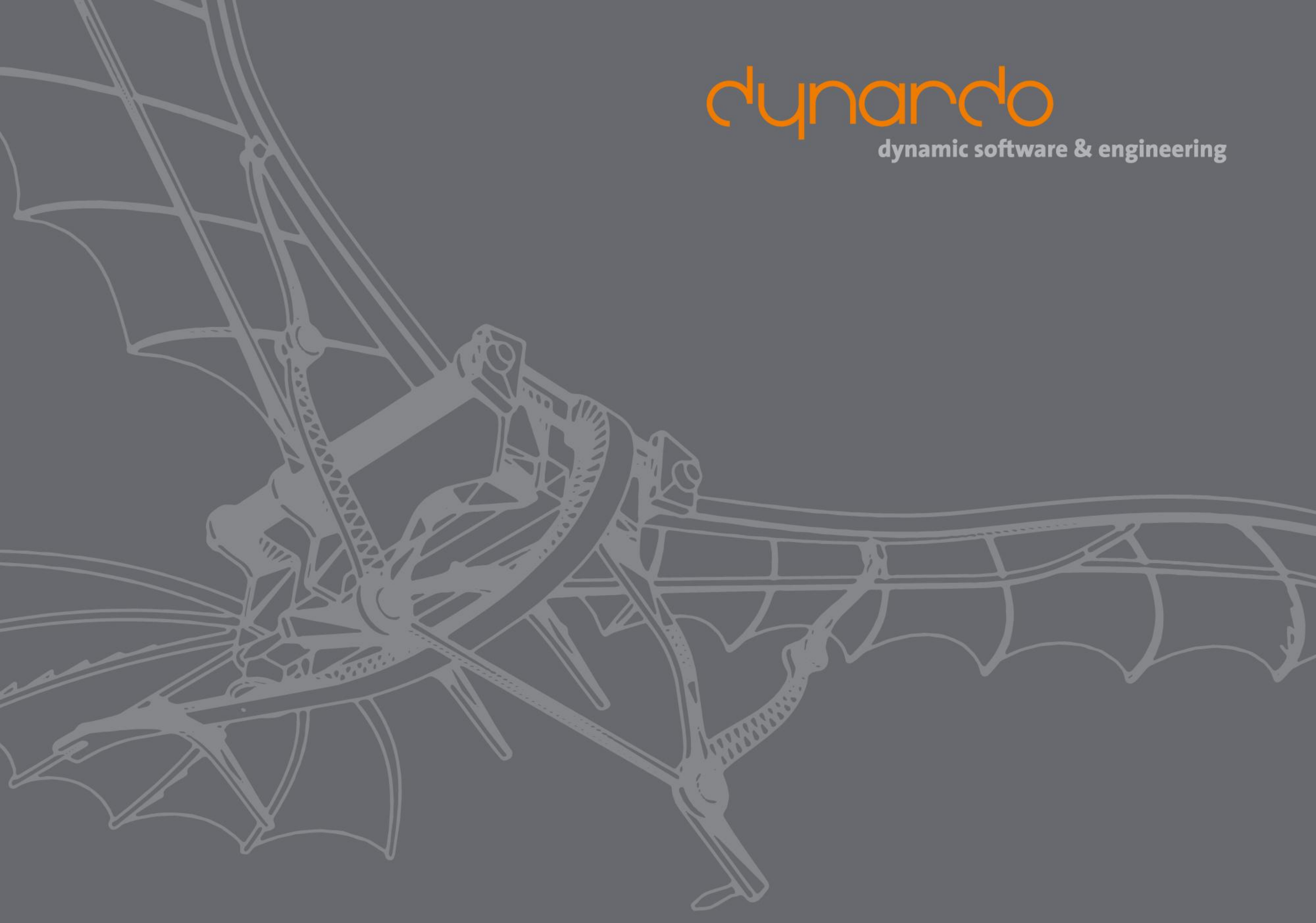
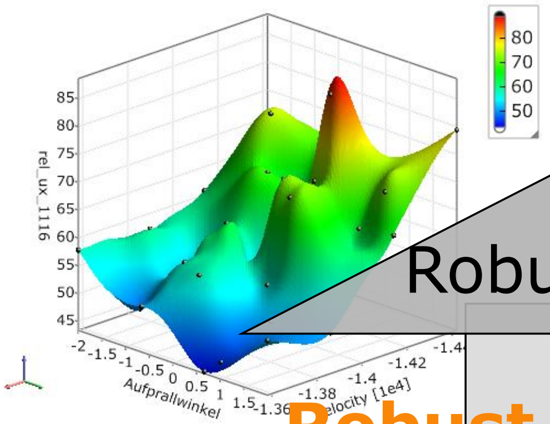
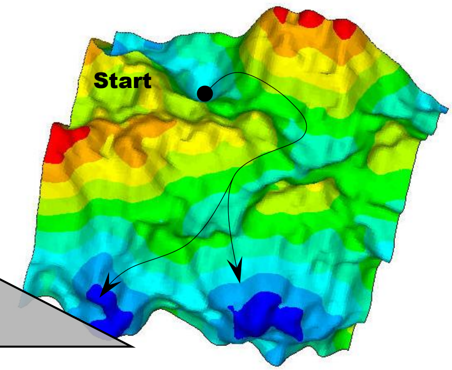
dynardo

dynamic software & engineering



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.)

