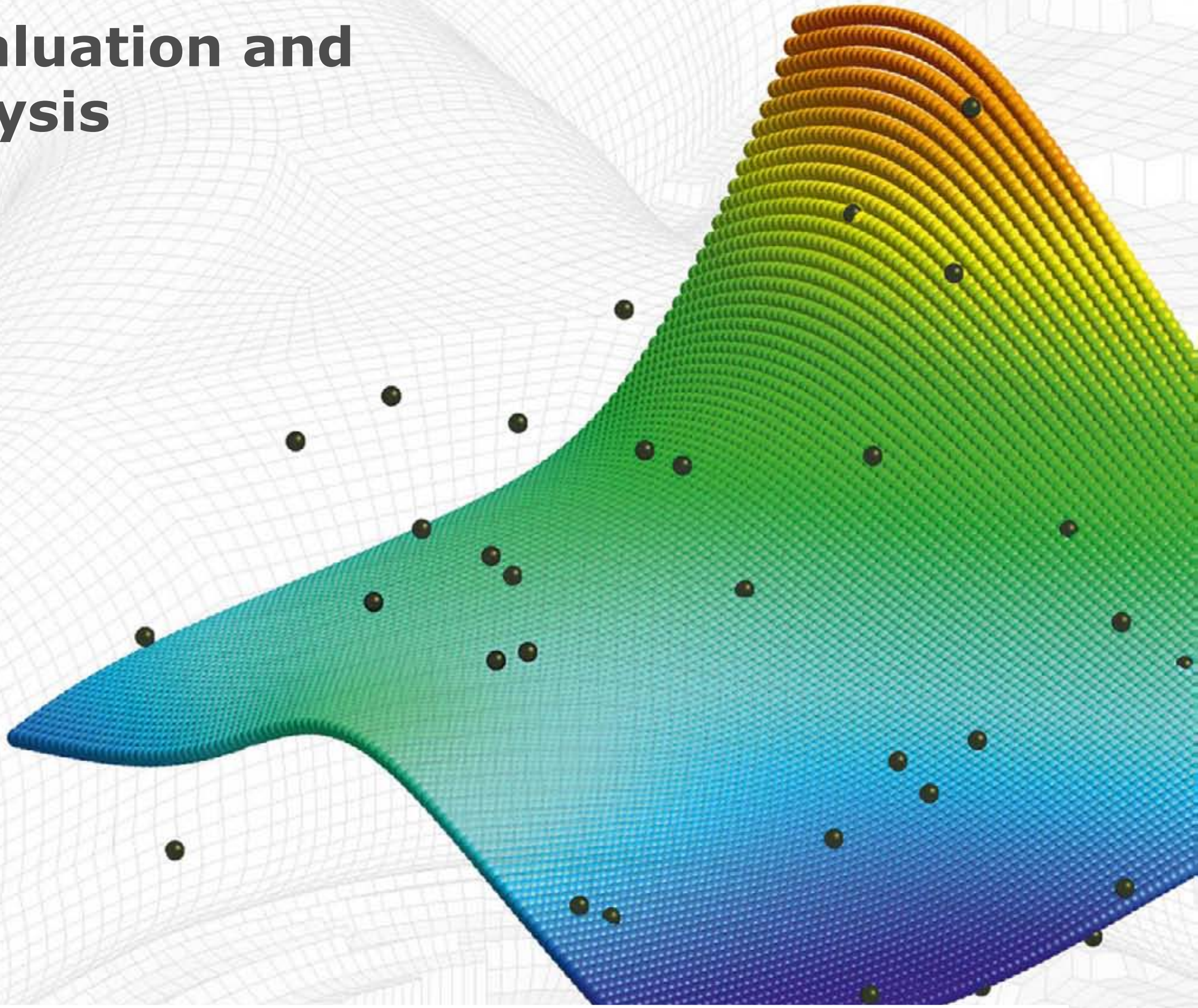


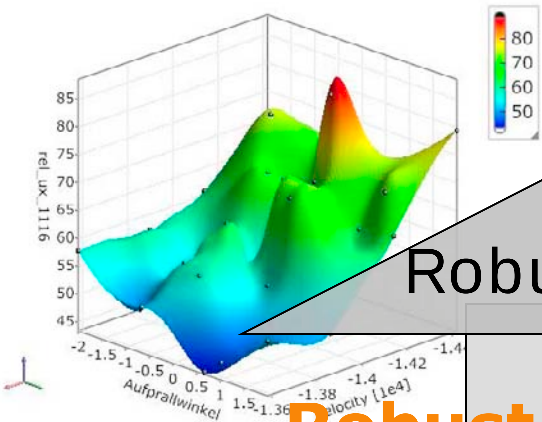


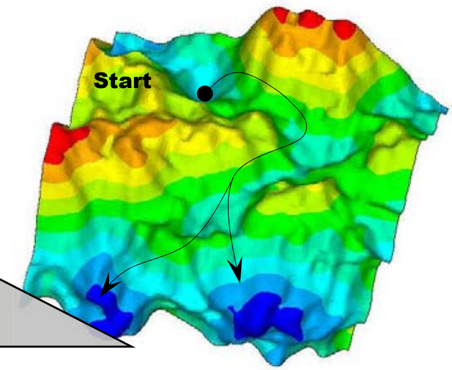
Frequency [Hz]

Using ARSM optimizer in subspace of most important <10 optimization variables shows reduction of noise levels.

Robustness Evaluation and Reliability Analysis







Robust Design Optimization

Robust Design

Variance based Robustness Evaluation

Probability based Robustness Evaluation, (Reliability analysis)

Optimization

Sensitivity Study

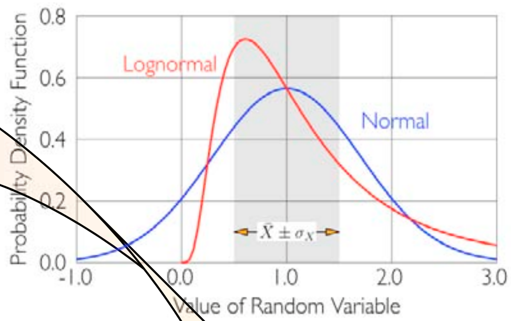
Single & Multi objective (Pareto) optimization

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

Successful industrial applications need the balance between

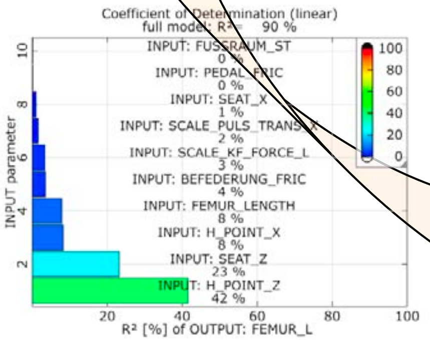
1. Reliable Input Definition

⇨ Distribution function
⇨ Correlations
⇨ Random fields



2. Reliable stochastic analysis

⇨ variance-based robustness evaluation using optimized LHS
⇨ suitable portfolio of Reliability Analysis

