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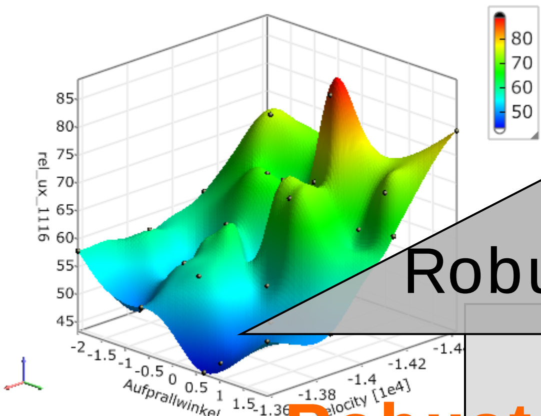
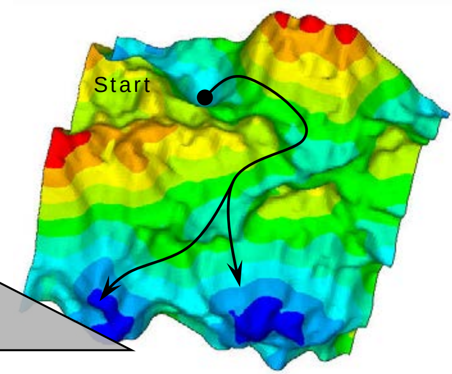
Robustness & Reliability Analysis





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.)

Robust Design Optimization Methodology

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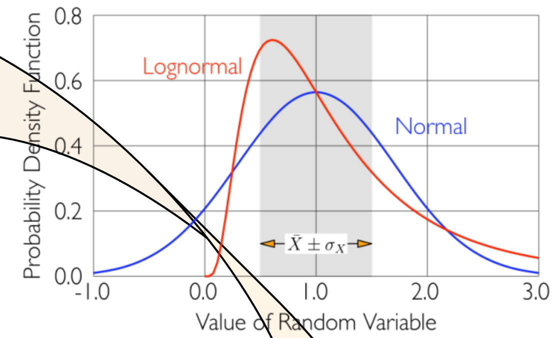
What is necessary for successful implementation?

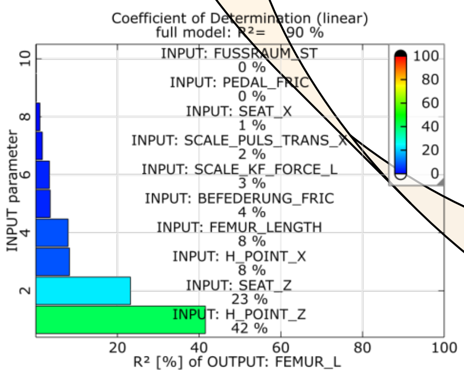
1. Introduction of realistic scatter definitions

- ⇨ Distribution function
- ⇨ Correlations
- ⇨ Random fields



2. Using of reliable stochastic methodology

- ⇨ Variance-based robustness evaluation using optimized LHS



3. Development of reliable robustness measurements

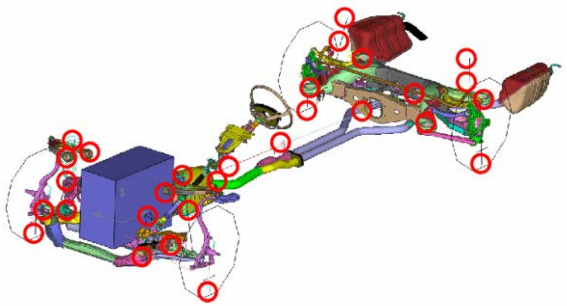
- ⇨ Standardized post processing
- ⇨ Significance filter
- ⇨ Reliable variation and correlation measurements

Acceptance of method / result documentation / communication!

Definition of Uncertainties

Uncertainties and Tolerances

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

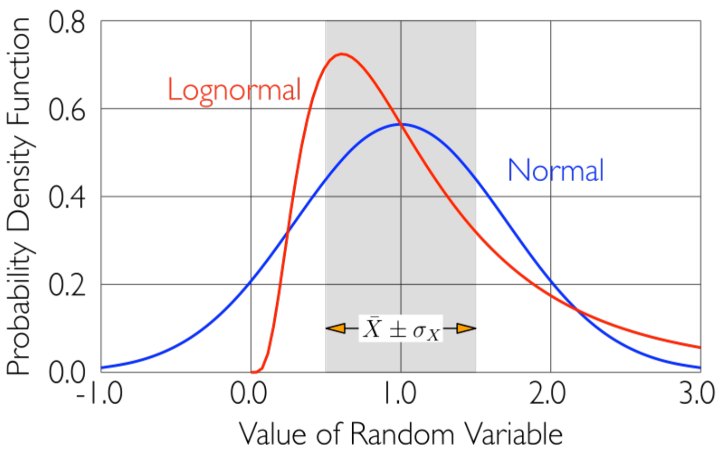


Property	SD / Mean %
Metallic materiales, yield	**15**
Carbon fiber rupture	17
Metallic shells, buckling strength	14
Bond insert, axial load	12
Honeycomb, tension	16
Honeycomb, shear, compression	10
Honeycomb, face wrinkling	8
Launch vehicle , thrust	5
Transient loads	**50**
Thermal loads	7.5
Deployment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

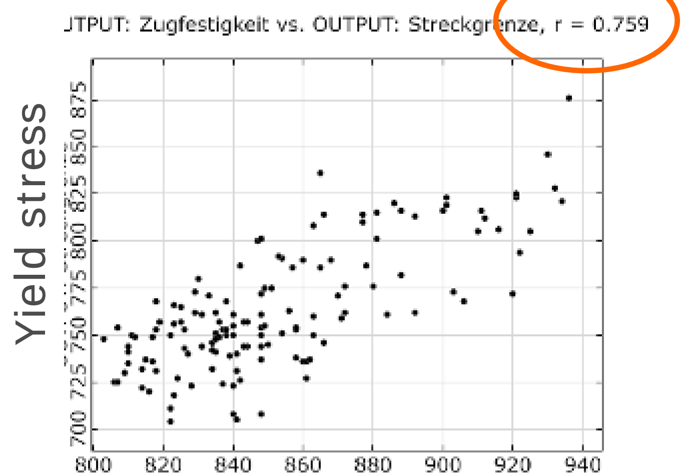
Klein, Schueller et.al. Probabilistic Approach to Structural Factors of Safety in Aerospace. Proc. CNES Spacecraft Structures and Mechanical Testing Conf., Paris 1994

Definition of Uncertainties

1) Translate know how about uncertainties into proper scatter definition



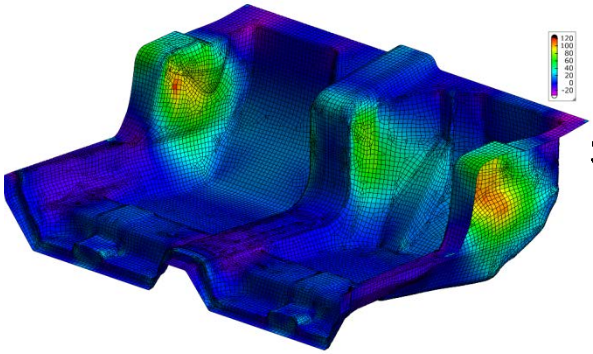
Distribution functions define variable scatter



Tensile strength

Correlation of single uncertain values

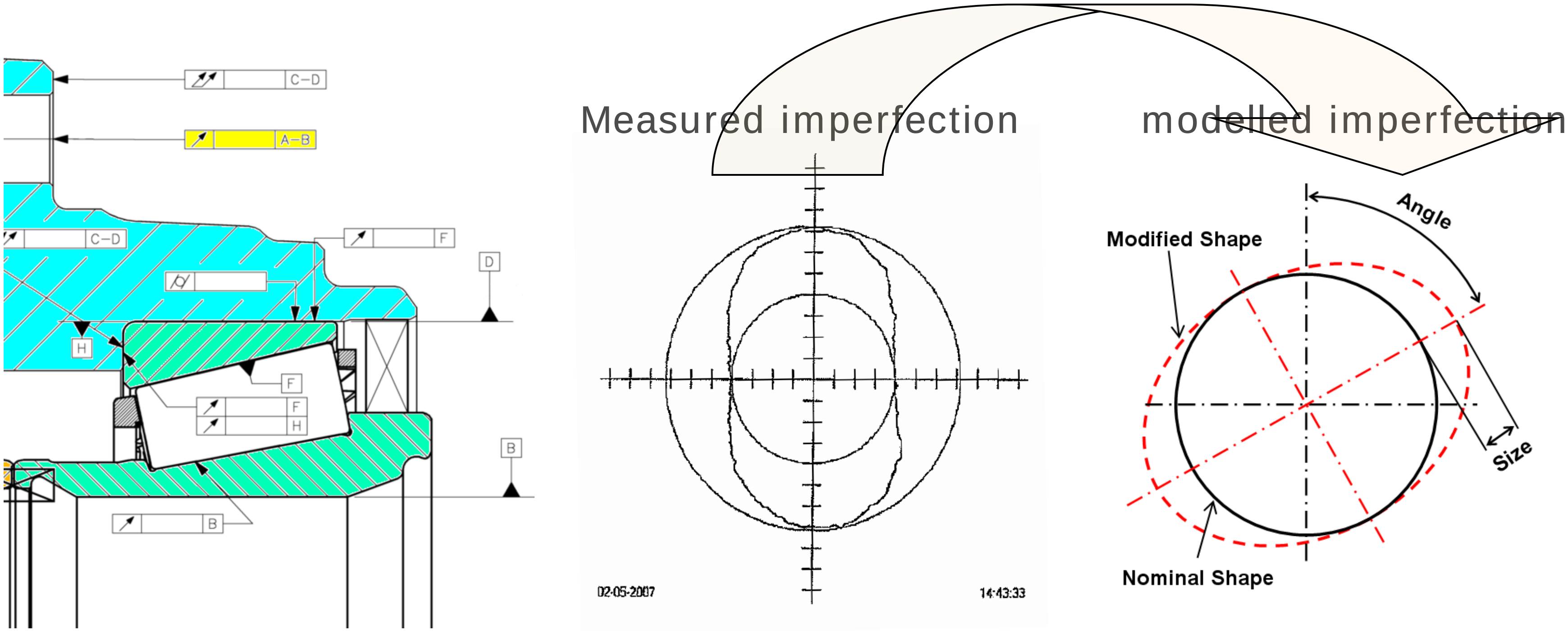
Correlation is an important characteristic of stochastic variables.



Spatial Correlation = random fields

Design “single” scatter shapes

- Use of CAD-parameter or mesh morphing functions to design “single” scatter shapes



Imperfection of cylindricity of truck wheel component

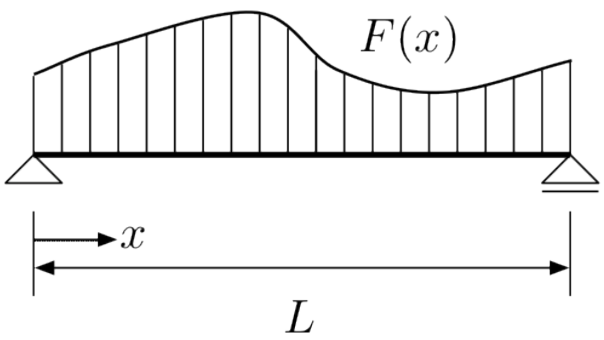
by courtesy of TIMKEN Where You Turn

Suchanek, J.; Will, J.: Stochastik analysis as a method to evaluate the robustness of light truck wheel pack; Proceedings WOSD 6.0, 2009, Weimar, Germany, www.dynardo.de]

Random Field Parametric

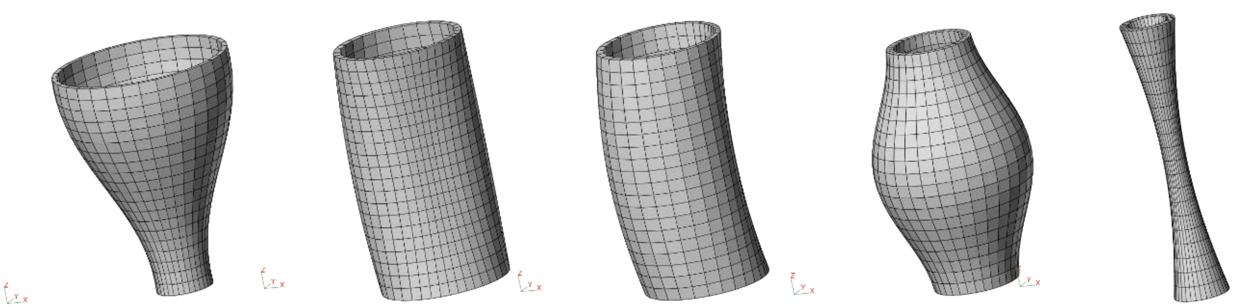
- Introduction of scatter of spatially correlated scatters need parametric of scatter shapes using random field theory.

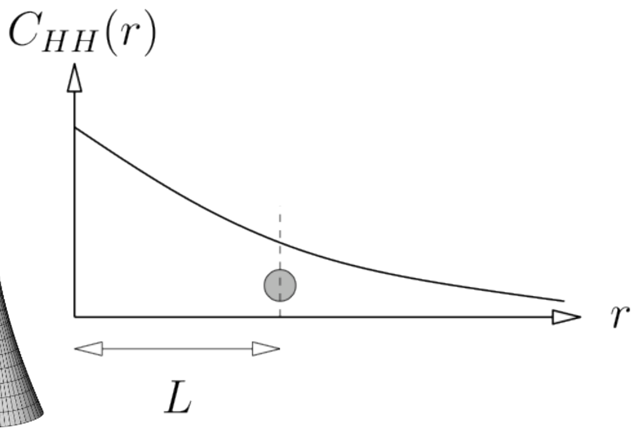
The correlation function represents the measure of “waviness” of random fields.



The infinite correlation length reduced the random field to a simple random variable.

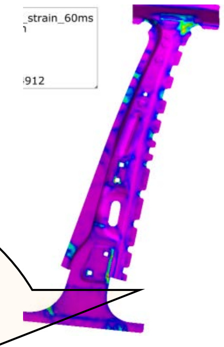
Usually, there exist multiple scatter shapes representing different scatter sources.