How to define Robustness of a Design

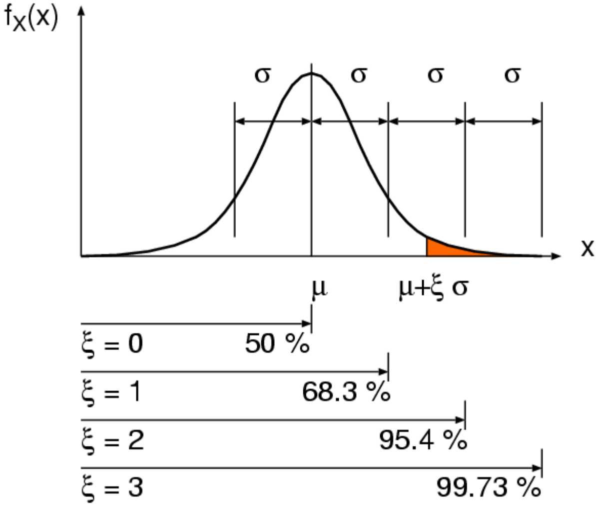
- Intuitively: The performance of a robust design is largely unaffected by random perturbations

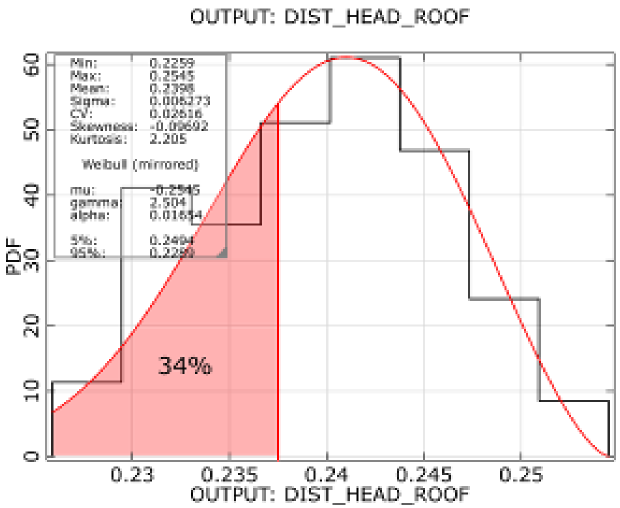
- Using **Variance indicator**: The coefficient of variation (CV) of the response, constraint, objective function values is smaller than the CV of the input variables

- Using **Sigma level**: The interval mean+/- sigma level does not reach an undesired performance
  (e.g. design for six-sigma)

- Using **Probability indicator:** The probability of reaching undesired performance is smaller than an acceptable value

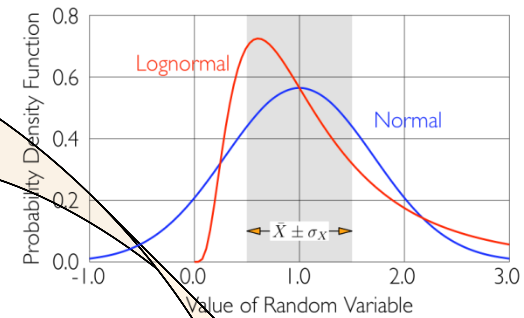
Robustness Evaluation / Reliability Analysis





- Variance-based robustness evaluation usually estimate product
  - safety and reliability for 1 & 2 (3) Sigma levels and identifies the most sensitive stochastic variables
  - high number of stochastic variables is no problem
- Probability-based robustness evaluation (reliability analysis) estimate product
  - safety and reliability for rare events (3,4,5,6-Sigma) with small number of variables
  - Most reliability algorithms suffer on high number of stochastic variables

Successful Robustness Evaluation need the balance between

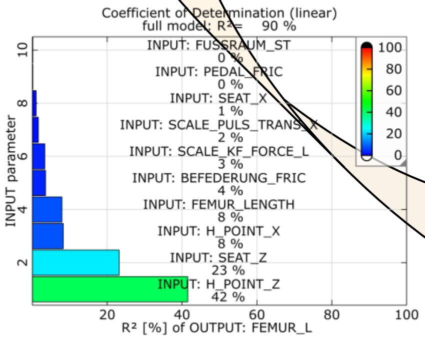


1. Reliable Input Definition

⇨ Distribution function
⇨ Correlations
⇨ Random fields

2. Reliable stochastic analysis

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



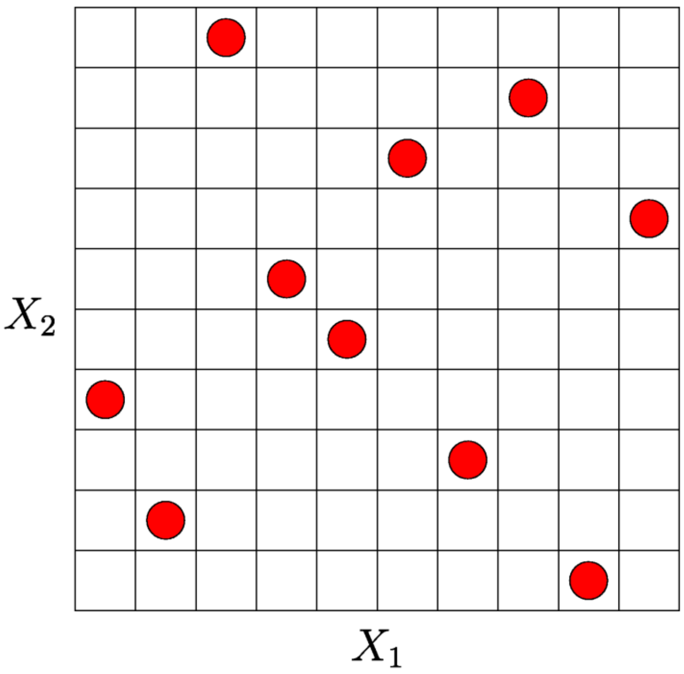
3. Reliable Post Processing

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

Acceptance of method/result documentation/communication!