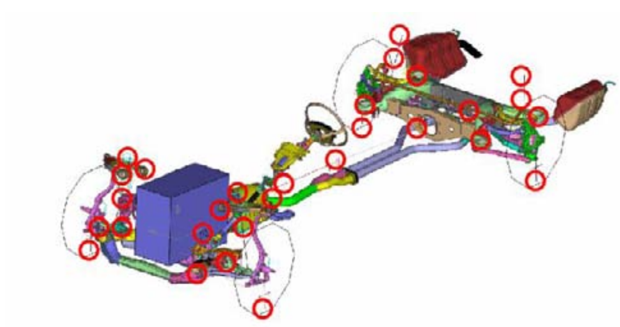


3. Reliable Post Processing

⇨ Coefficient of Prognosis
⇨ Reliable variation and correlation measurements
⇨ easy and safe to use

Uncertainties and Tolerances

- Design variables
- Material, geometry, loads, constrains,…
- Manufacturing
- Operating processes (misuse)
- Resulting from Deterioration
- …

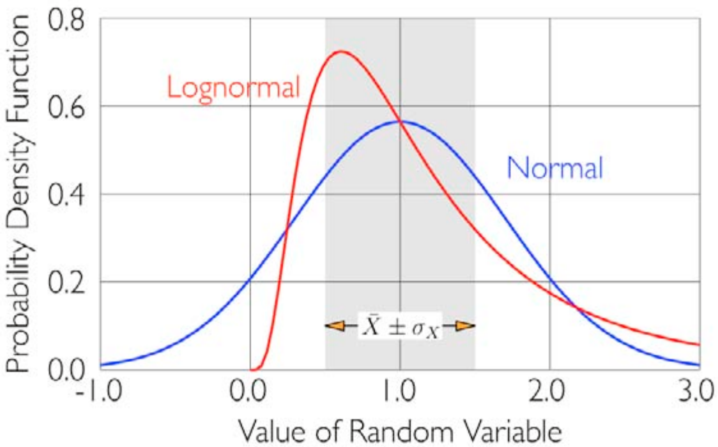


Property	SD/Mean %
Metallic materiales, yield	**15**
Carbon fiber rupture	17
Metallic shells, buckling strength	14
Bond insert, axial load	12
Honeycomb, tension	16
Honeycomb, shear, compression	10
Honeycomb, face wrinkling	8
Launch vehicle , thrust	5
Transient loads	**50**
Thermal loads	7.5
Deployment shock	10
Acoustic loads	**40**
Vibration loads	20

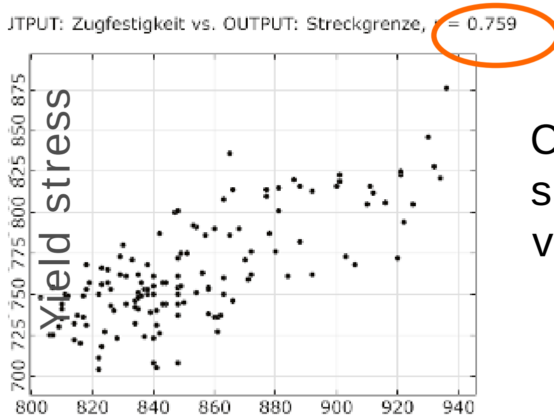
Klein, Schueller et.al. Probabilistic Approach to Structural Factors of Safety in Aerospace. Proc. CNES Spacecraft Structures and Mechanical Testing Conf., Paris 1994

Definition of Uncertainties

Distribution functions define variable scatter

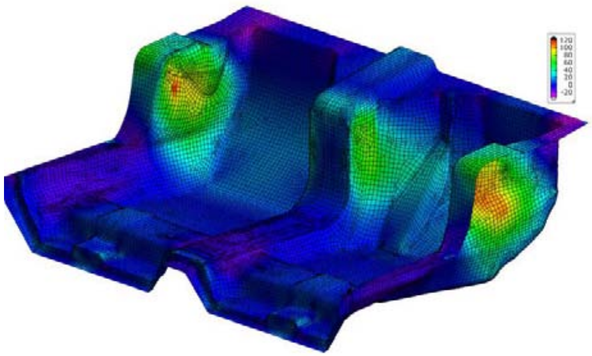


Correlation is an important characteristic of stochastic variables.