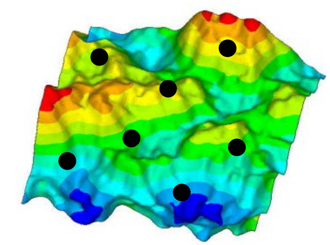




Use simulation to generate Random Fields

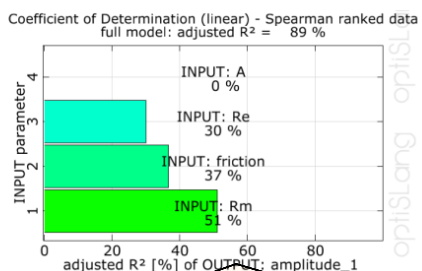
4. Mapping to crash mesh

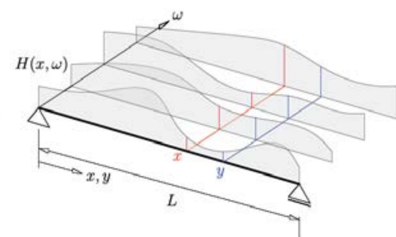


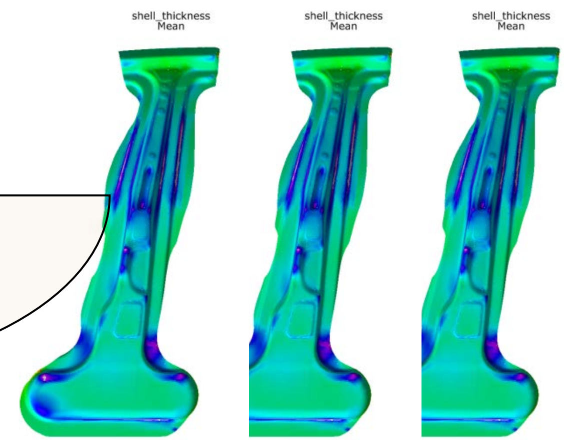


3. Generation of n-imperfect formed parts using Random Field parametric

5. Run Robustness Evaluation of assembly including scatter from forming







2. Identification of most important random fields for scattering forming result values (Thickness)

1. Running Robustness evaluation of forming simulation

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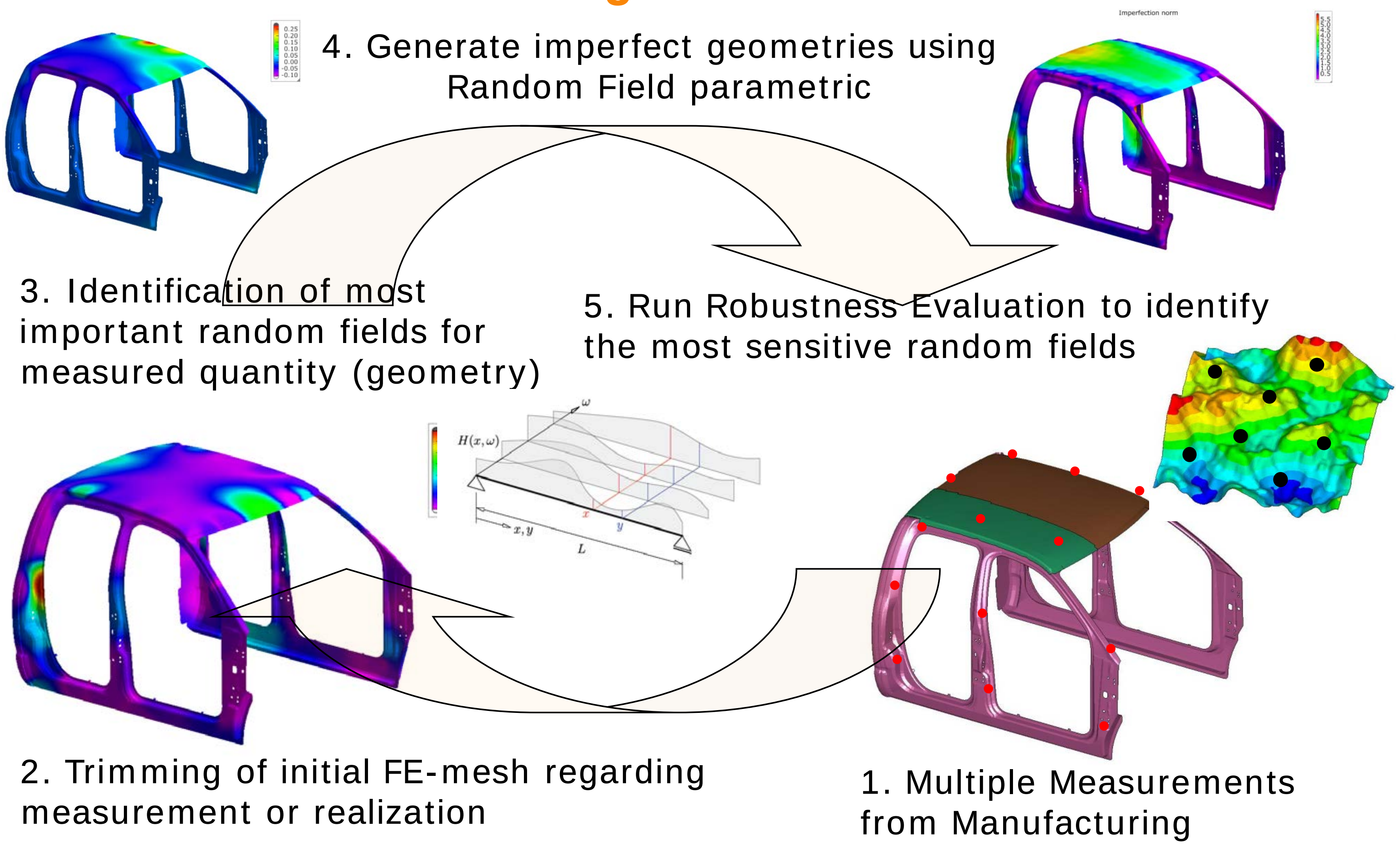
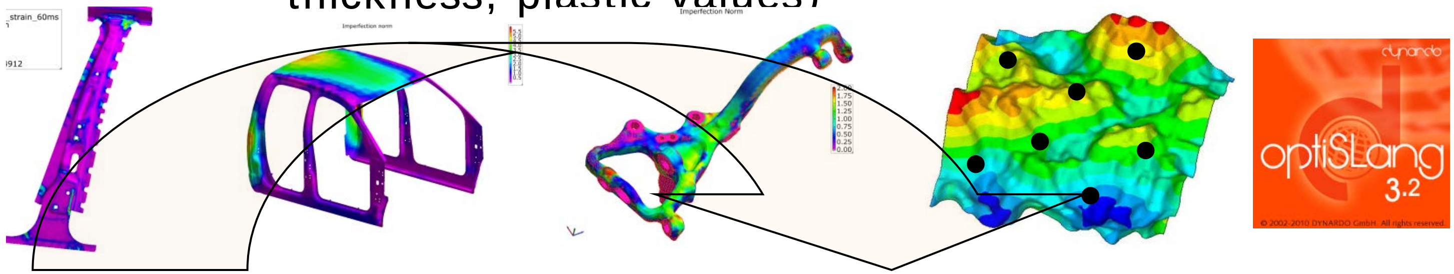
Use measurements to generate Random Fields



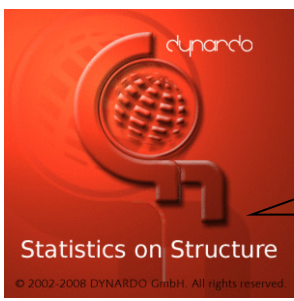
Implementation of Random Field Parametric

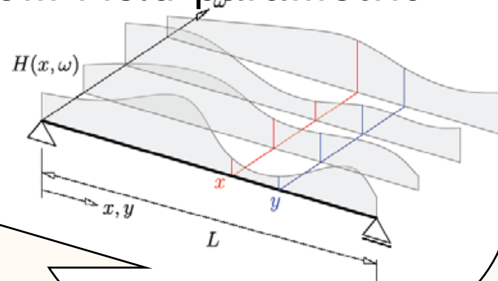
Introduction of spatial correlated scatter to CAE-Parameter (geometry, thickness, plastic values)

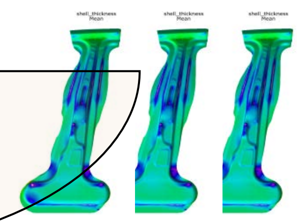


3. Generation of multiple imperfect structures using Random Field parametric

4. Running Robustness Evaluation including Random Field effects







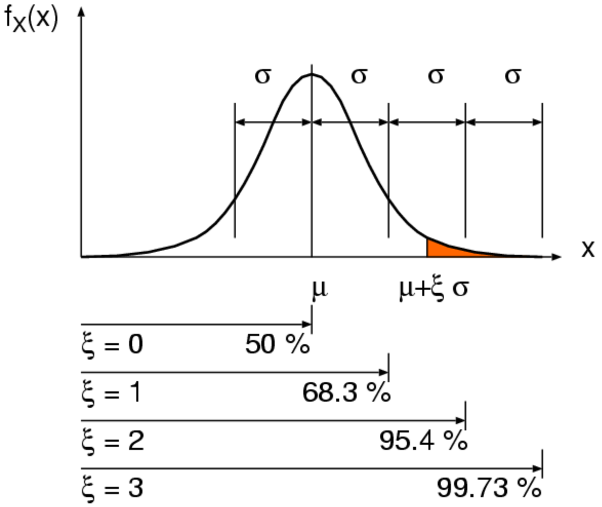
2. Generation of scatter shapes using Random field parametric, quantify scatter shape importance

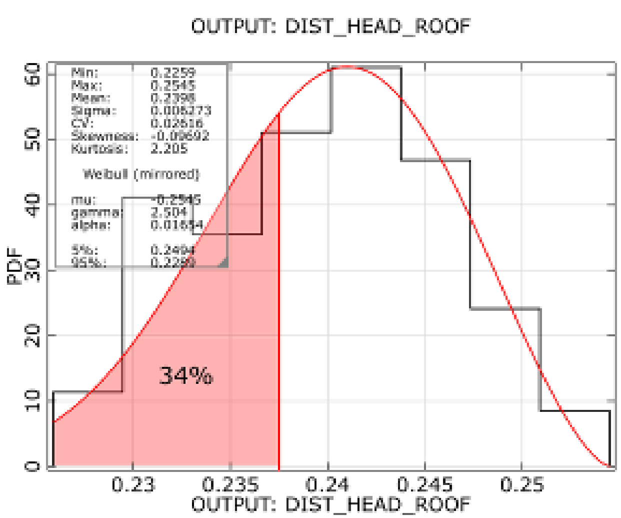
1. Input: multiple process simulation or measurements

How to define Robustness of a Design

- Intuitively: The performance of a robust design is largely unaffected by random perturbations
- Variance indicator: The coefficient of variation (CV) of the objective function and/or constraint values is smaller than the CV of the input variables
- Sigma level: The interval mean+/- sigma level does not reach an undesired performance (e.g. design for six-sigma)
- Probability indicator: The probability of reaching undesired performance is smaller than an acceptable value

Robustness Evaluation / Reliability Analysis

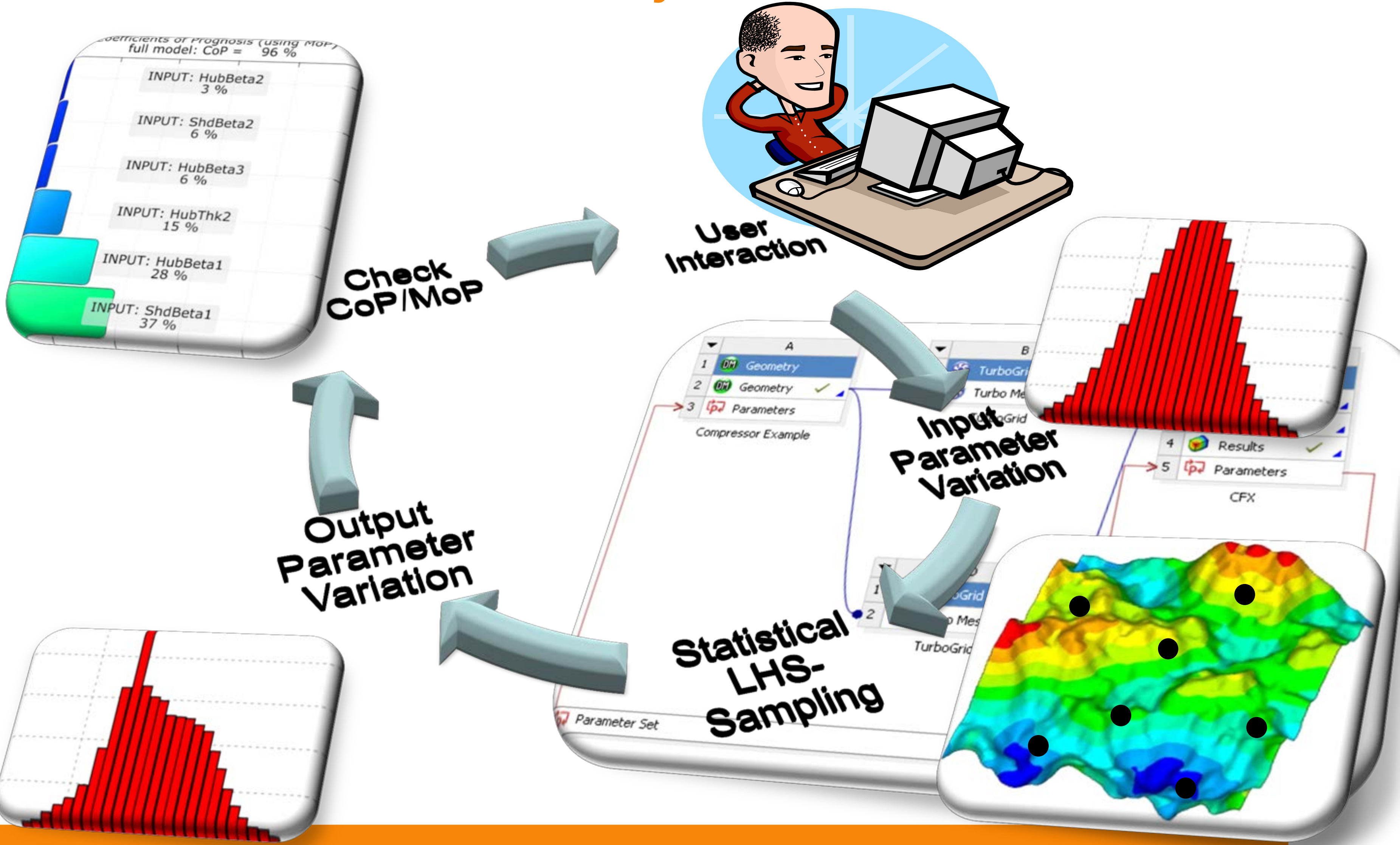




- <u>Variance-based robustness evaluation</u> measure product serviceability
  - Safety and reliability for 1 & 2 (3) Sigma levels and identifies the most sensitive stochastic variables
  - Possible with high number of stochastic variables
- <u>Probability-based robustness evaluation</u> (reliability analysis) measure product serviceability
  - Safety and reliability for high reliability levels (3,4,5,6-Sigma) with small number of variables
  - Possible with a limited number of stochastic variables