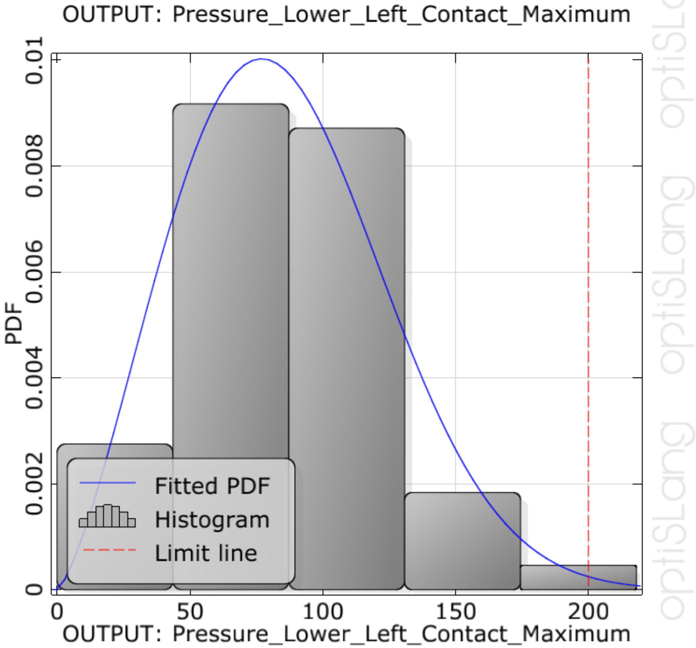
Latin Hypercube Sampling

- Values for input parameters are sampled randomly
- User specified distribution function used for sampling
- Sampling process does have a “memory” (avoids clustering)
- No. of simulations does not depend on the number of input parameters
- Requires approximately 10% of MCS samples
- Dynardo’s optimized LHS minimizes the input correlation errors



Statistic Measurements

- Evaluation of robustness with statistical measurements
  - **Variation** analysis (histogram, coefficient of variation, standard deviation, sigma level, distribution fit, probabilities)
  - **Correlation** analysis (linear, nonlinear, multi variant)
  - **Forecast quality of variation**: Coefficient of Prognosis (CoP)

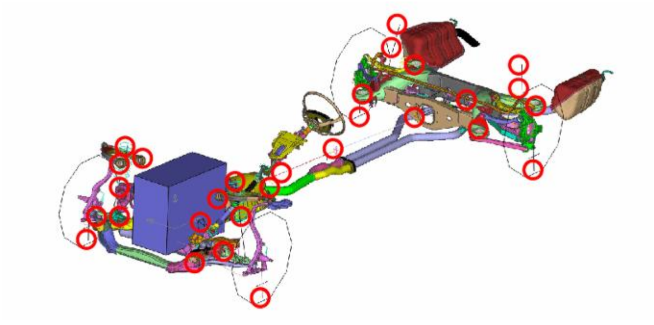


Statistic data			
Min:	0	Max:	218
Mean:	85.84	Sigma:	38.42
CV:	0.4476		
Skewness:	0.7196	Kurtosis:	4.684
Fitted PDF: Extreme Typ III (Max) Weibull			
Mean:	85.84	Sigma:	38.42
Lower cut:	0		
Limit x = 200			
P_rel:	0.98	1 - P_rel:	0.02
P_fit:	0.996332	1 - P_fit:	0.00366786
Sigma-Level:	2.97151		

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

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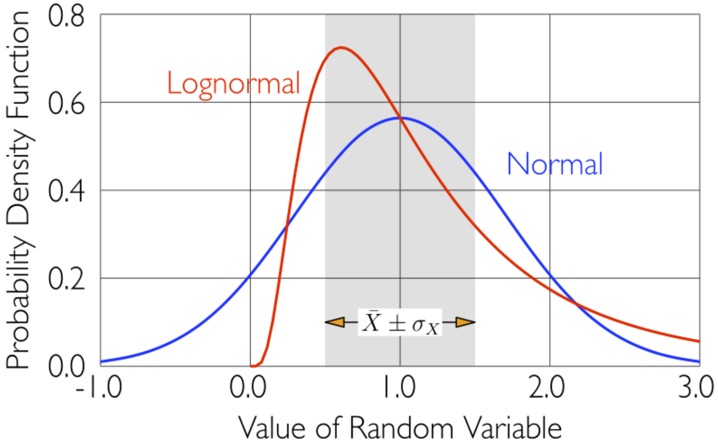
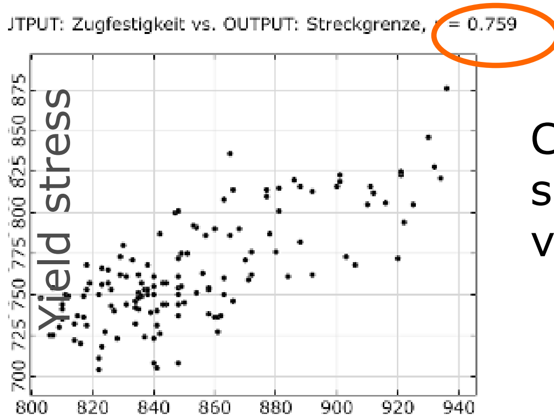
Definition of Uncertainties