Tensile strength

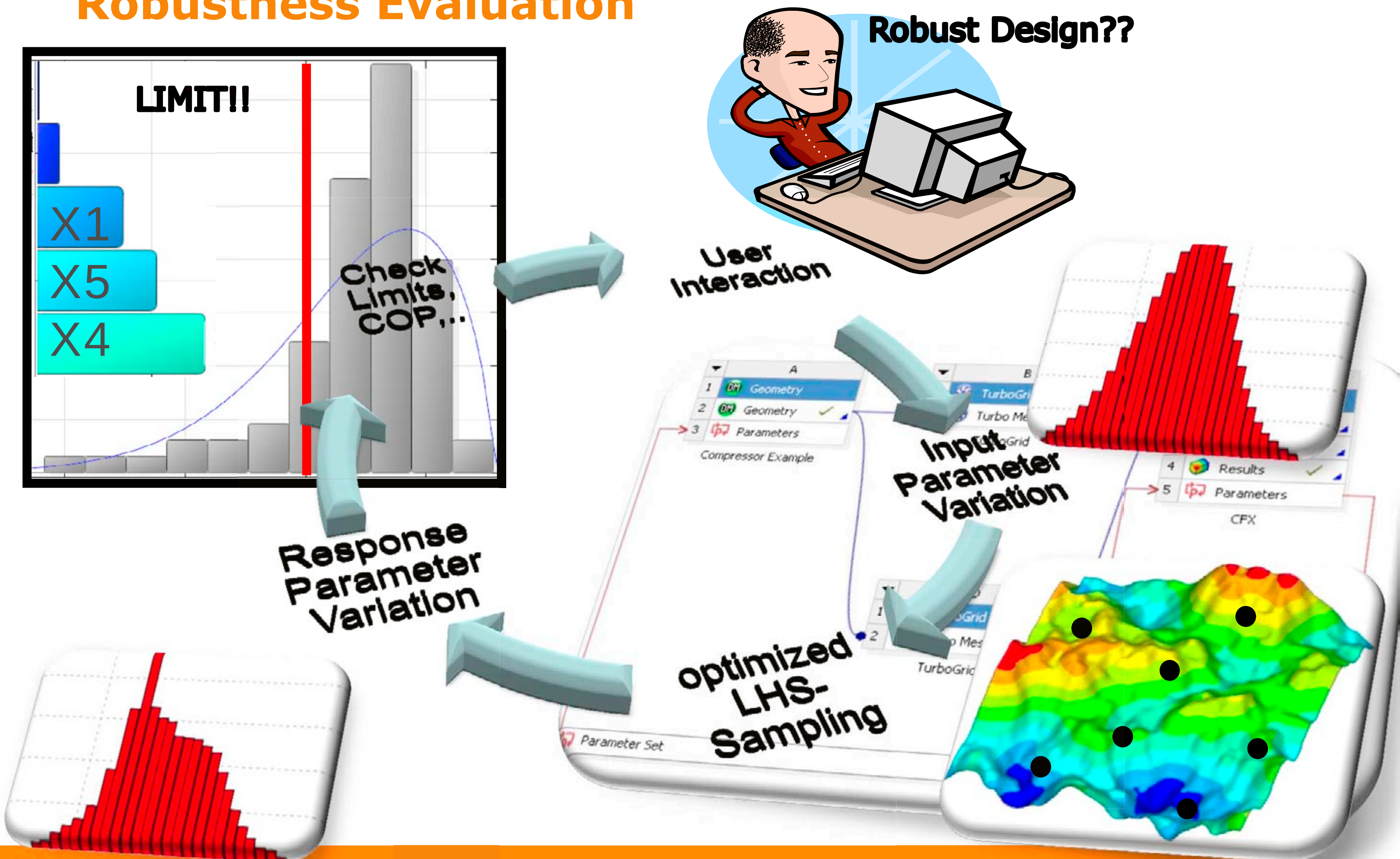
Correlation of single uncertain values



Spatially correlated field values

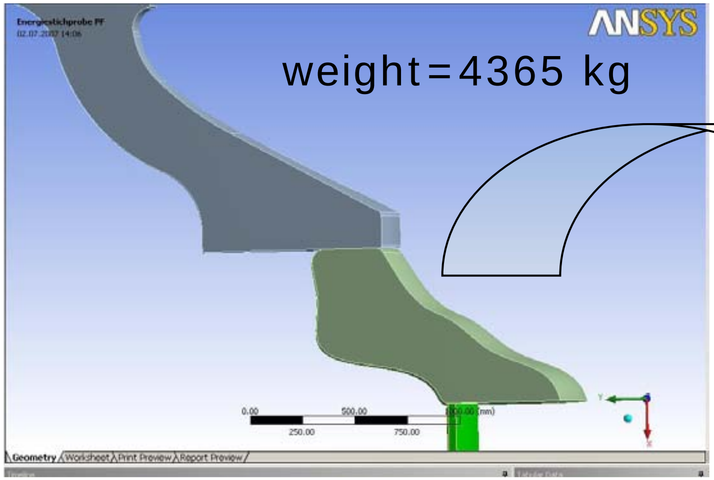
Translate know how about uncertainties into proper scatter definition

Robustness Evaluation

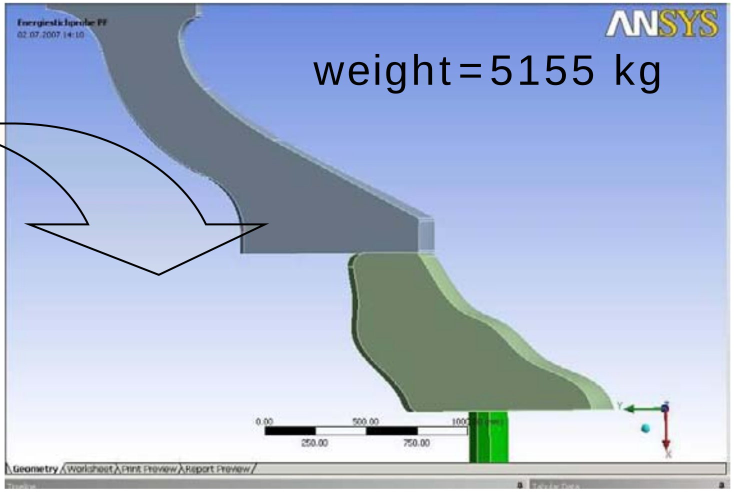


Optimization of see hammer

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

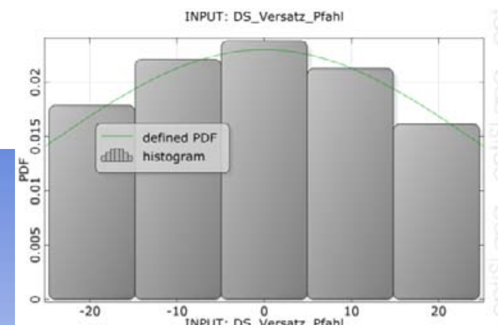


Optimized design valid for **four** pile diameter

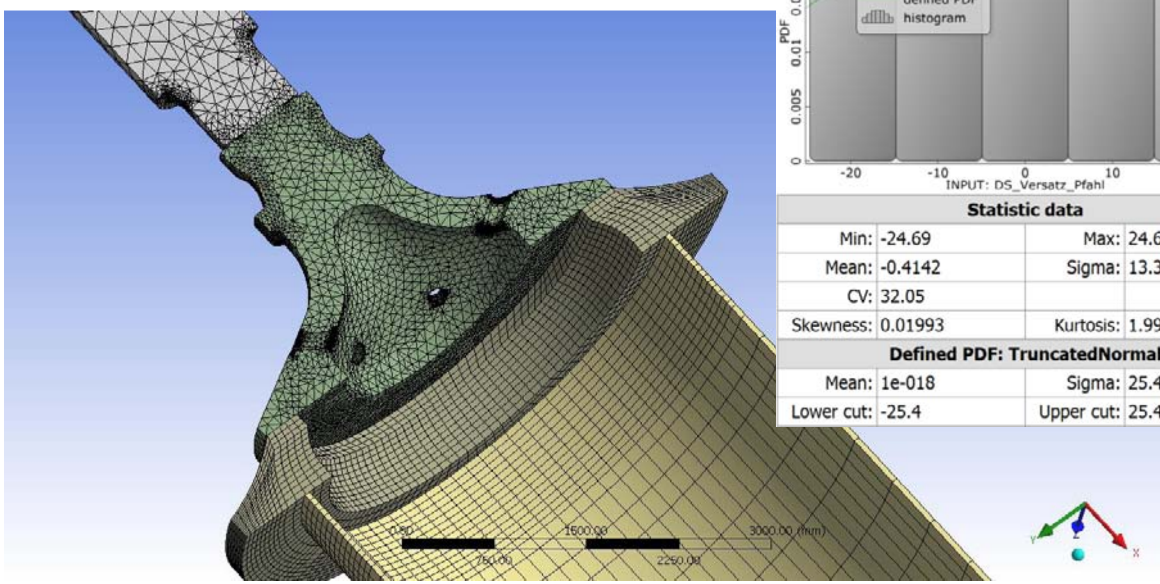
Design Evaluations: 200 times 4 loadcase
CAE: ANSYS workbench
CAD: ProEngineer

Robustness check of optimized designs

- **With the availability of parametric modeling environments like ANSYS workbench an robustness check becomes very easy!**
- Menck see hammer for oil and gas exploration (up to 400m deep)
- Robustness evaluation against tolerances, material scatter and working and environmental conditions
- 60 scattering parameter

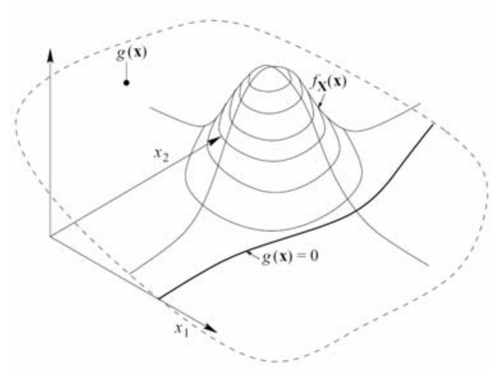


Statistic data			
Min:	-24.69	Max:	24.69
Mean:	-0.4142	Sigma:	13.32
CV:	32.05		
Skewness:	0.01993	Kurtosis:	1.993
Defined PDF: TruncatedNormal			
Mean:	1e-018	Sigma:	25.4
Lower cut:	-25.4	Upper cut:	25.4