Variance-based Robustness Analysis

Robustness = Sensitivity of Uncertainties



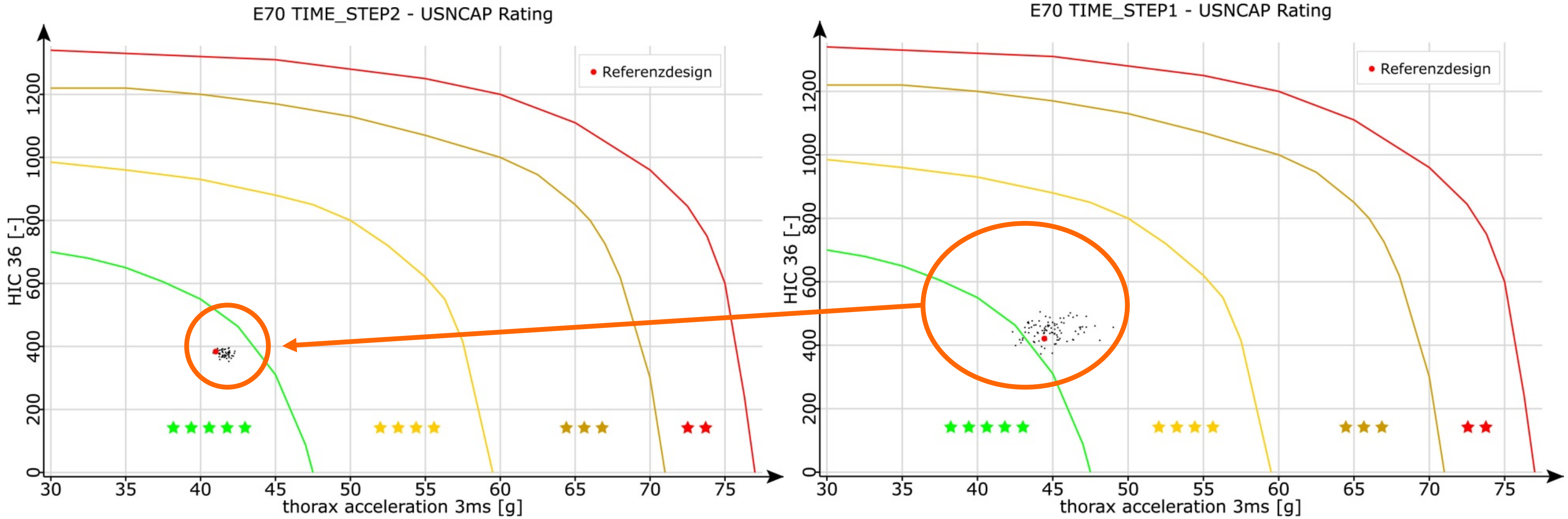
by courtesy of ANSYS

Which Robustness do You Mean?

Robustness evaluation due to naturally given scatter

Goal: measurement of variation and correlation

Methodology: variance-based robustness evaluation



Positive side effect of robustness evaluation: The measurement of prognosis quality of the response variation answer the question - Does numerical scatter significantly influence the results?

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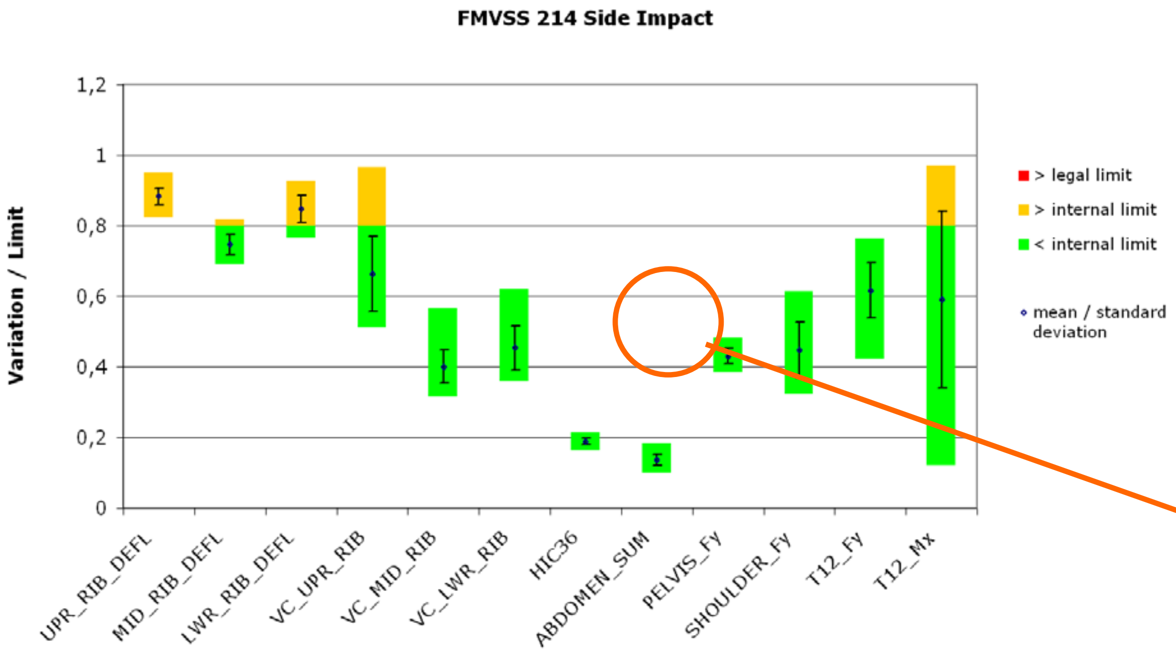
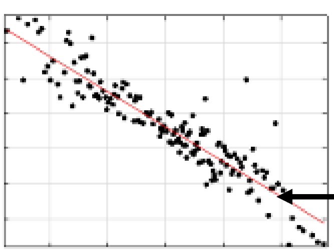
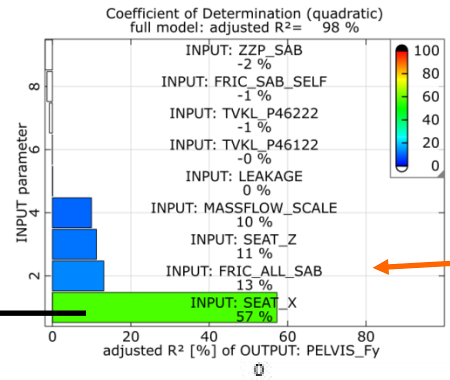
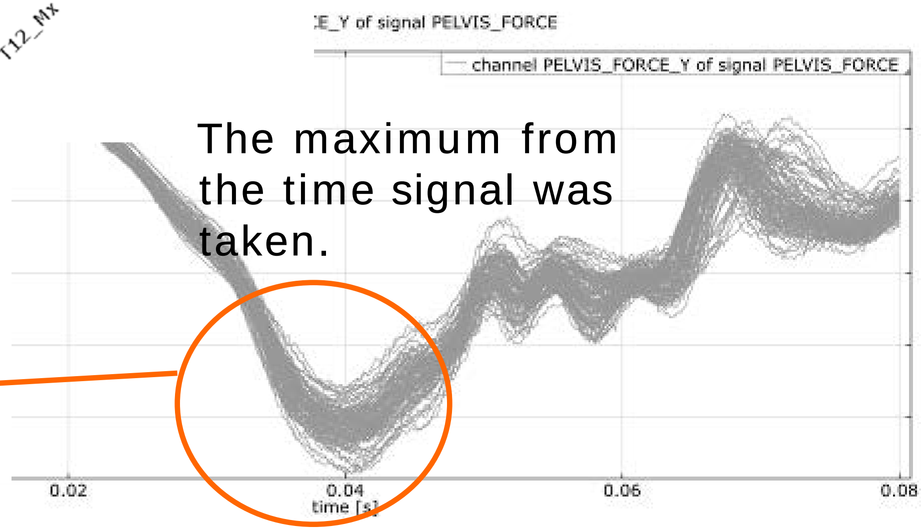
Standardized and Automated Post Processing



Example how the post processing is automated for passive safety at BMW





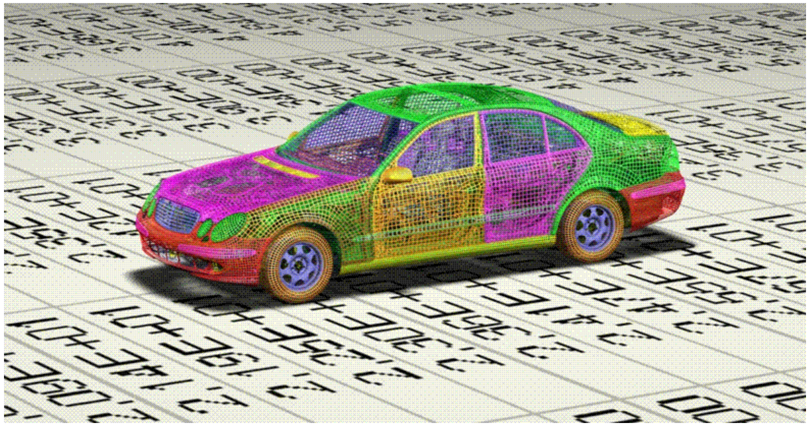


The maximum from the time signal was taken.

Robustness Evaluation of NVH Performance

Start in 2002, since 2003 used for Production Level
How does body and suspension system scatter influence the NVH performance?

- Consideration of scatter of body in white, suspension system
- Prognosis of response value scatter
- Identify correlations due to the input scatter
- CAE-Solver: NASTRAN
- Up-to-date robustness evaluation of body in white have 300 .. 600 scattering variables
- Using filter technology to optimize the number of samples



by courtesy of DAIMLER

Will, J.; Möller, J-St.; Bauer, E.: Robustness evaluations of the NVH comfort using full vehicle models by means of stochastic analysis, VDI-Berichte Nr.1846, 2004, S.505-527, www.dynardo.de

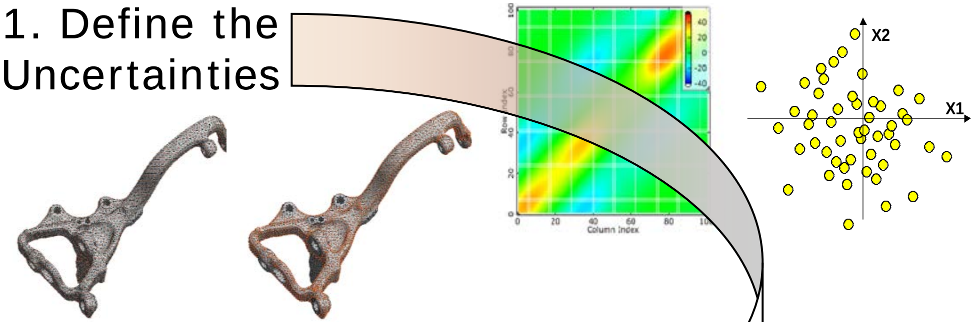
Robustness Evaluation of break systems

Start in 2007, since 2008 used for Production Level

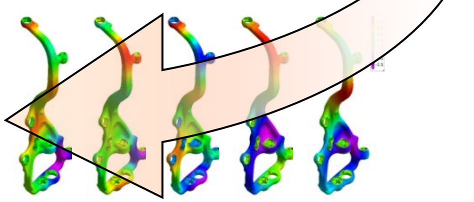
How does material and geometric scatter influence the break noise performance ?

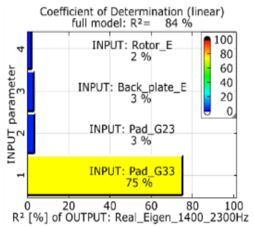
- Consideration of material and geometry scatter
- Prognosis of noise (instabilities)
- Identify correlations due to the input scatter
- CAE-Solver: NASTRAN, ABAQUS, ANSYS
- Up-to-date robustness evaluation of body in white have 20 ..30 scattering variables
- Integration of geometric scatter via random fields

1. Define the Uncertainties



2. Simulate random parameters





4. Post processing

3. Generate set of random specimen, replace in FE assembly to compute

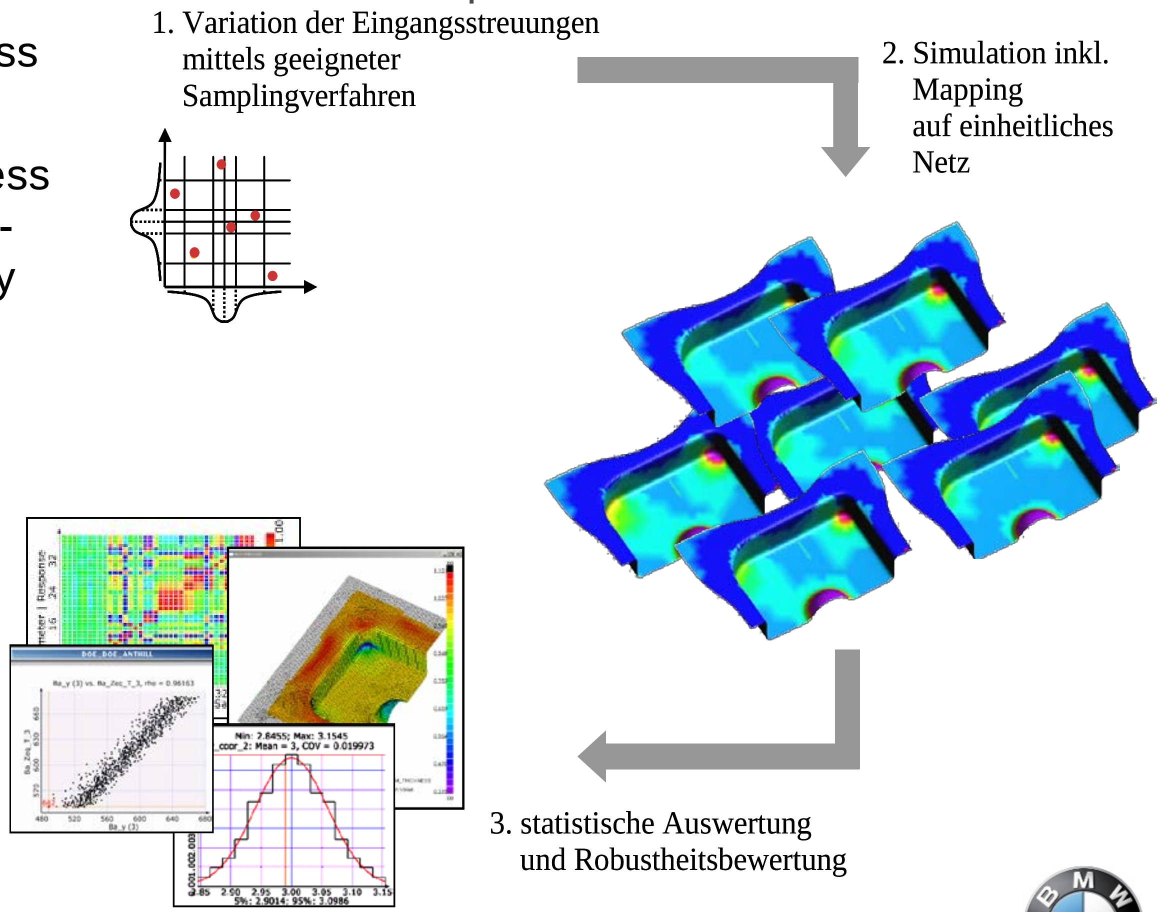
by courtesy of DAIMLER

Will, J.; Nunes, R.: Robustness evaluations of the break system concerning squeal noise problem, Weimarer Optimierungs- und Stochastiktage 2009, www.dynardo.de