Distribution functions define variable scatter



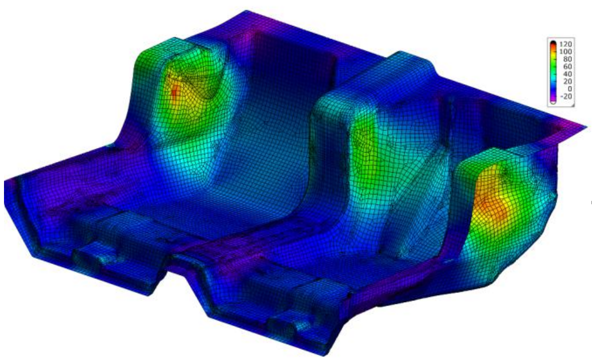
Correlation is an important characteristic of stochastic variables.



Yield stress

Tensile strength

Correlation of single uncertain values

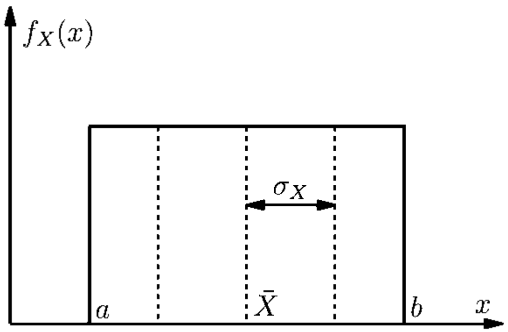


Spatially correlated field values

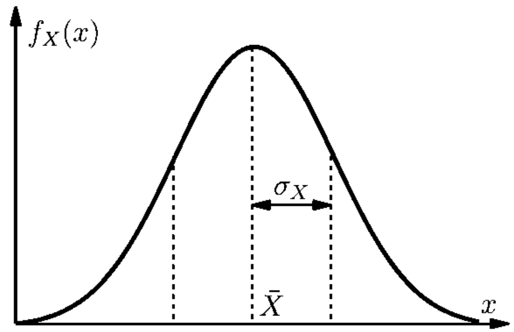
Translate know how about uncertainties into proper scatter definition