Design Evaluations: 100
Process chain: ProE-ANSYS workbench- optiSLang

Reliability Analysis



- Robustness verify relatively high probabilities

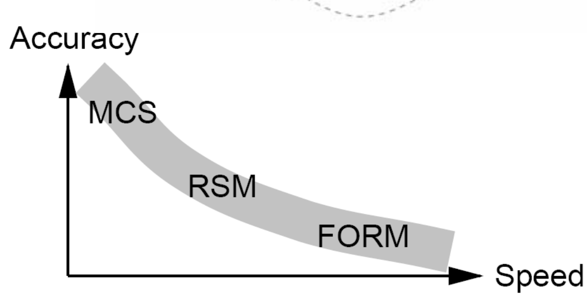
($\pm 2\sigma$, *like 1% of failure*)

- Reliability analysis verify rare event probabilities

($\geq 3\sigma$, *smaller then 1 out of 1000)*

There is no one magic algorithm to estimate probabilities with "minimal" sample size.

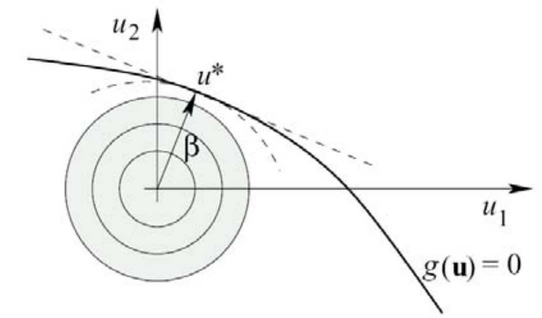
It is recommended to use two different algorithms to verify rare event probabilities



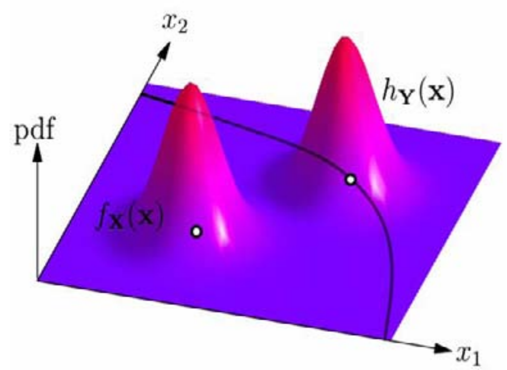
- First order reliability method (FORM), $\geq 2\sigma$, gradient based
- Importance sampling using design point (ISPUD), $\geq 2\sigma$, $n \leq 10$
- Adaptive importance sampling, $\geq 2\sigma$, $n \leq 10$
- Directional sampling, $\geq 2\sigma$, $n \leq 10$
- Monte-Carlo-Simulation, independent of n, but very high effort for $\geq 2\sigma$
- Latin Hypercube sampling, independent of n, still very high effort for $\geq 2..3\sigma$
- Asymptotic Sampling, $\geq 2\sigma$, $n \geq 10$
- Directional Sampling using global adaptive response surface method, $\geq 2\sigma$, $n \leq 5..10$

Reliability Analysis Algorithms

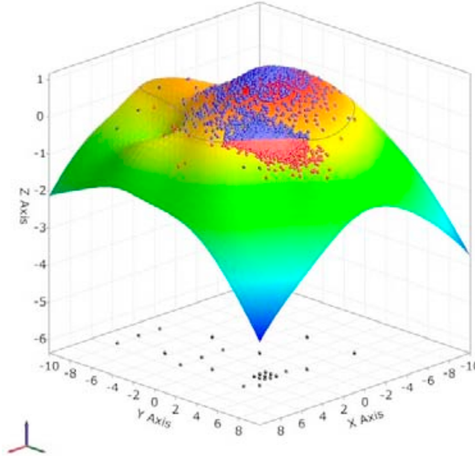
Gradient-based algorithms = First Order Reliability algorithm (FORM)



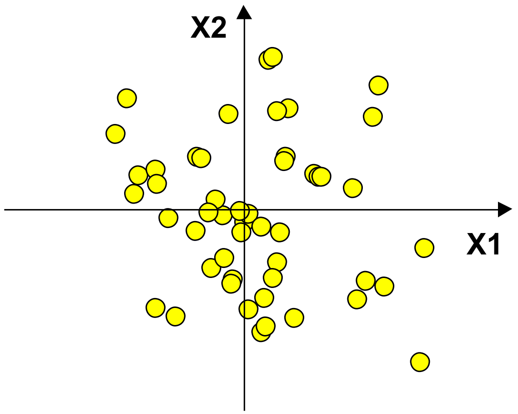
ISPUD Importance Sampling using Design Point