Robustness Evaluation of Forming Simulations

Start in 2004 - since 2006 used for production level

- Consideration of process and material scatter
- Determination of process robustness based on 3-Sigma-values of quality criteria
- **Projection and determination of statistical values on FE-structure necessary**



CAE-Solver: LS-DYNA, AUTOFORM and others

by courtesy of

Will, J.; Bucher, C.; Ganser, M.; Grossenbacher, K.: Computation and visualization of statistical measures on Finite Element structures for forming simulations; Proceedings Weimarer Optimierung- und Stochastiktage 2.0, 2005, Weimar, Germany

Robustness Evaluation of Passive Safety

- Consideration of scatter of material and load parameters as well as test conditions
- Prognosis of response value variation = is the design robust!
- Identify correlations due to the input scatter
- Quantify the amount of numerical noise
- CAE-Solver: MADYMO, ABAQUS

Start in 2004, since 2005 used for productive level
Goal: Ensuring Consumer Ratings and Regulations & Improving the Robustness of a System

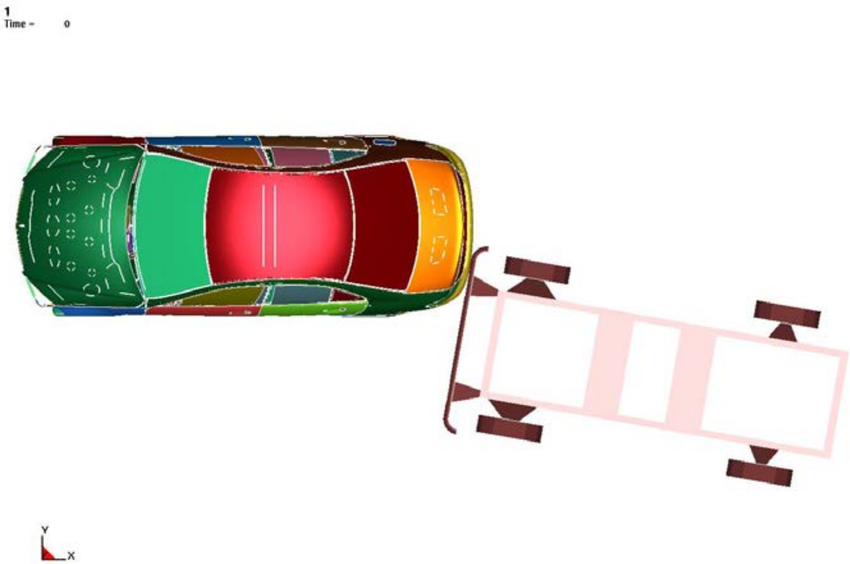
by courtesy of BMW

Will, J.; Baldauf, H.: Integration of Computational Robustness Evaluations in Virtual Dimensioning of Passive Passenger Safety at the BMW AG , VDI-Berichte Nr. 1976, 2006, Seite 851-873, www.dynardo.de

Robustness Evaluation Crashworthiness

Start in 2004 – since 2007 use for Production Level

- Consideration of scatter of thickness, strength, geometry, friction and test condition
- CAE-Solver: LS-DYNA, Abaqus
- Prognosis of intrusions, failure and plastic behavior
- Identify Coefficient of Prognosis and nonlinear correlations
- Check model robustness
- 100 .. 200 scattering variables
- Introduction of forming scatter via Random Fields



by courtesy of the Daimler AG

In comparison to robustness evaluations for NVH, forming or passive safety, crashworthiness has very high demands on methodology and software!

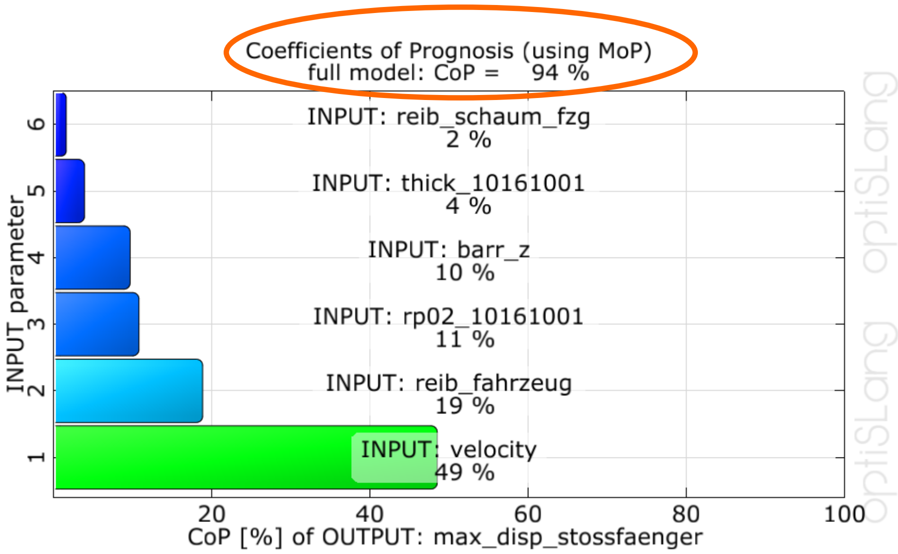
by courtesy of DAIMLER

Will, J.; Frank, T.: Robustness Evaluation of crashworthiness load cases at Daimler AG; Proceedings Weimarer Optimierung- und Stochastiktage 5.0, 2008, Weimar, Germany, www.dynardo.de

Robustness and Stability of the Model

Which quantity of „numerical noise“ is acceptable?

⇨ Quantification via coefficients of prognosis (CoP)
⇨ Estimation of numerical noise: 100% - CoP



Experience in passive safety, CFD or crashworthiness tells that result values with lower CoP than 80% show:

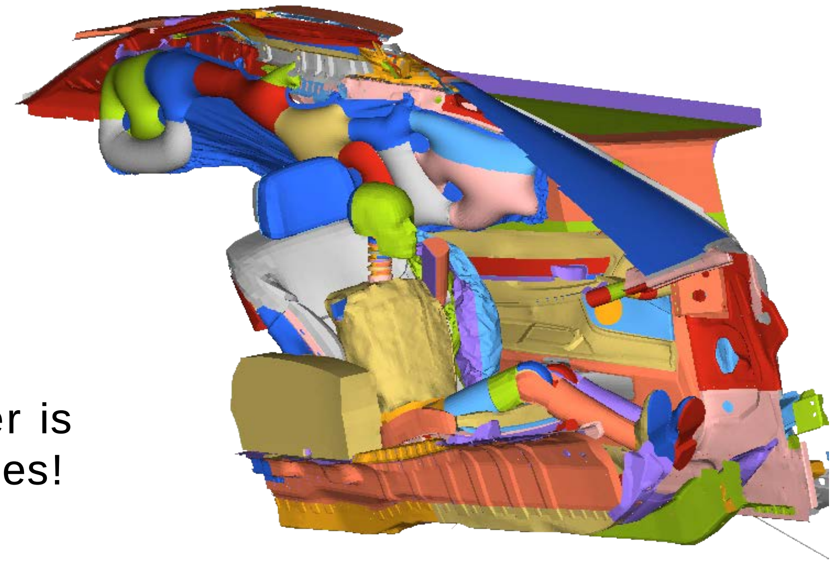
- High amount of numerical noise resulting from numerical approximation method (meshing, material, contact,..)
- Problems of result extractions
- Physically instable behavior

Numerical Robustness Passive Safety

Response	CoV	CoD lin[%]	CoD lin adj [%]	CoD quad [%]	CoD quad adj [%]
UPR_RIB_DEFL [mm]	0.027	40	34	93	83
MID_RIB_DEFL [mm]	0.038	95	94	98	96
LWR_RIB_DEFL [mm]	0.046	75	72	93	82
VC_UPR_RIB [m/s]	0.161	84	82	96	91
VC_MID_RIB [m/s]	0.118	33	25	88	73
VC_LWR_RIB [m/s]	0.138	84	83	96	91
HIC36 [-]	0.048	84	82	95	87
ABDOMEN_SUM [N]	0.119	53	48	93	84
PELVIS_Fy [N]	0.051	97	96	99	98
SHOULDER_Fy [N]	0.179	98	98	100	99
T12_Fy [N]	0.127	51	46	90	77
T12_Mx [Nmm]	0.424	81	79	92	82

ABAQUS side crash case

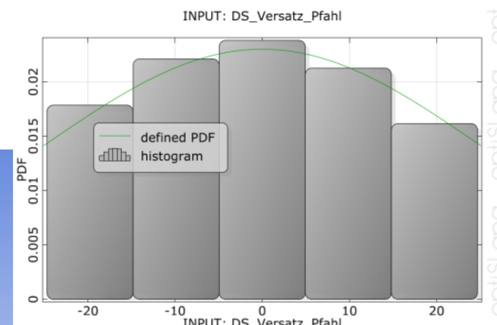
Robustness evaluation against airbag parameter, dummy position and loading scatter shows Coefficients of determination between 73 and 99%.



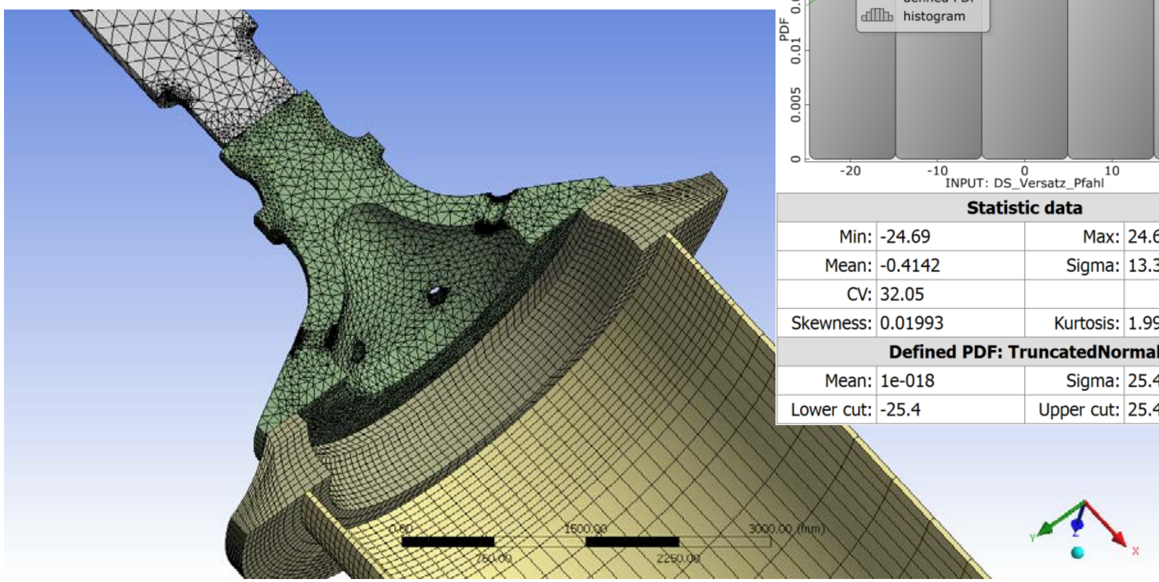
In qualified FE-models, numerical scatter is not dominating important response values!

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

Robustness evaluation as early as possible

Goal: Tolerance check before any hardware exist!

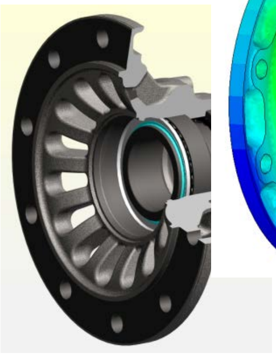
Classical tolerance analysis tend to be very conservative

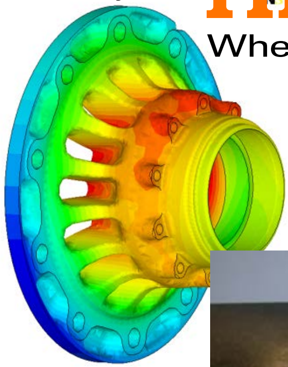
Robustness evaluation against production tolerances and material scatter (43 scattering parameter) shows:

- Press fit scatter is o.k.
- only single tolerances are important (high cost saving potentials)

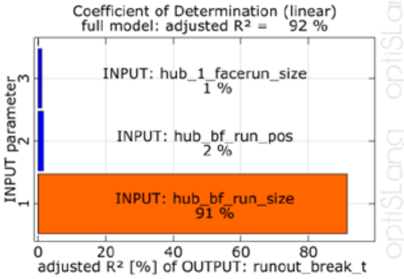
Production shows good agreement!

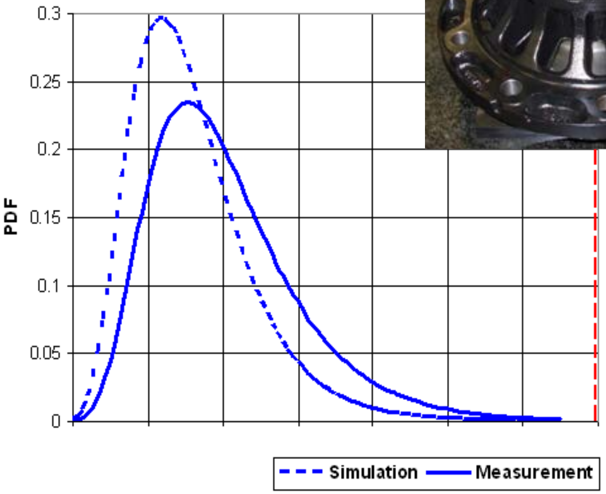
by courtesy of TIMKEN Where You Turn





Design Evaluations: 150
solver: ANSYS/optiSLang





Suchanek, J.; Will, J.: Stochastik analysis as a method to evaluate the robustness of light truck wheel pack; Proceedings WOSD 6.0, 2009, Weimar, Germany, www.dynardo.de

Benefits of Robustness Evaluation

1) Estimation of result variation: By comparison of the variation with performance limits, we can answer the question: Is the design robust against expected material, environmental and test uncertainties? By comparison of the variation with test results, we can verify the prediction quality of the model.