Distribution types

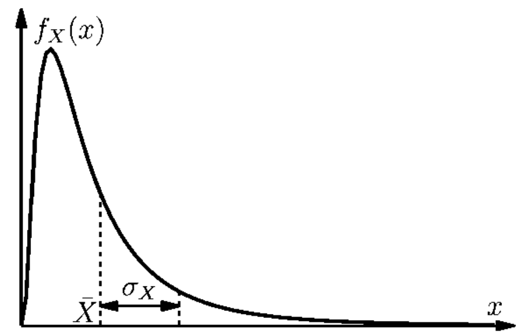
Uniform



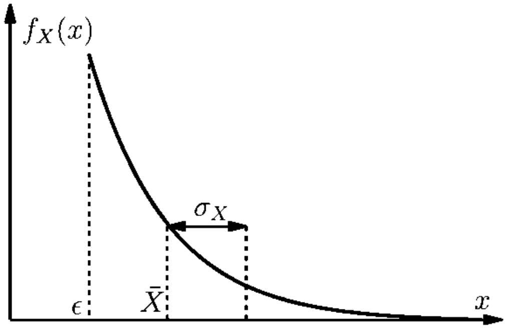
Normal



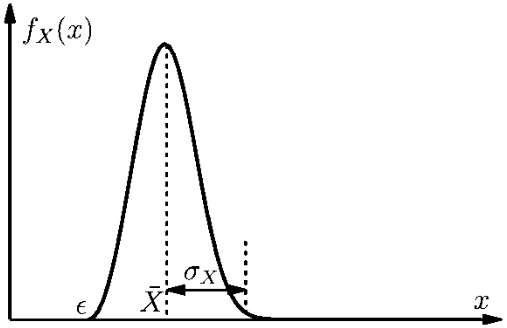
Log-normal



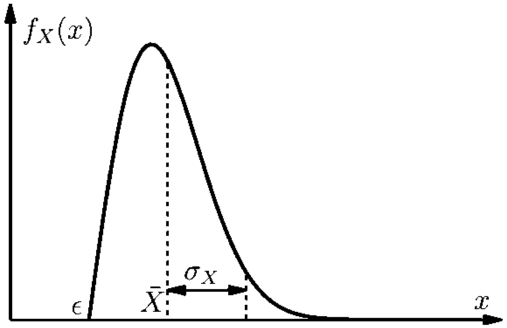
Exponential



Weibull

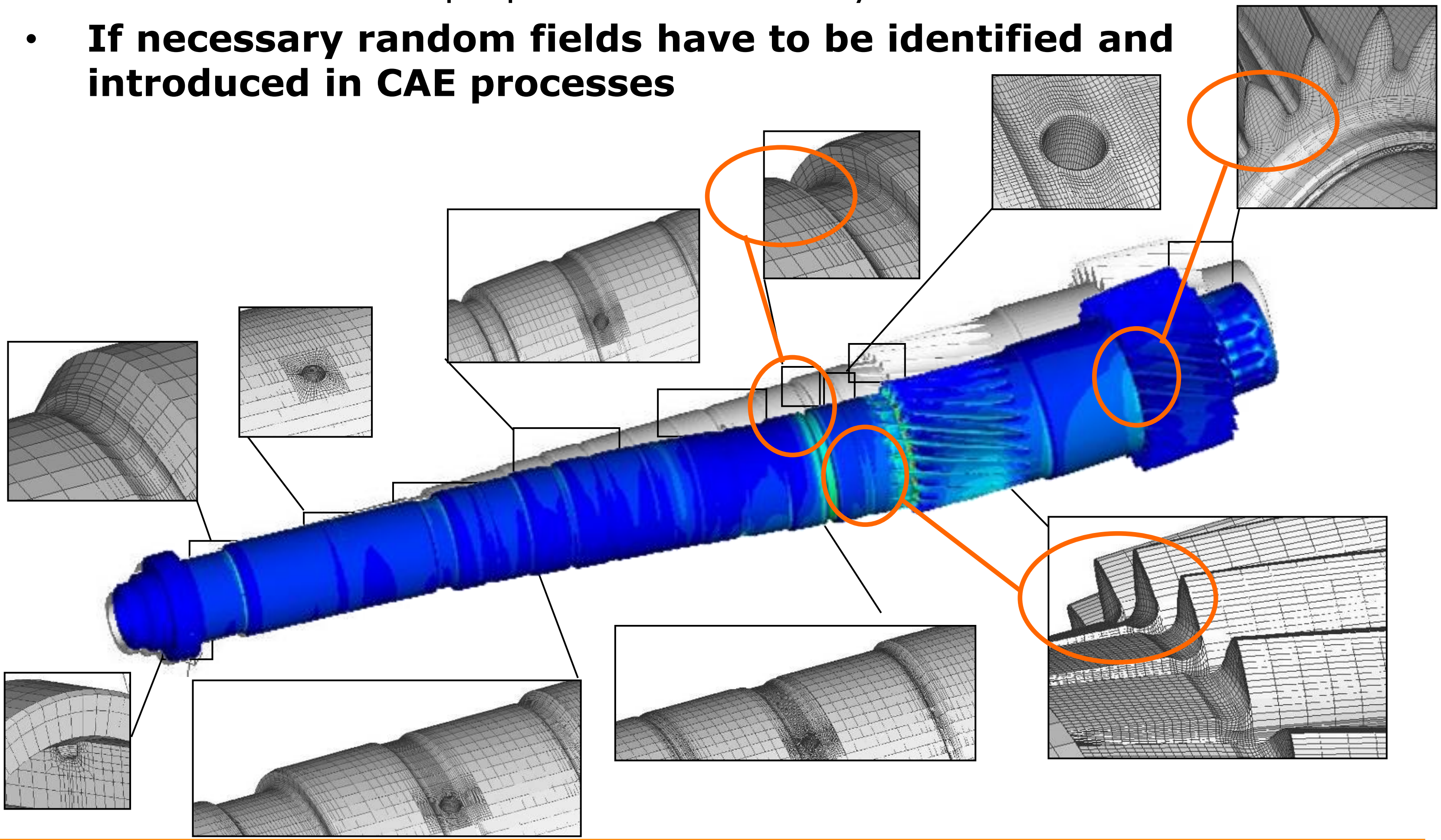


Rayleigh



Spatially correlated random variables

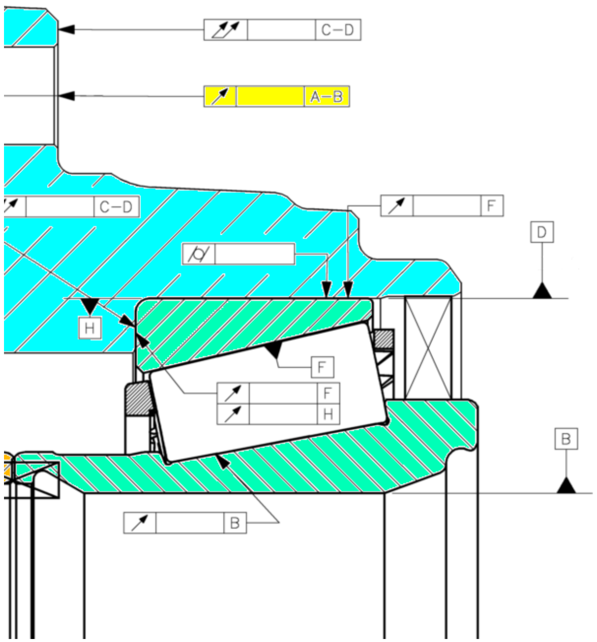
- For some robustness tasks, detailed consideration of spatial correlated random properties is necessary
- **If necessary random fields have to be identified and introduced in CAE processes**