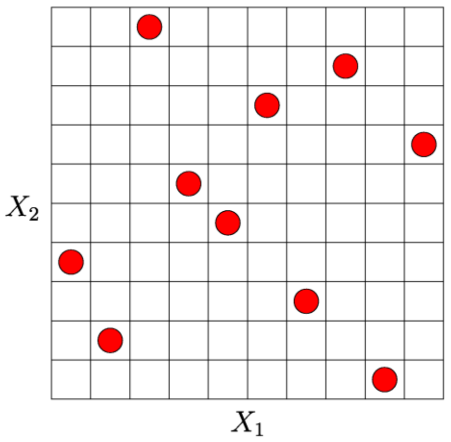
Adaptive Response Surface Method



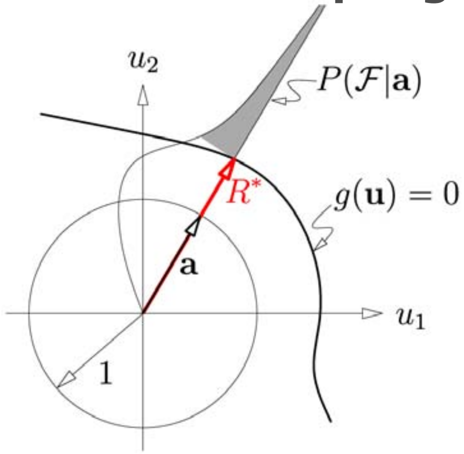
Monte Carlo Sampling



Latin Hypercube Sampling

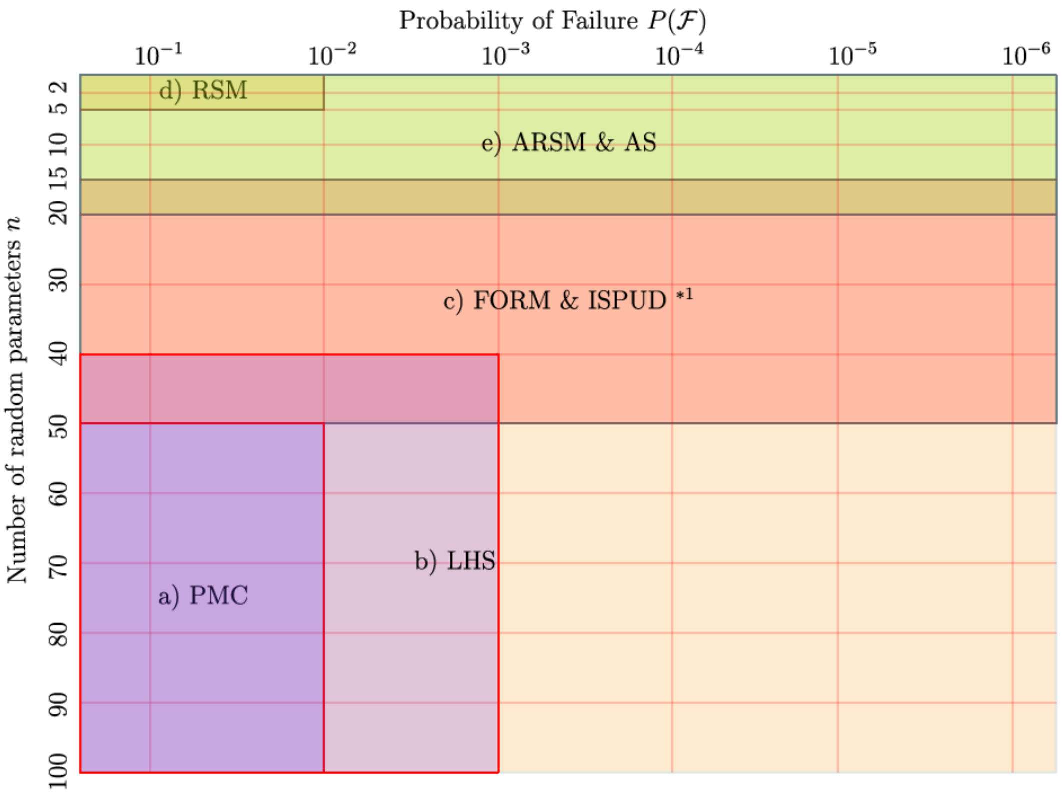


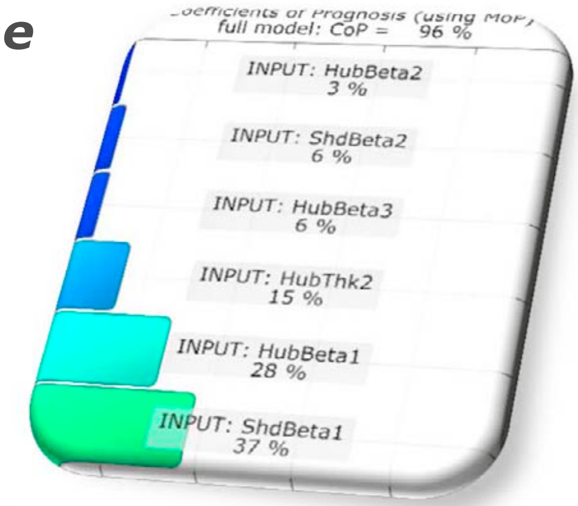
Directional Sampling

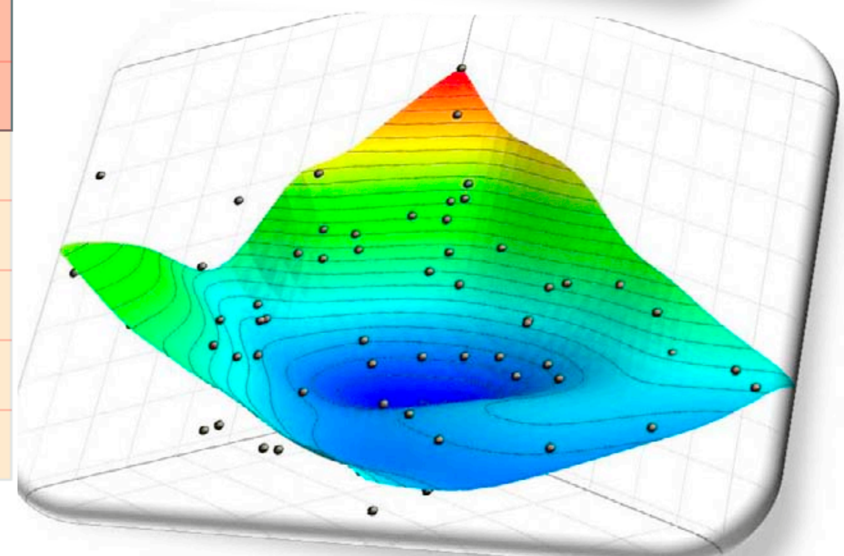


How choosing the right algorithm?