2) Calculation of correlations, including the coefficient of determination, which quantify the “explainable” amount of response variation. Here, we identify the most important input scatter which are responsible for the response scatter.

3) Due to robustness evaluation, possible problems are identified early in the development process and design improvements are much cheaper than late in the development process.

4) Side effect: Validation of the modeling quality (quantification of numerical noise and identification of modeling errors)

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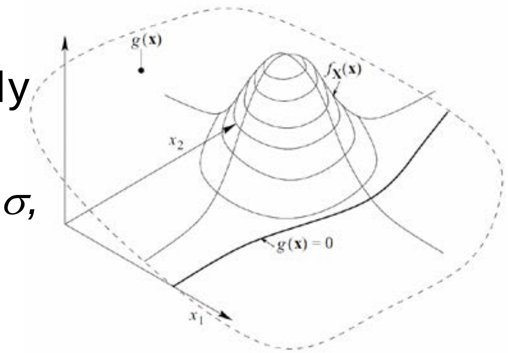
Reliability Analysis

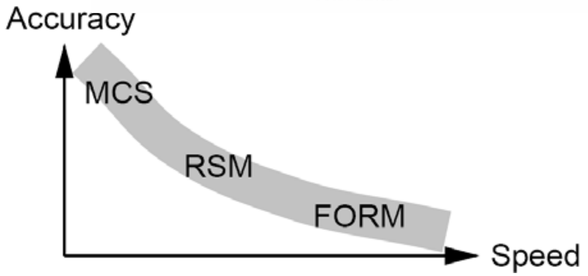
Reliability Analysis



- Robustness can verify relatively high probabilities only ($\pm 2\sigma$, *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.

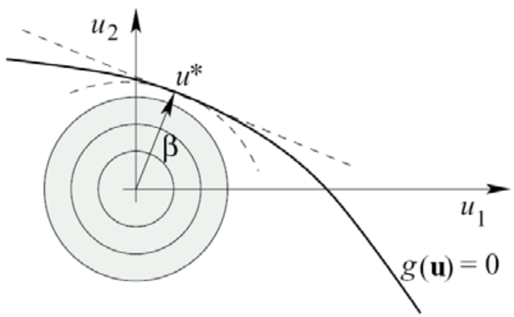
It is recommended to use two different algorithms to verify rare event probabilities



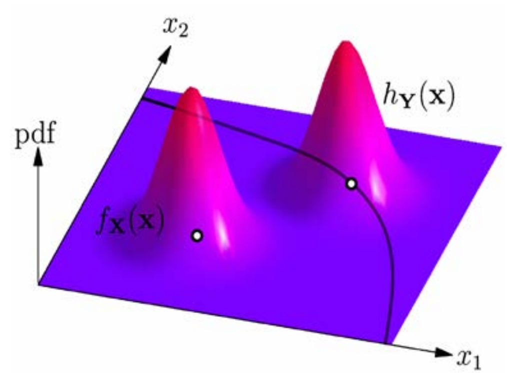
- First order reliability method (FORM), $\geq 2\sigma$, gradient based
- Importance sampling using design point (ISPUD), Sigma level ≥ 2, $n \leq 50$
- Monte-Carlo-Simulation, independent of n, but very high effort for $\geq 2\sigma$
- Latin Hypercube sampling, independent of n, still very high effort for $\geq 2..3\sigma$
- Asymptotic Sampling, $\geq 2\sigma$, $n \geq 10$
- Adaptive importance sampling, $\geq 2\sigma$, $n \leq 10$
- Directional sampling, $\geq 2\sigma$, $n \leq 10$
- Directional Sampling using global adaptive response surface method, $\geq 2\sigma$, $n \leq 5..10$

Reliability Analysis Algorithms

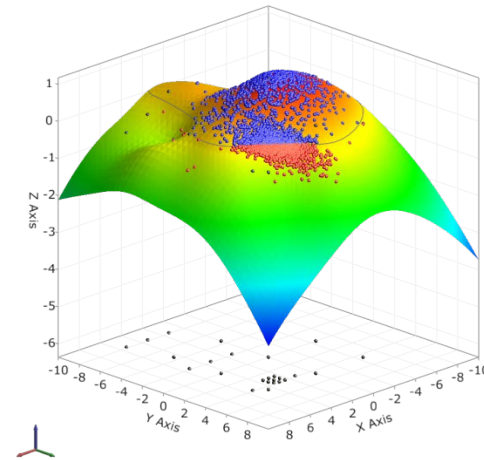
Gradient-based algorithms = First Order Reliability algorithm (FORM)



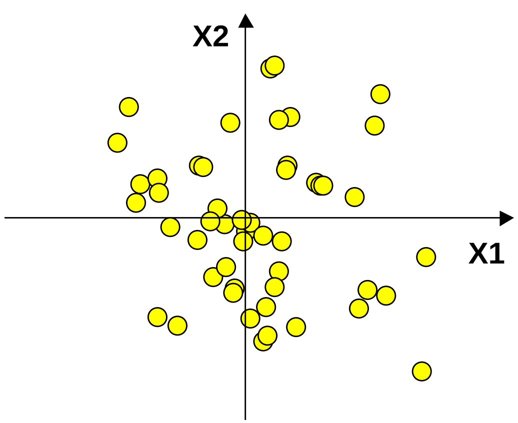
ISPUD Importance Sampling using Design Point



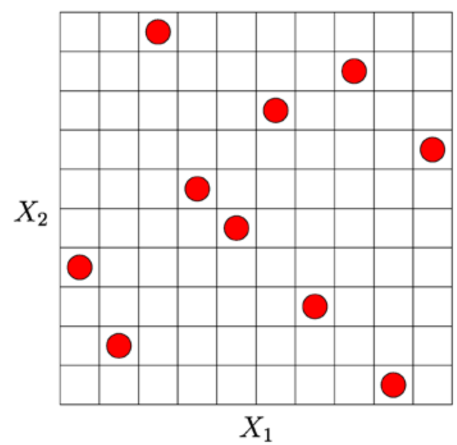
Adaptive Response Surface Method



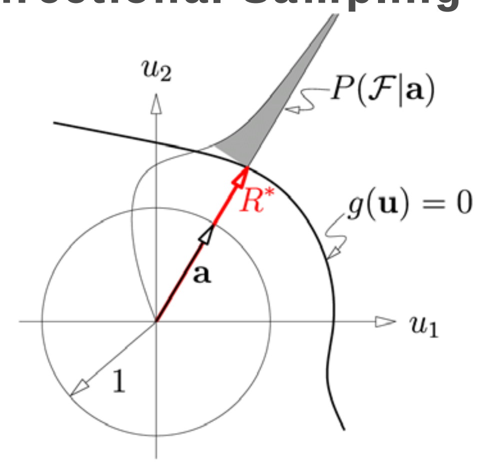
Monte Carlo Sampling



Latin Hypercube Sampling

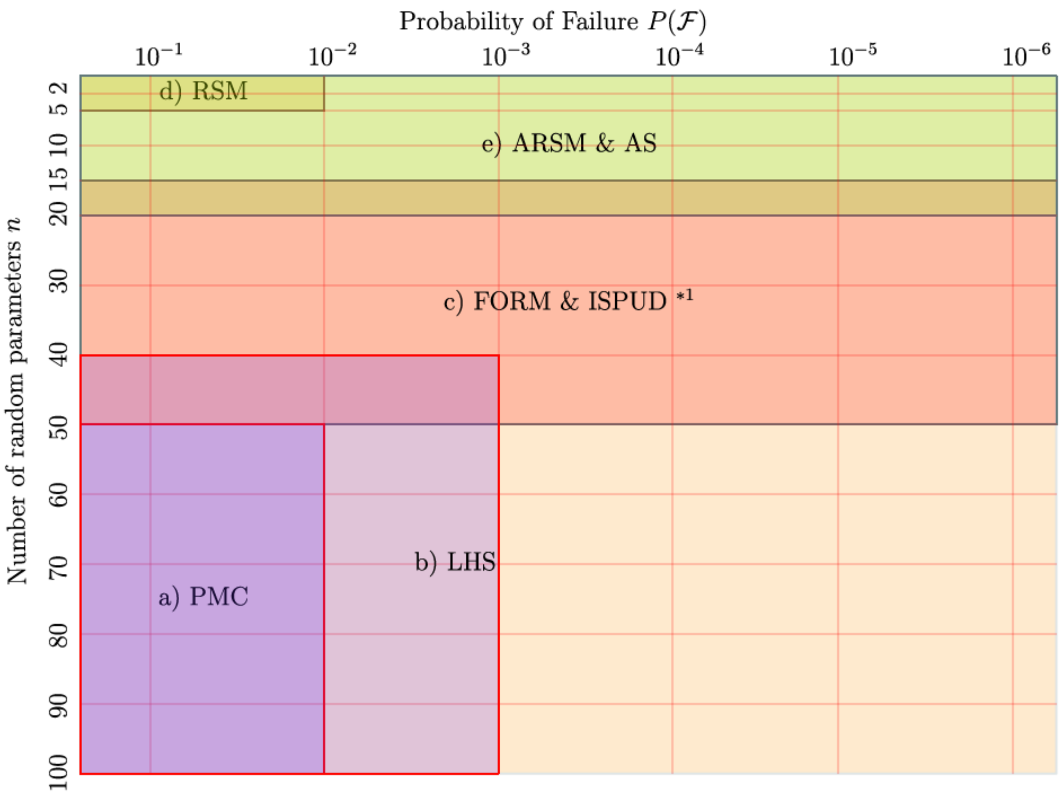


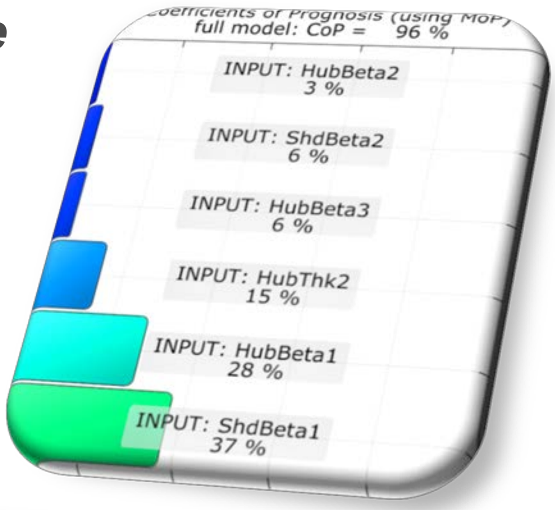
Directional Sampling

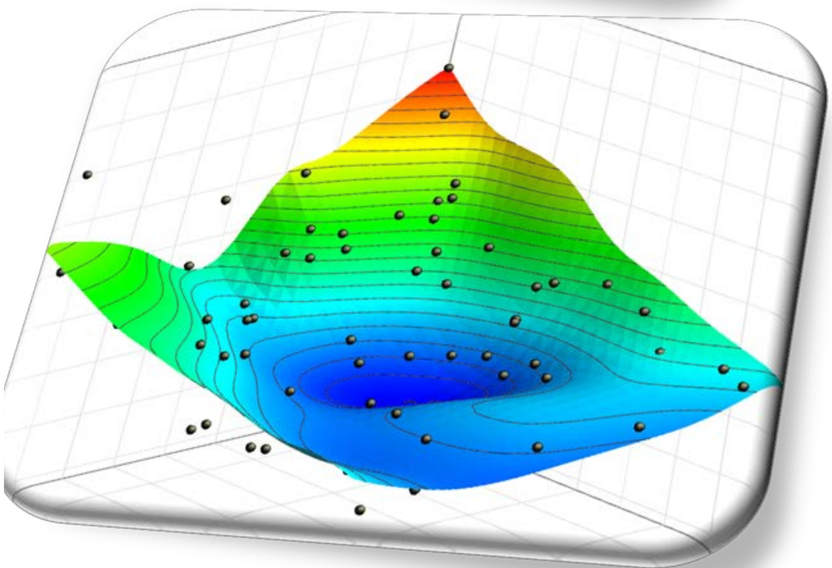


How choosing the right algorithm?

Robustness Analysis provide the knowledge to choose the appropriate algorithm



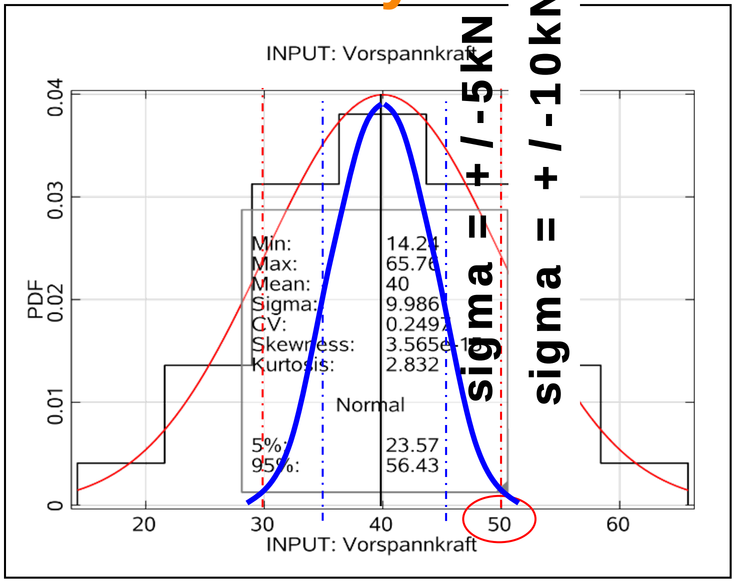


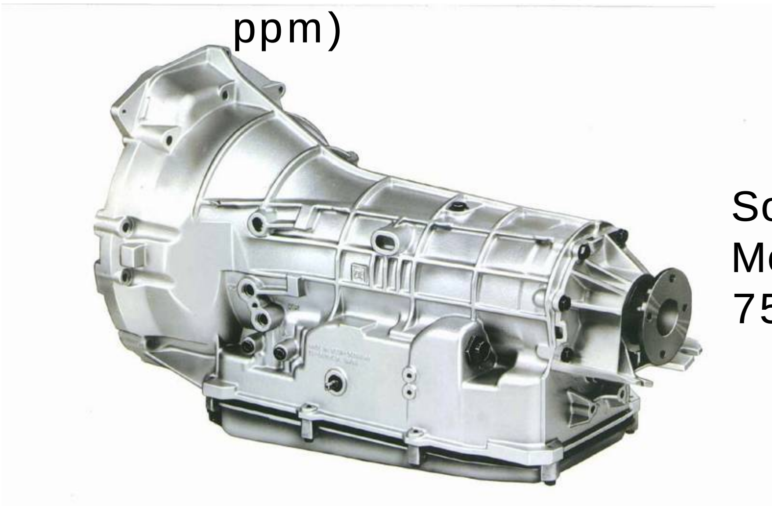


Robustness & Reliability Algorithms

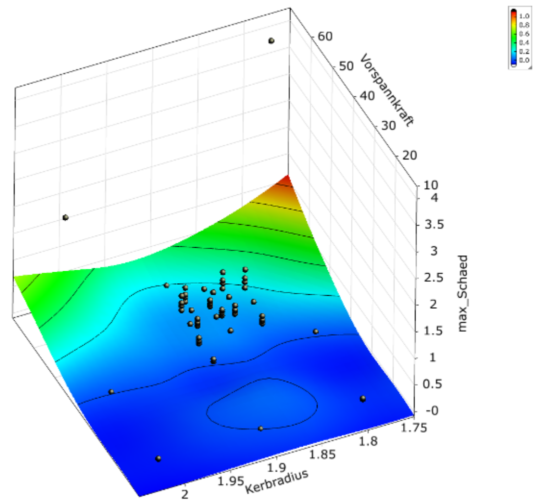
Application Example ARSM for Reliability