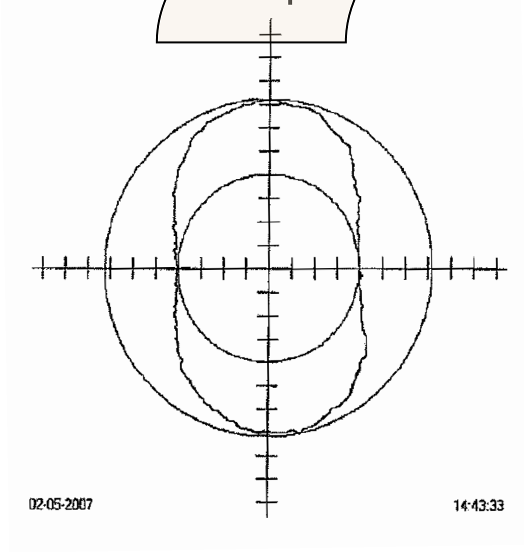
by courtesy of ZF

Design spatial correlation with "single" scatter shapes

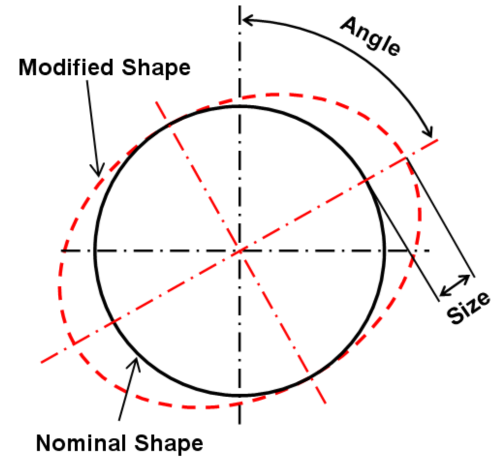
- Use of CAD-parameter or mesh morphing functions to design "single" scatter shapes



Measured imperfection



modelled imperfection



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]

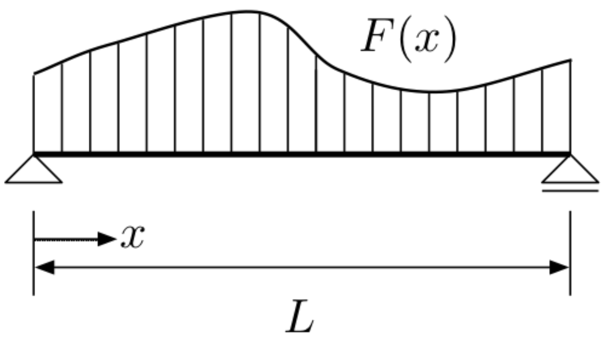
Random Field Parametric

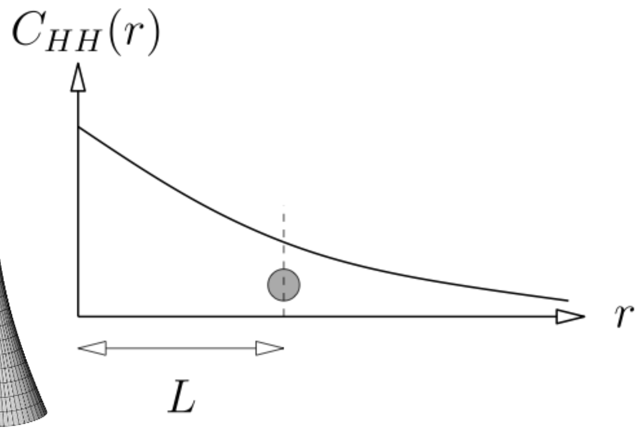
- spatially correlated random variables can be defined using random field theory.

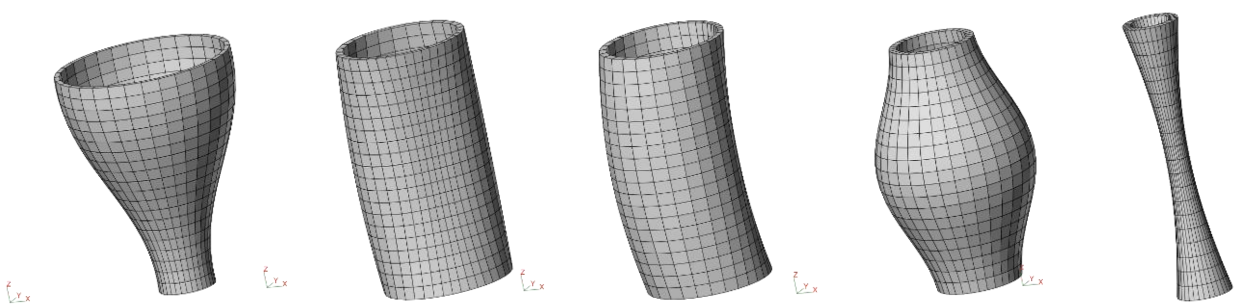
The correlation function represents the measure of "waviness" of random fields.