Robustness Analysis provide the knowledge to choose the appropriate algorithm



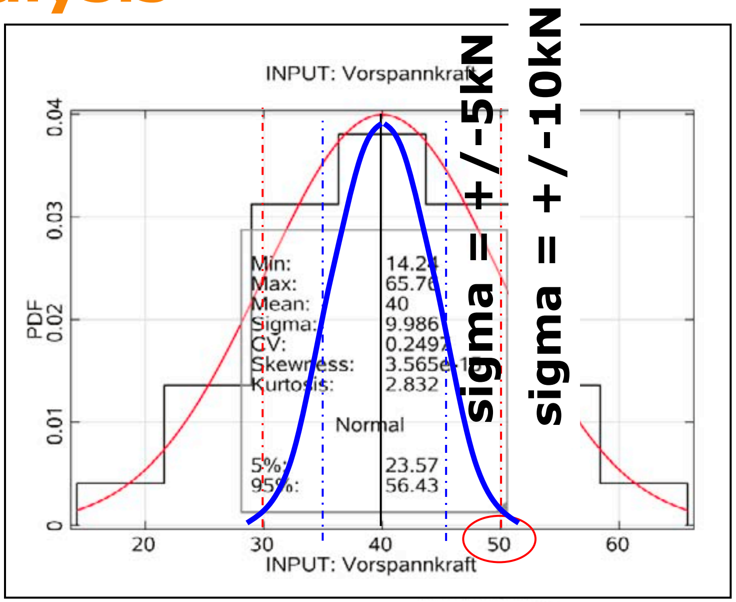


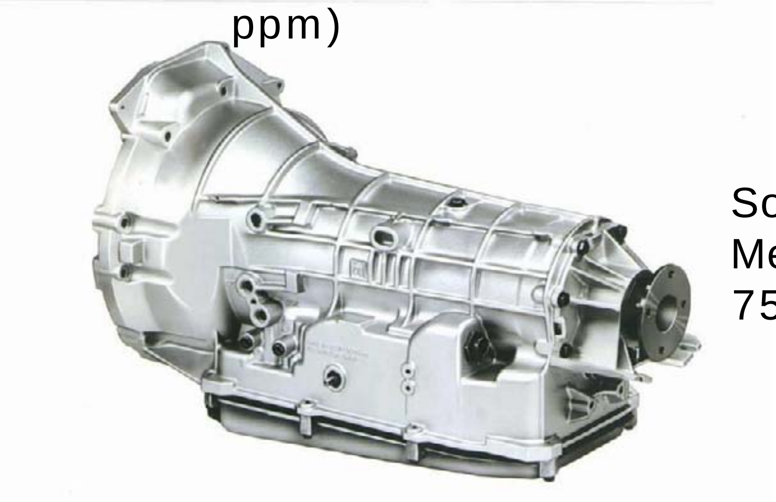


Robustness & Reliability Algorithms

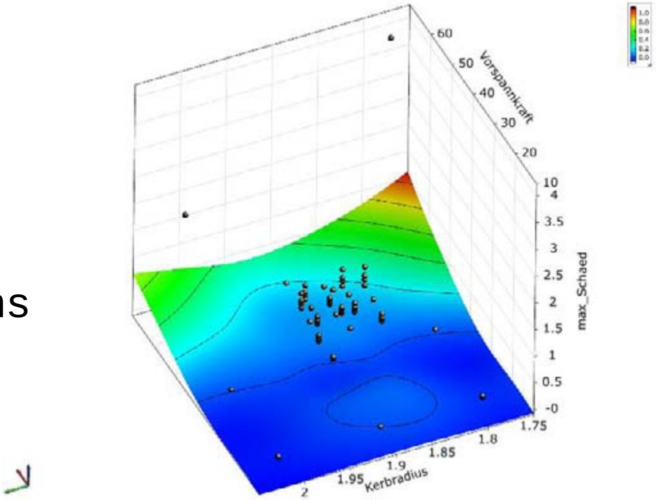
Application of Reliability Analysis

- Fatigue life analysis of Pinion shaft
- Random variables
  - Surface roughness
  - Boundary residual stress
  - Prestress of the shaft nut
- Target: calculate the probability of failure
- Probability of Failure:
  - Prestress I: $P(f)=2.3\ 10^{-4}$ (230 ppm)
  - Prestress II: $P(f)=1.3\ 10^{-7}$ (0.13 ppm)





Solver: Permas
Method: ARSM
75 Solver evaluations



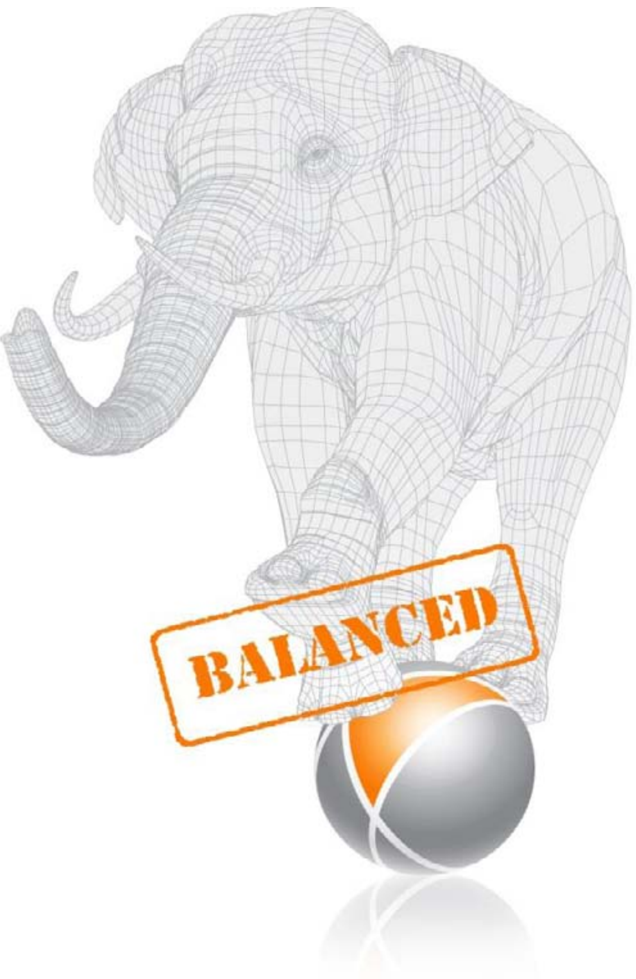
Summary

- Highly optimized structures tend to loose robustness
- Variance-based robustness analysis can estimate sigma level
- Reliability analysis is necessary to proof small failure probabilities
- Use specific robustness/reliability measurements
- Stochastic analysis needs a balance between input definitions, stochastic analysis method and post processing
- Because all RDO strategies will try to minimize solver runs for robustness measures, a final proof of robustness/reliability is mandatory
- Carefully translation and introduction of material scatter is crucial
- Start with robustness evaluation, continue with iterative RDO approach using safety distances
- Iterative optimization/variance-based Robustness Evaluation with final reliability proof is often our method of choice

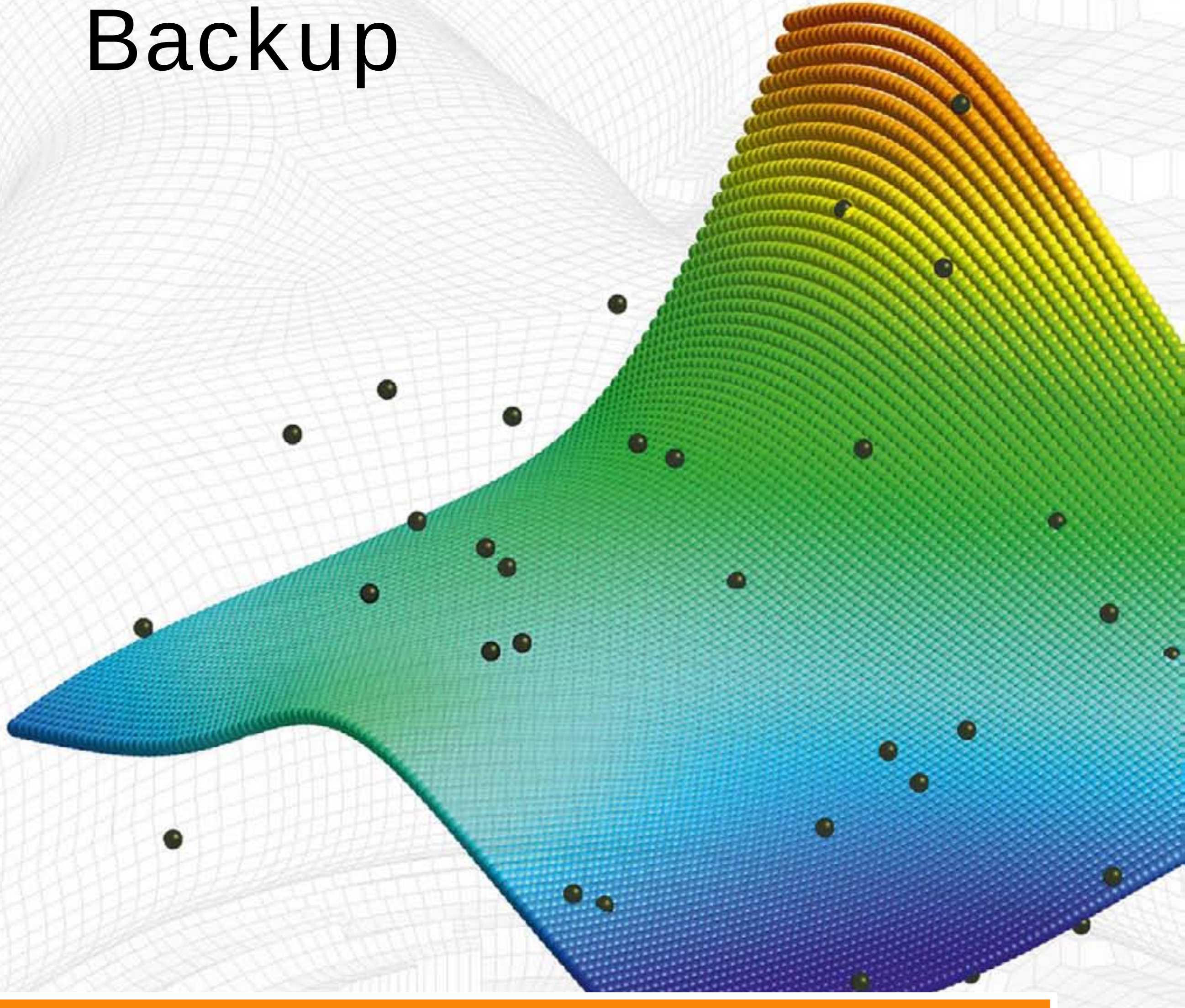
Robust Design Optimization (RDO) in virtual product development

optiSLang enables you to:

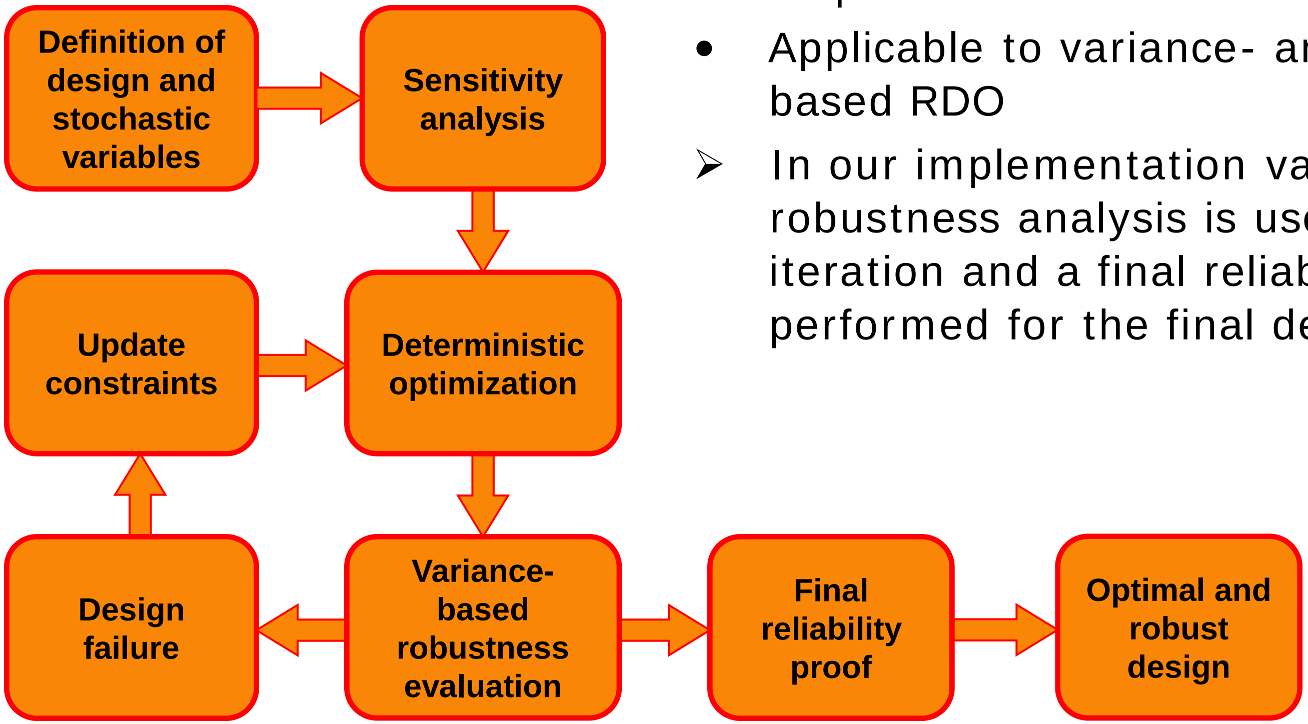
- **Quantify risks**
- **Identify optimization potentials**
- **Adjust safety margins without limitation of input parameters**
- **Secure resource efficiency**
- **Improve product performance**
- **Save time to market**



Backup



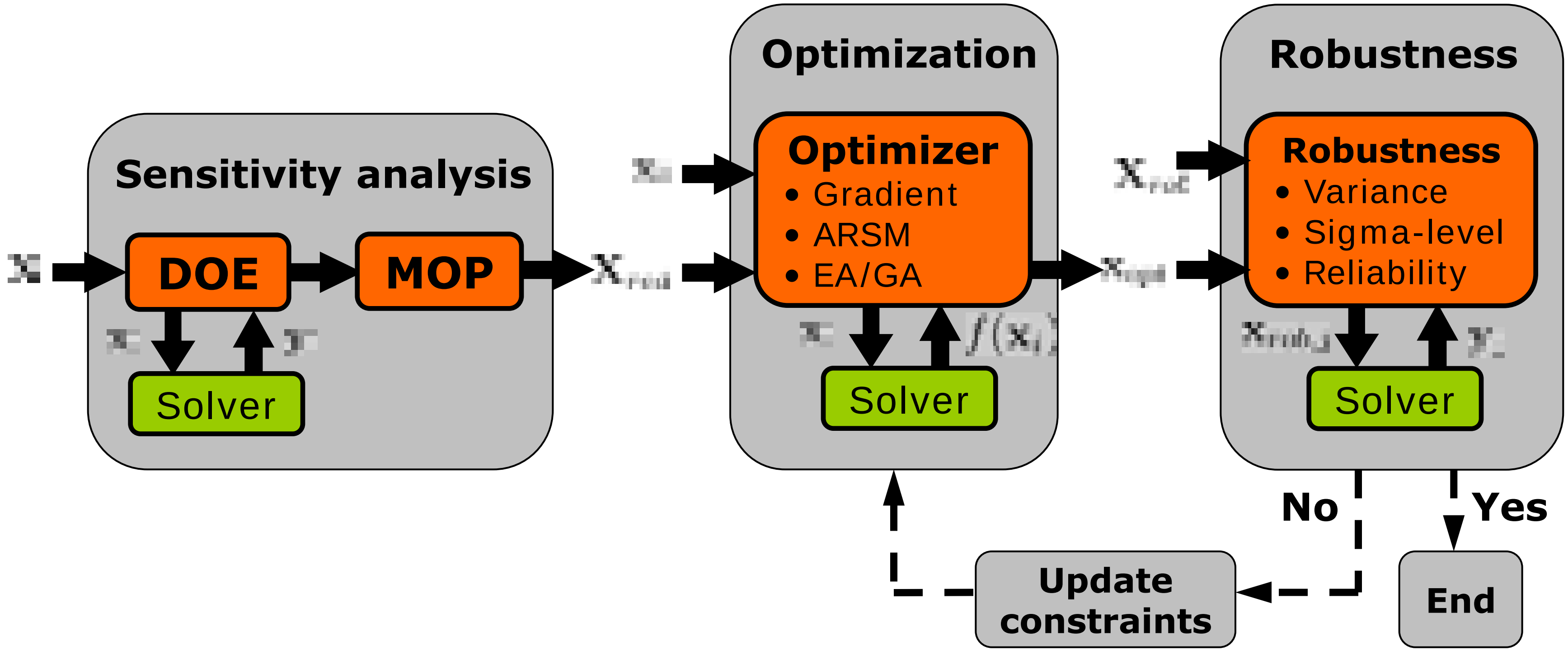
Iterative Robust Design Optimization



- Decoupled optimization and robustness/reliability analysis
- For each optimization run the safety factors are adjusted for the critical model responses
- Applicable to variance- and reliability-based RDO