- 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)



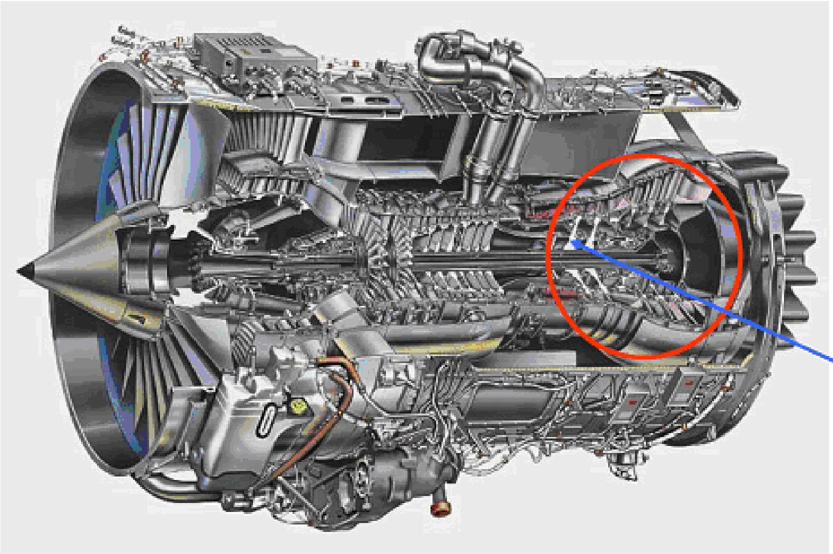


Solver: Permas
Method: ARSM
75 Solver evaluations



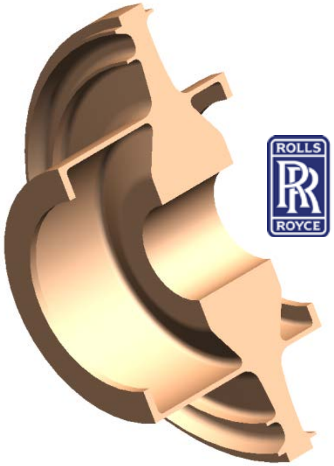
by courtesy of ZF

Reliability Analysis of turbo machines



Turbine

High
Pressure
Turbine Disc
HPT-Disc



Rolls-Royce

3D Model of HPT-Disc

Analysis Disciplines:

Thermal Analysis
Stress Analysis

Performance needs to be proven which a given Probability of Failures (POF)

Basic Design Objectives:

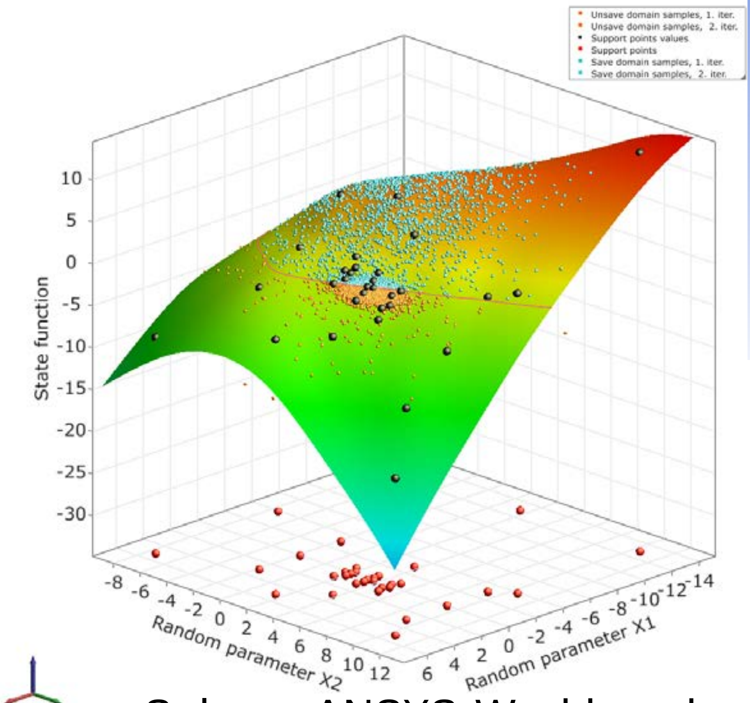
- Life of the disc
- Mass of the disc

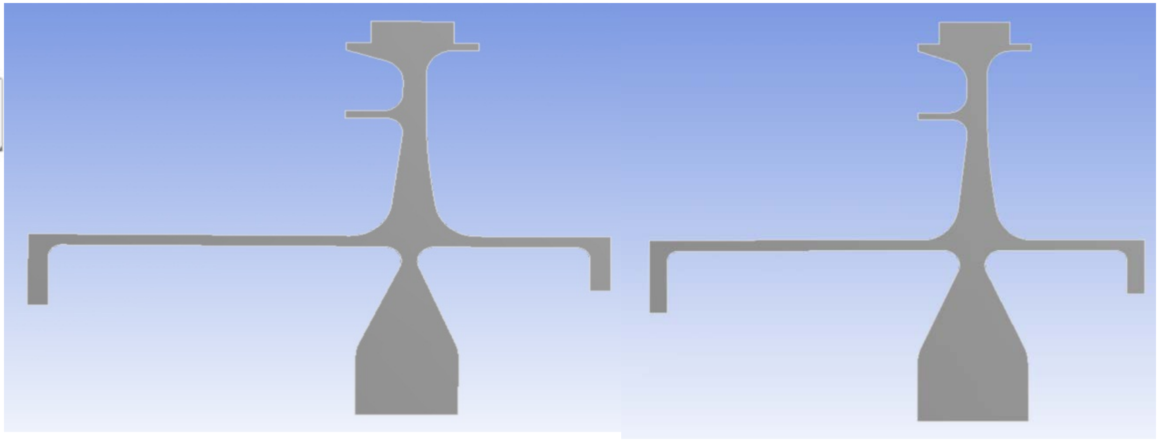
Basic Costumer Requirements

- Lifecycles → High
- Mass → Low

Check reliability of predicted life

For example: requirement of
POF for predicted life < $1.0*10^{-6}$



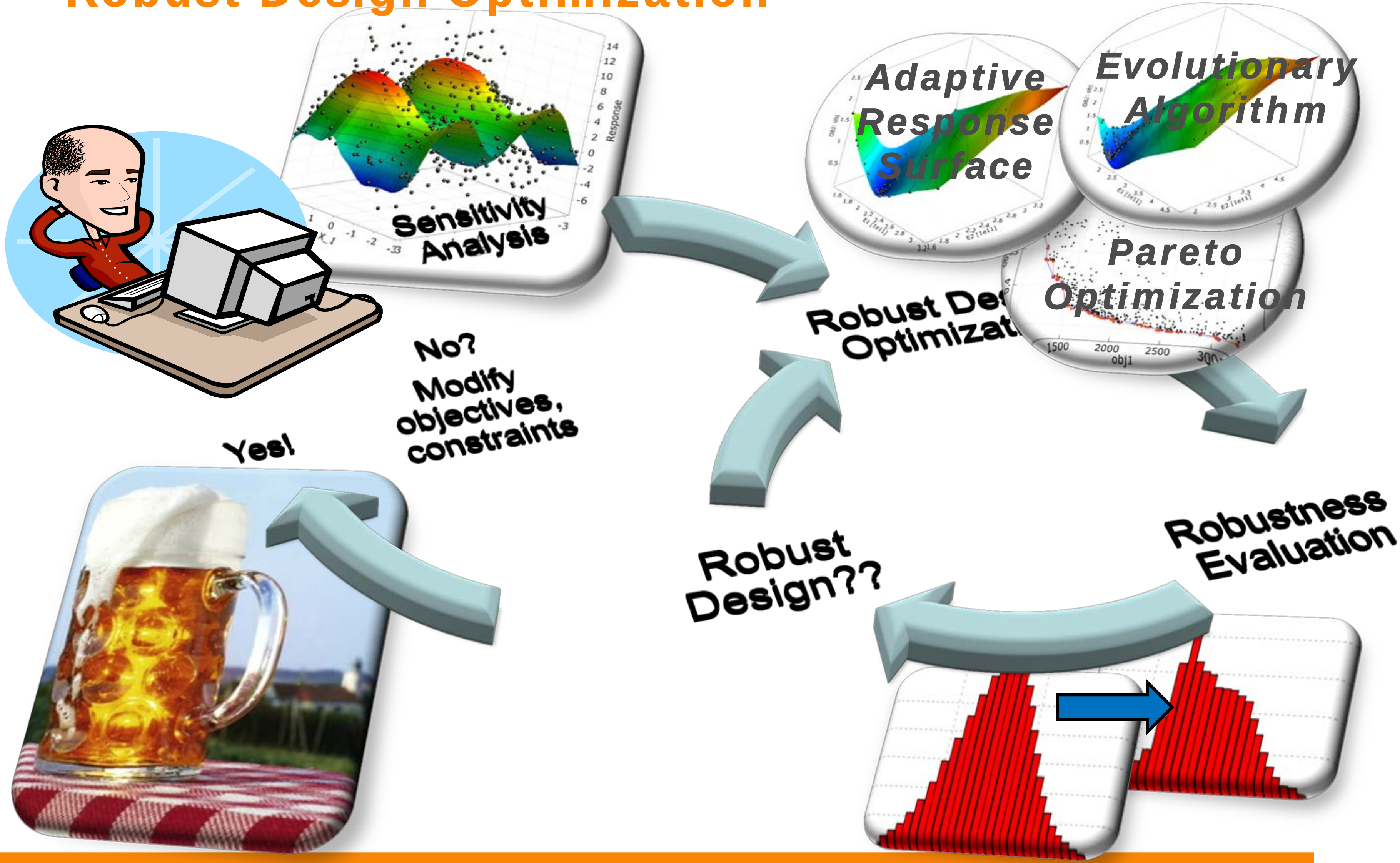


	Design 1	Design 2
Limit state (Lifecycles)	30000 cycles	28000 cycles
Probability of Failure (POF)	$3.0*10^{-5}$	$1.3*10^{-8}$
	Requirement not fulfilled	Requirement **fulfilled**

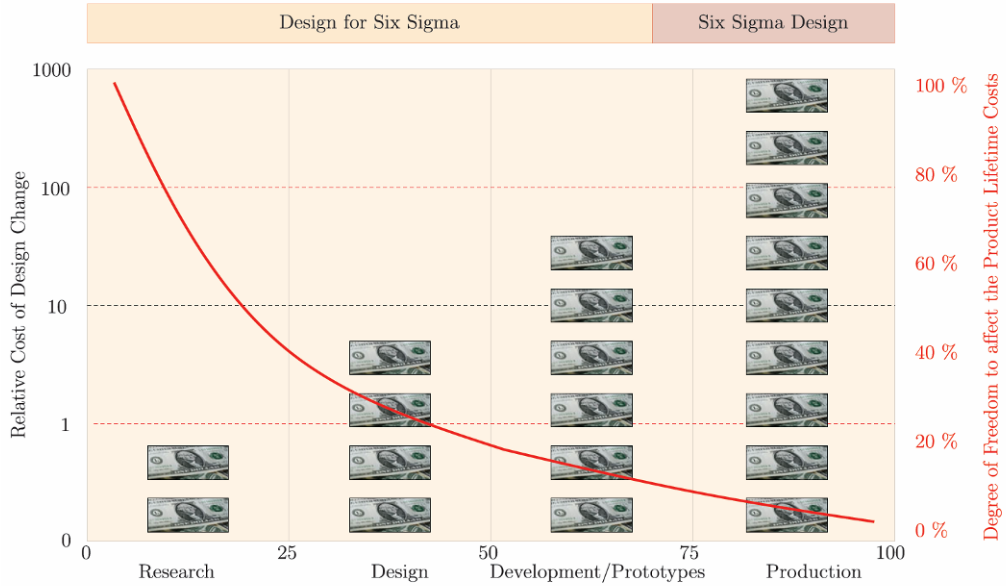
Solver: ANSYS Workbench
Method: ARSM
30..50 Solver evaluations

Robust Design Optimization

Robust Design Optimization



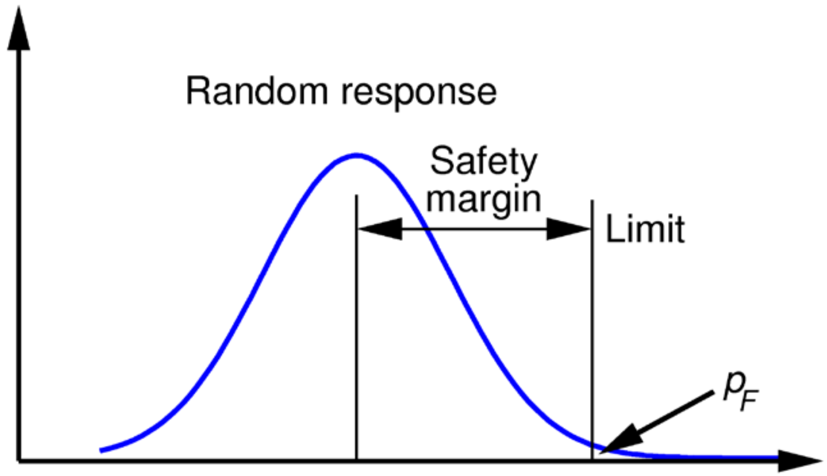
Design for Six Sigma



- Six Sigma is a concept to optimize the manufacturing processes such that automatically parts conforming to six sigma quality are produced
- Design for Six Sigma is a concept to optimize the design such that the parts conform to six sigma quality, i.e. quality and reliability are explicit optimization goals
- Because not only 6 Sigma values have to be used as measurement for a robust design, we use the more general classification Robust Design Optimization