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

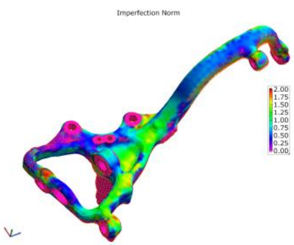
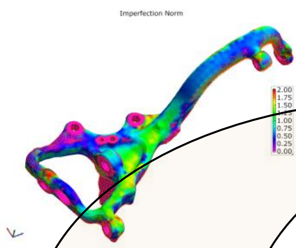
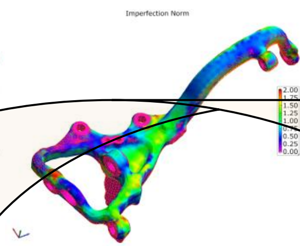
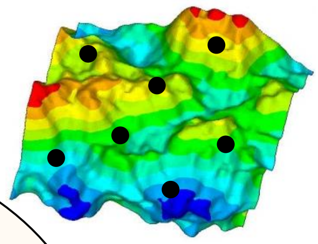
Usually, there exist **multiple scatter shapes** representing different scatter sources.





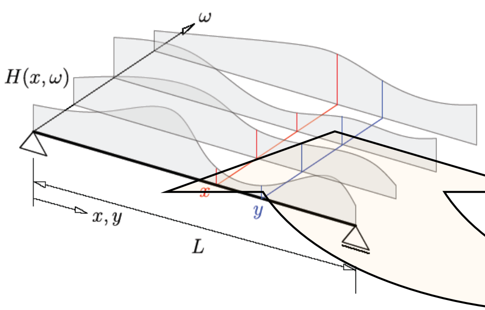


Identify Scatter Shapes from single Measurements

3. Trimming of FE volume mesh to generated samples

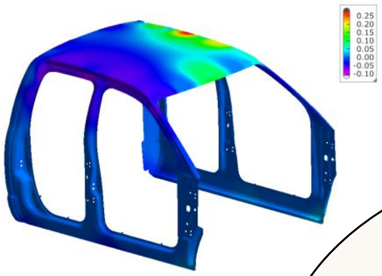
4. Run Robustness evaluation of brake noise to check sensitivity of geometric scatter



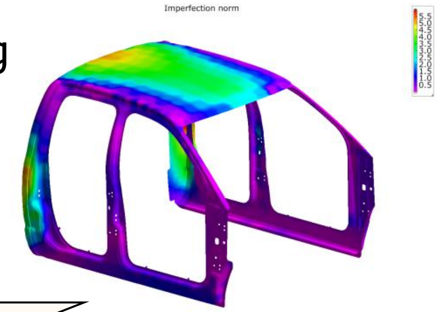
2. Estimation of scatter shapes and their amplitudes and simulating of imperfect designs

1. Use **limited number** of measurements for estimation of scatter shapes

Identify Scatter Shapes from Measurements

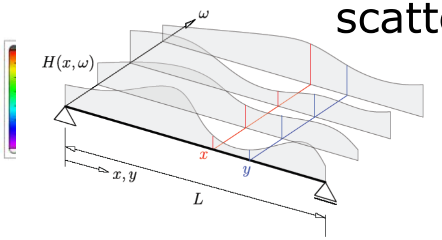


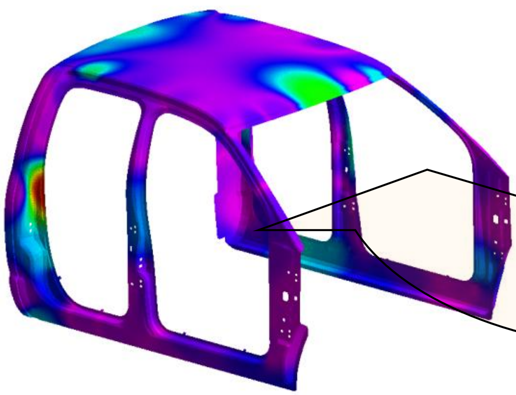
4. Generate imperfect geometries using Random Field parametric

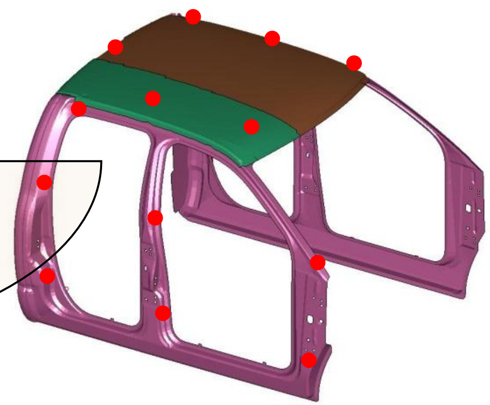


3. Identification of most important scatter fields for measured quantity (geometry)

5. Run Robustness Evaluation to check sensitivity of body in white geometry scatter to roll over load case





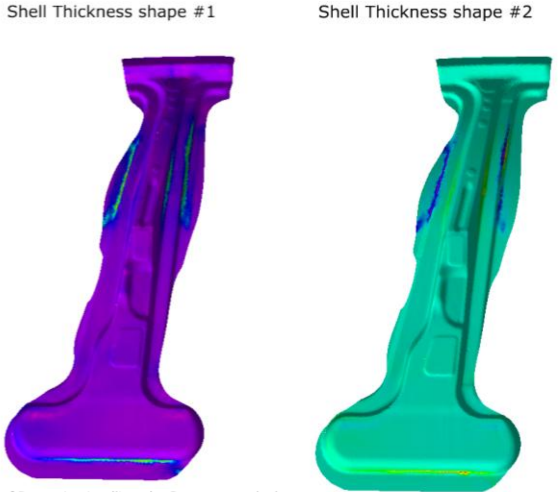


2. Trimming of initial FE-mesh regarding measurement or realization

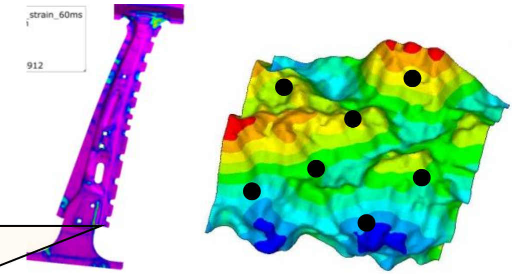
1. **Use a suitable set (100) of Measurements** from Manufacturing