➢ In our implementation variance-based robustness analysis is used inside the iteration and a final reliability proof is performed for the final design

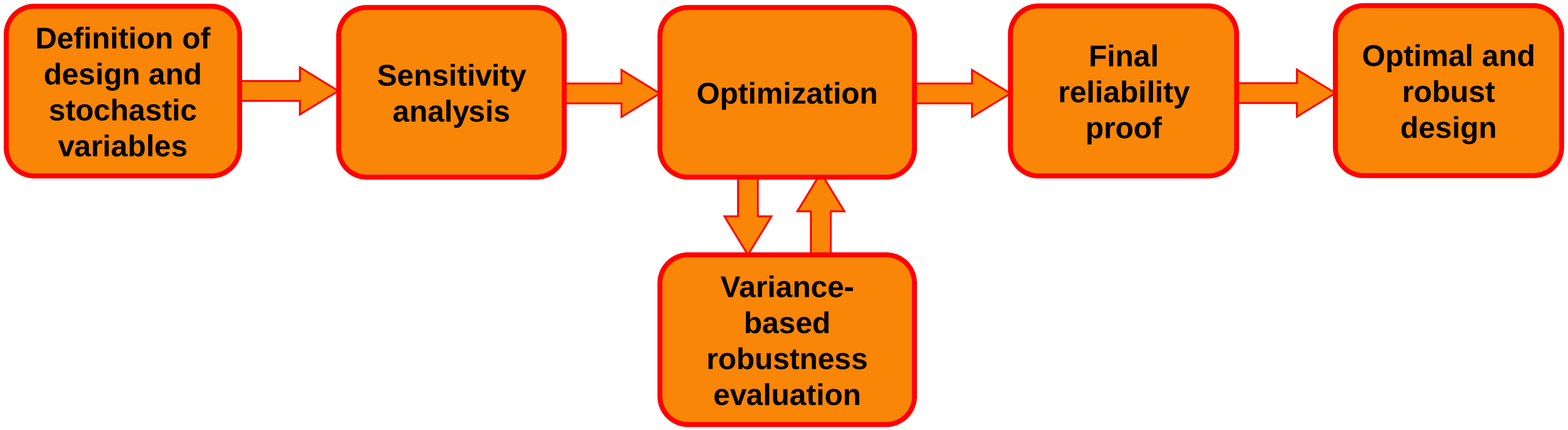
Iterative Robust Design Optimization



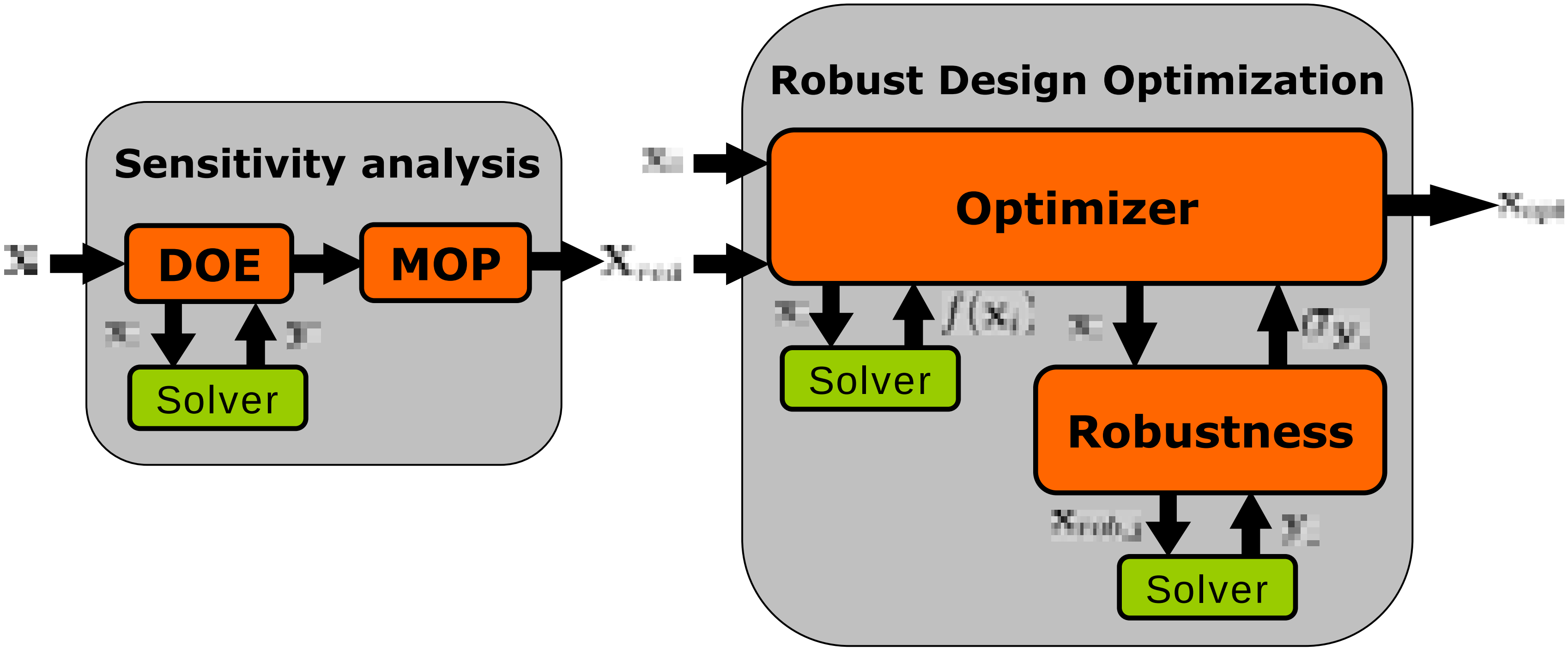
- Sensitivity analysis gives reduced optimization variable space $\mathbf{X}_{red}$
- Optimizer determines optimal design $\mathbf{x}_{opt}$ by direct solver calls
- Robustness evaluation
  - Robust optimum – end of iteration
  - Non-robust optimum - update constraints and repeat optimization + robustness evaluation

Simultaneous Robust Design Optimization

- Fully coupled optimization and robustness/reliability analysis
- For each optimization (nominal) design the robustness/reliability analysis is performed
- Applicable to variance-, reliability- and Taguchi-based RDO
- ➢ Our efficient implementation uses small sample variance-based robustness measures during the optimization and a final (more accurate) reliability proof
- ➢ But still the procedure is often not applicable to complex CAE applications



Simultaneous Robust Design Optimization



- Sensitivity analysis gives reduced optimization variable space $\mathbf{X}_{red}$
- Optimizer determines optimal design $\mathbf{x}_{opt}$ by direct solver calls with simultaneous robustness evaluation for every design
- Each robustness evaluation determines robustness values by direct solver calls