Robust Design Optimization

Robustness in terms of constraints



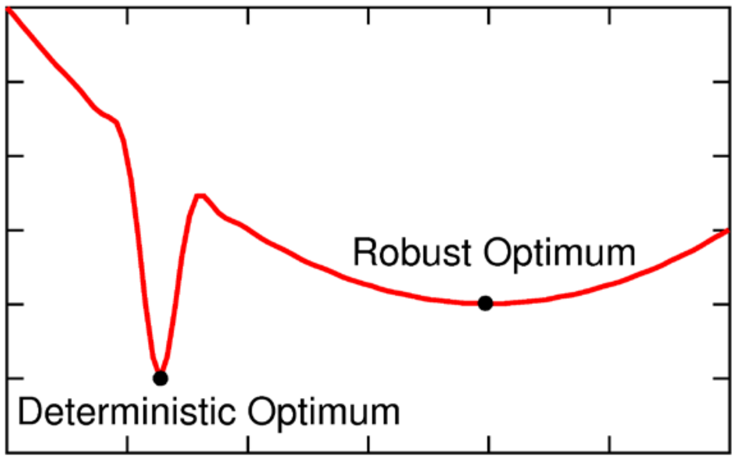
- Safety margin (sigma level) of one or more responses *y*:

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

- Reliability (failure probability) with respect to given limit state:

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

Robustness in terms of the objective

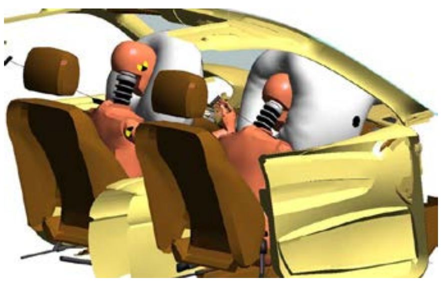


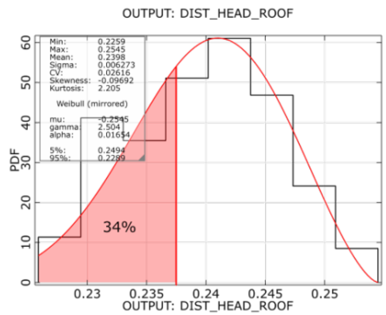
- Performance (objective) of robust optimum is less sensitive to input uncertainties
- Minimization of statistical evaluation of objective function *f* (e.g. minimize mean and/or standard deviation):

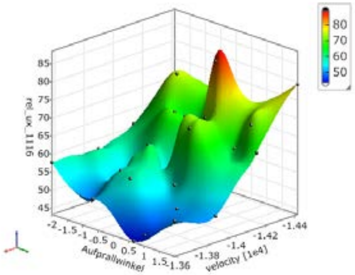
$$\bar{f} \rightarrow min \text{ or } \bar{f} + \sigma_f \rightarrow min$$

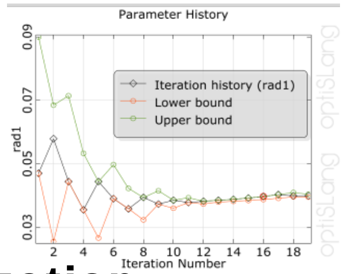
Robust Design Optimization - RDO

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.

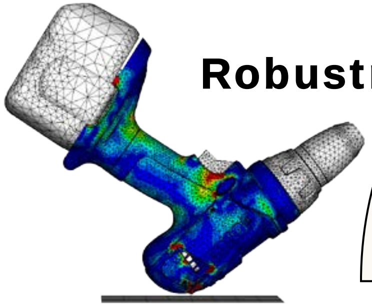


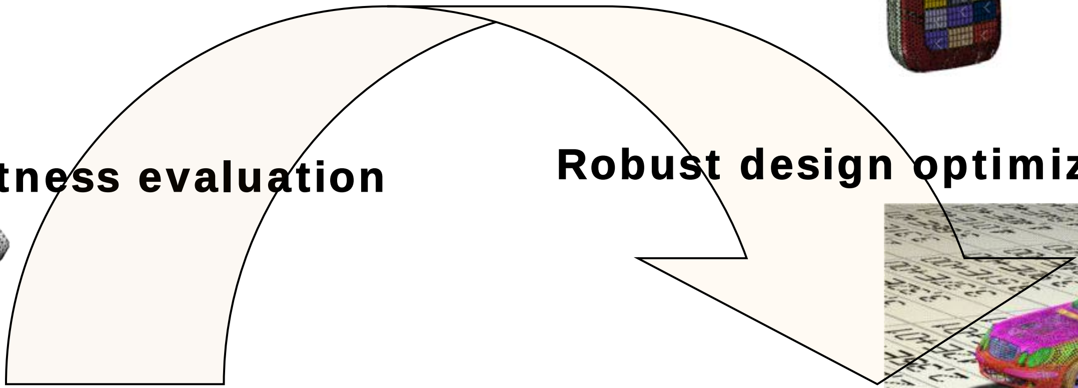






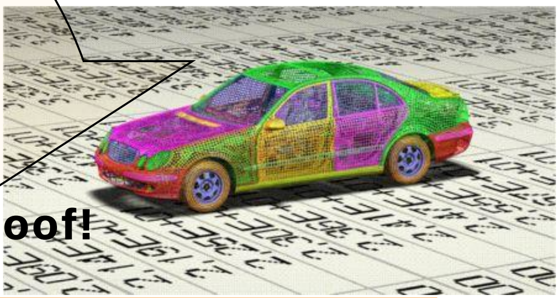
Define safety factors





Robustness evaluation

Robust design optimization



Sensitivity analysis

Robustness proof!

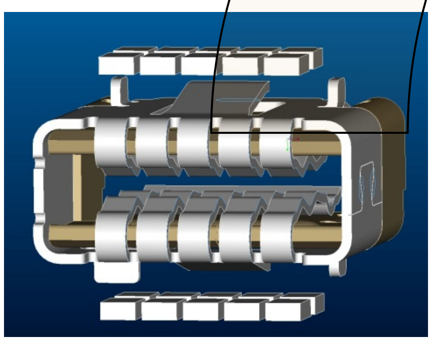
Iterative RDO Application Connector

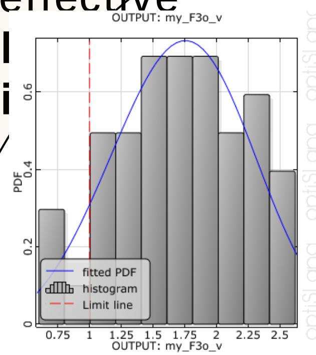
2) The DX Six Sigma design was checked in the space of 36 scattering variables using **optiSLang Robustness evaluation**. Some Criteria show high failure probabilities!

3) From optiSLang Robustness Evaluation safety margins are derived.

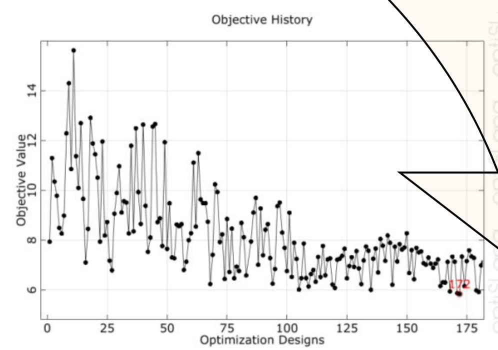
4) Three steps of optimization using **optiSLang ARSM and EA** optimizer improve the design to an optiSLang Six sigma design.

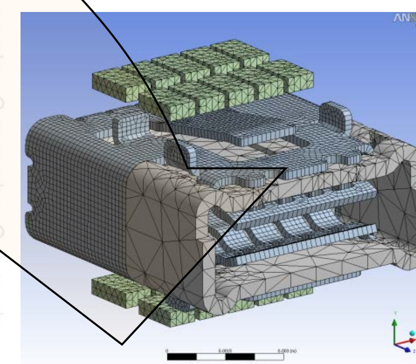
1) From the 31 optimization parameter the most effective one are selected **with optiSLang Sensitivity analysis**.





Statistic data			
Min:	0.5997	Max:	2.622
Mean:	1.728	Sigma:	0.525
CV:	0.3038		
Skewness:	-0.2233	Kurtosis:	2.251
Fitted PDF: Weibull (2p)			
Mean:	1.728	Sigma:	0.525
Limit x = 1			
P_rel =	0.08	P_fit =	0.08832
Probability P(X<x) = 0.001			
x_rel =	0.5997	x_fit =	0.2905





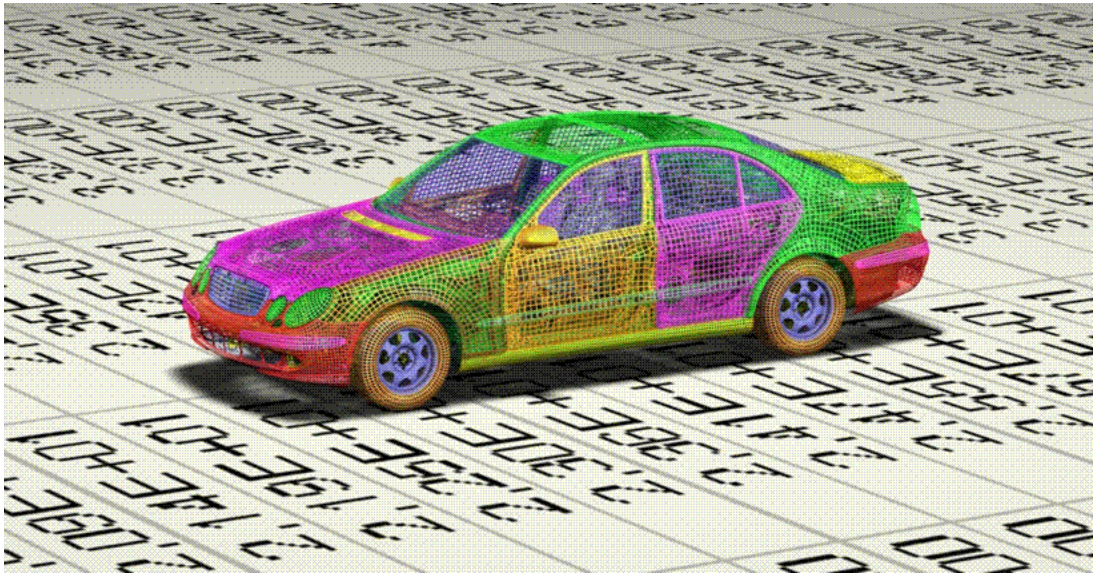
5) Reliability proof using **ARSM** to account the failure probability did **proof six sigma quality.**

Start: Optimization using 5 Parameter using DX Six Sigma, then customer asked: How save is the design?

by courtesy of Tyco Electronics

Application of Driving Comfort

With the sensitivity analysis, the design space of optimization is investigated. In reduced dimensions, an optimization (genetic optimization, ARSM, Pareto optimization) is performed. With robustness evaluations, the robustness of important responses is checked and the correlation structure is identified.



by courtesy of Daimler AG

In running digital car development cycles, with the help of robustness evaluation, sensitivity analysis and optimization, the performance and robustness could be improved.

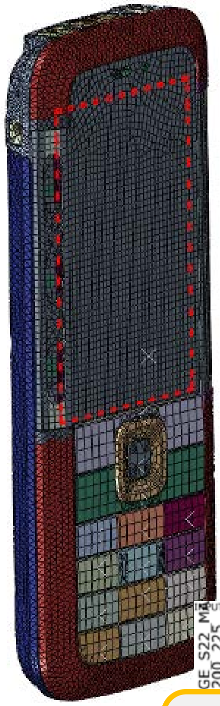
RDO procedure of consumer goods

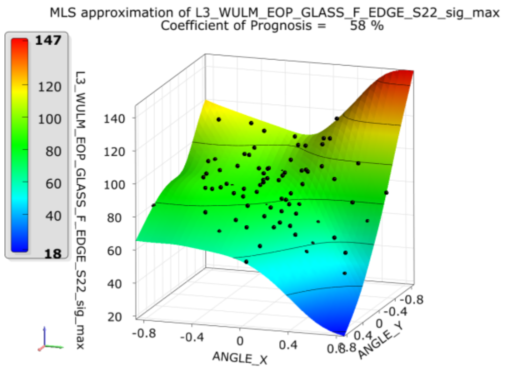
Goal: Check and improve Robustness of a mobile phone against drop test conditions!

Using sensitivity analysis the worst case drop test position as well as optimization potential out of 51 design variables was identified

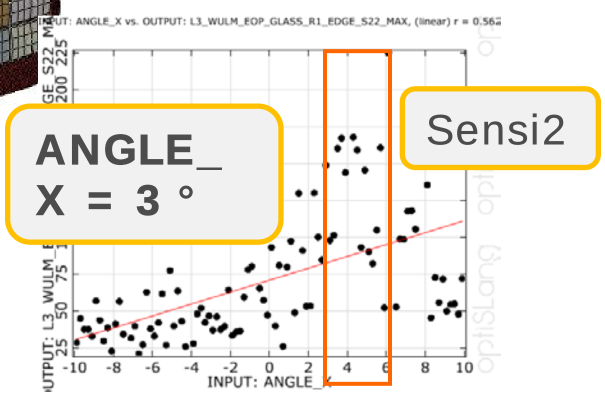
Robustness evaluation against production tolerances and material scatter (209 scattering parameter) shows need for improvements

Safety margins are calculated with Robustness evaluation after design improvements





CoD lin adj	CoD quad adj	CoD lin adj Spearman	CoP
48	48	46	58



Design Evaluations:
Sensitivity 100, Robustness 150
solver: ABAQUS-optiSLang

by courtesy of NOKIA

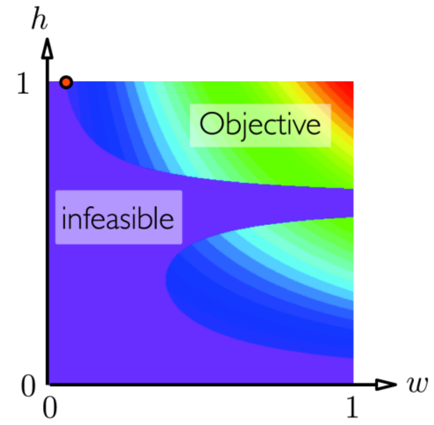
Ptchelintsev, A.; Grewolls, G.; Will, J.; Theman, M.: Applying Sensitivity Analysis and Robustness Evaluation in Virtual Prototyping on Product Level using optiSLang; Proceeding SIMULIA Customer Conference 2010 , www.dynardo.de

(Simultaneously) RDO Methodology

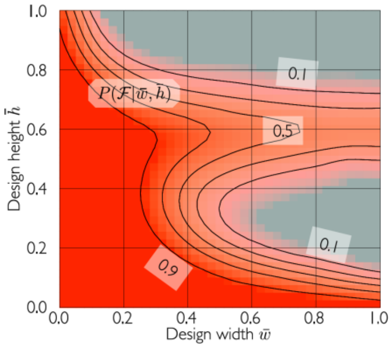
Of course, the final dream of virtual product development is an automatic robust design optimization procedure with a simultaneous dealing of optimization and reliability domain.

Because RDO simultaneously deals with optimization and robustness analysis, the computational effort becomes very high. Therefore, the challenge in applying RDO is to find a payable balance between effort and reliability of the robustness measurements.

Co-simulation of optimization and reliability analysis like doing a Latin Hypercube sampling for every optimization design is possible, but the effort multiplies.



Optimization domain

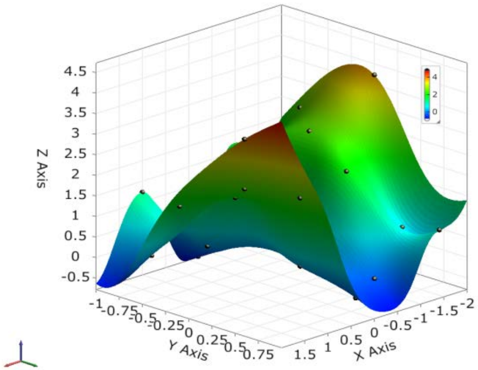


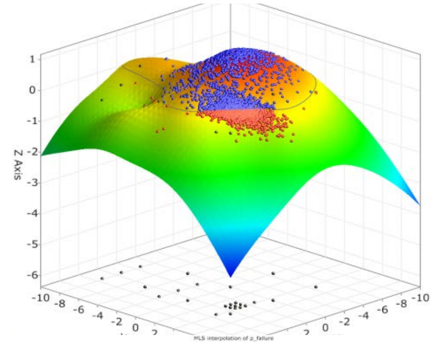
Reliability domain

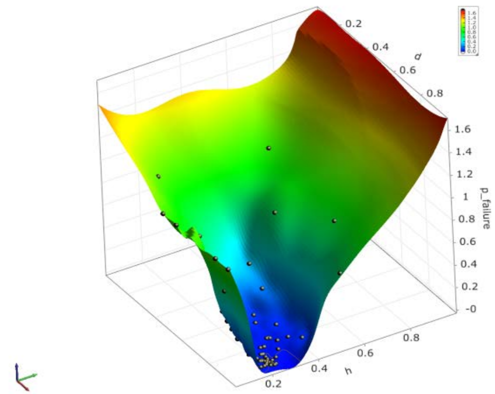
optiSLang (Simultaneously) RDO

- Variance-based RDO
  - Evolutionary, genetic and adaptive Response Surface method for optimization domain
  - Variance via Sampling (LHS) at reliability space or adaptive Response Surface method

- Probability-based RDO
  - Evolutionary, genetic and adaptive Response Surface method for optimization domain
  - Reliability: LHS, Adaptive Sampling, FORM, ISPUD or adaptive Response Surface Methodology at reliability space

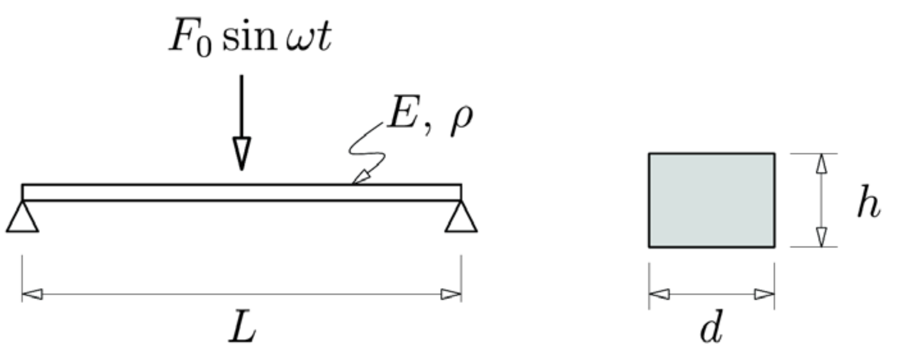






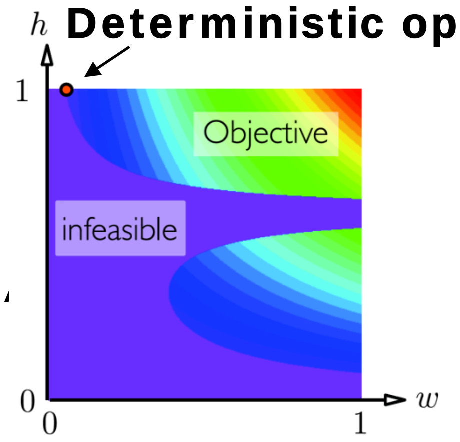
RDO Performance Illustration Example

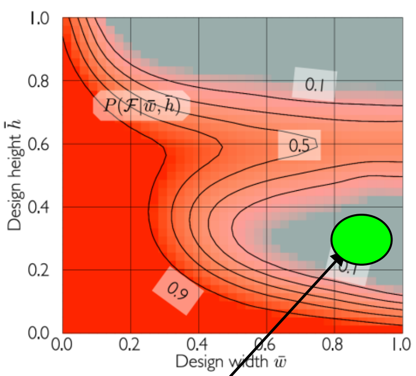
- **2 optimization and 2 reliability parameter**
- Random input parameter
  - Dynamic load amplitude
  - Frequency
- Design parameter
  - Height and width



- Constrain
  - Maximum displacements
- Objective
  - Minimal mass (cross section=
    failure probability < 1%

Deterministic optima



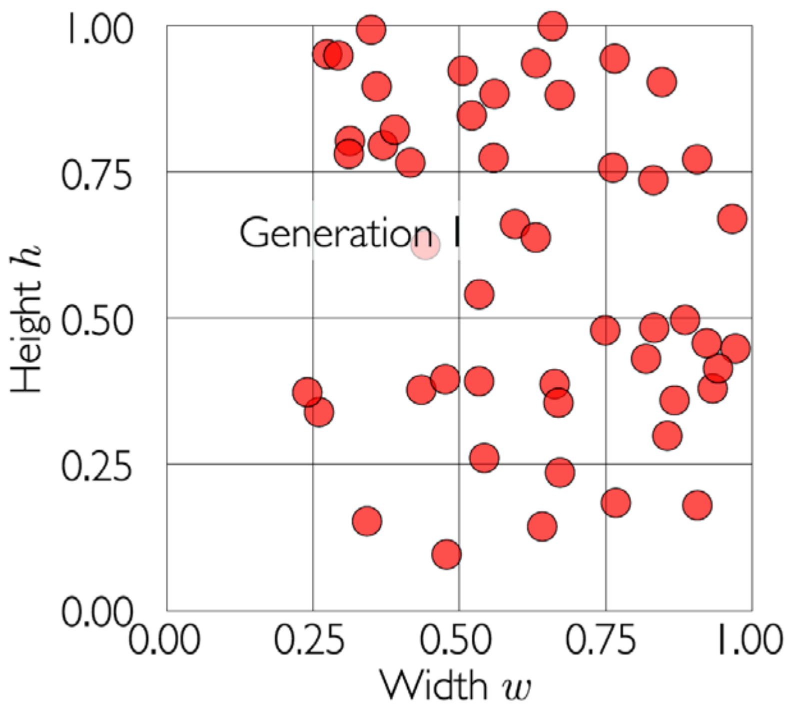


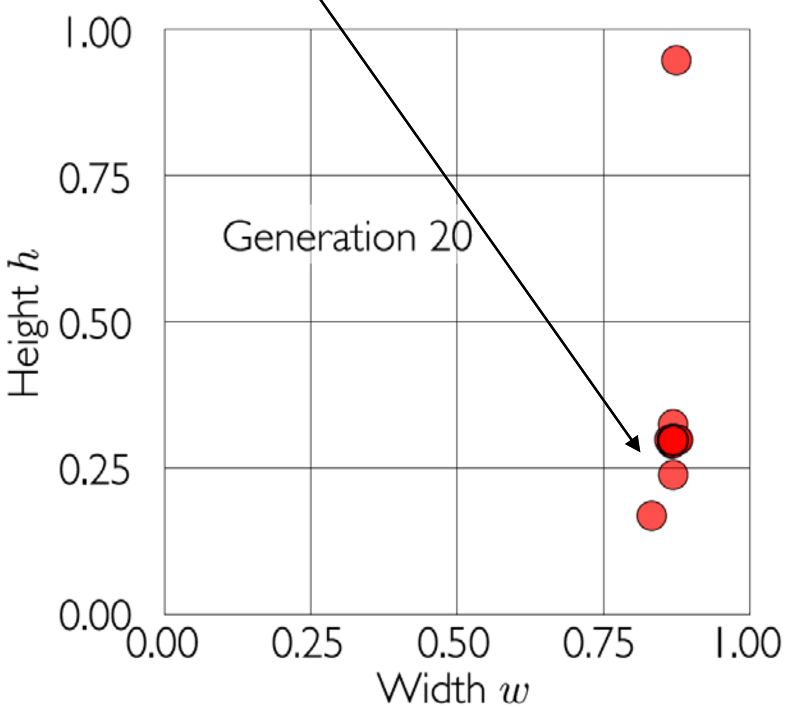
RDO optima

RDO Illustration Example optiSLang 2006

Using FORM for Reliability Analysis and GA for Optimization

- **N=50*20*15=15000 Simulation**
- Best robust design: w= 0.888, h= 0.289, A=0.256
- Failure probability 0.0098% < 1%
- Cross sectional area was 0.256 which is considerably higher than the value of 0.06 obtained in the deterministic case

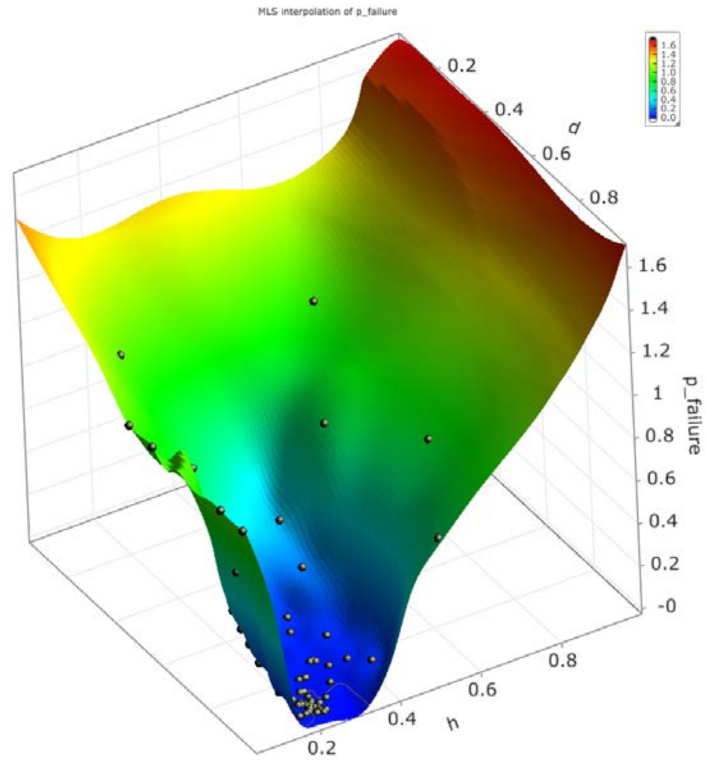




RDO Illustration Example optiSLang 2007

Using ARSM for Reliability and Optimization Domain

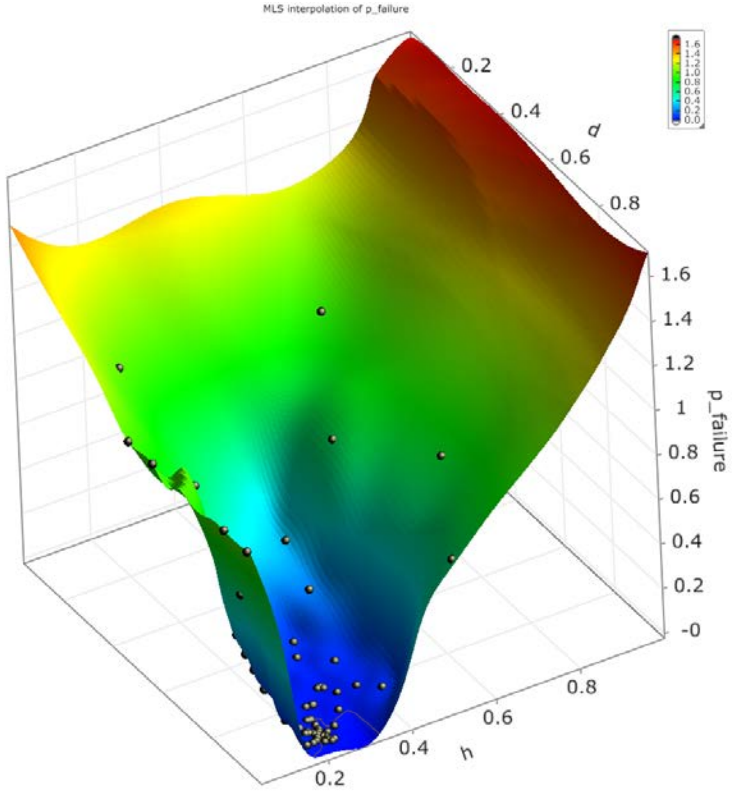
- ARSM in design space
- ARSM on random space
- **N = 66*18=1188**
- design evaluations
- Best robust design:
- d = 0.925, h = 0.22 A=0.20
- Failure probability:
- 0.0098% < 1%
- Cross sectional area was **0.20** which is considerably higher than the value of 0.06 obtained in the deterministic case, but lower than the value 0.256 found with EA+FORM



RDO Illustration Example optiSLang 2009

Using ARSM for Reliability and Optimization Domain

- ARSM in design space
- ARSM on random space
- **N = 201** design evaluations
- Best robust design: d = 0.896, h = 0.215, A=0.2035
- Failure probability: 0.003% < 1%
- Cross sectional area was **0.19** which is considerably higher than the value of 0.06 obtained in the deterministic case, but lower than the value 0.256 found with EA+FORM



Benefits of Robust Design Optimization

Identify product design parameters which are critical for the achievement of a performance characteristic!

- Quantify the effect of variations on product behavior and performance
- Adjust the design parameter to hit the target performance
  - ✓Reduces product costs

- Understanding potential sources of variations
- Minimize the effect of variations (noise)
  - ✓More robust and affordable designs

- Cost-effective quality inspection
  - ✓No inspection for parameters that are not critical for the performance