Identify Scatter Shapes from Process Simulation

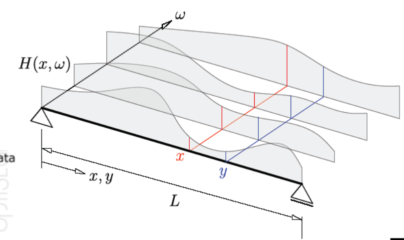
3. Generation of n-imperfect formed parts using Random Field parametric

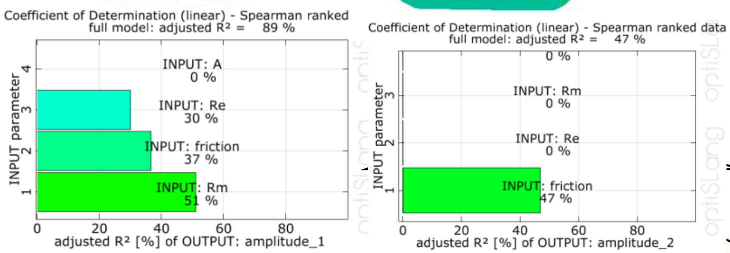


4. Mapping to crash mesh

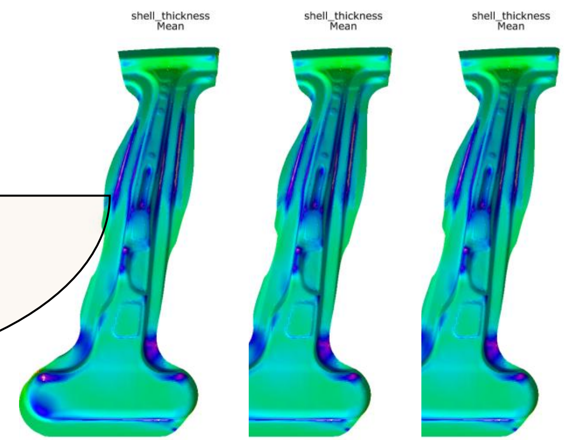


5. Run Robustness Evaluation of crash load case including scatter from forming process





2. Identification of most important scatter fields for scattering forming result values (thickness, hardening)



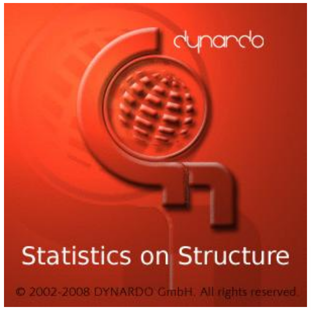
1. **Use a suitable number (100) Robustness evaluation** of the forming process

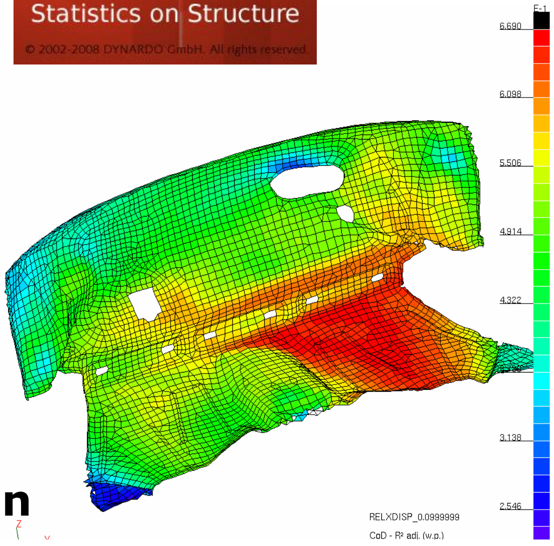
Dynardo's SoS – Statistic on Structure

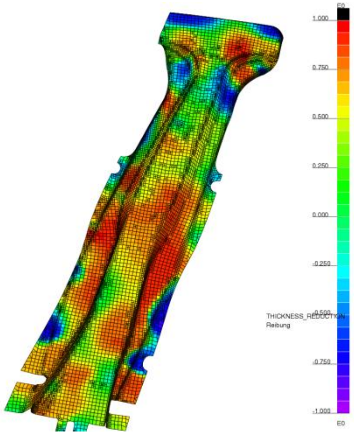
The post processor for Statistics on finite element Structures

- Statistic Measurements
  - Single Designs
  - Differences between Designs
  - Variation interval
  - Minimum/Maximum
  - Mean Value
  - Standard deviation
  - Coefficient of variation
  - Quantile (3 σ)
- Correlation & CoD
  - Linear correlation & CoD
  - At nodal/element level
- Process quality criteria Cp, Cpk process indices

- **Random field generation**
  - **Scatter shape identification and visualisation**





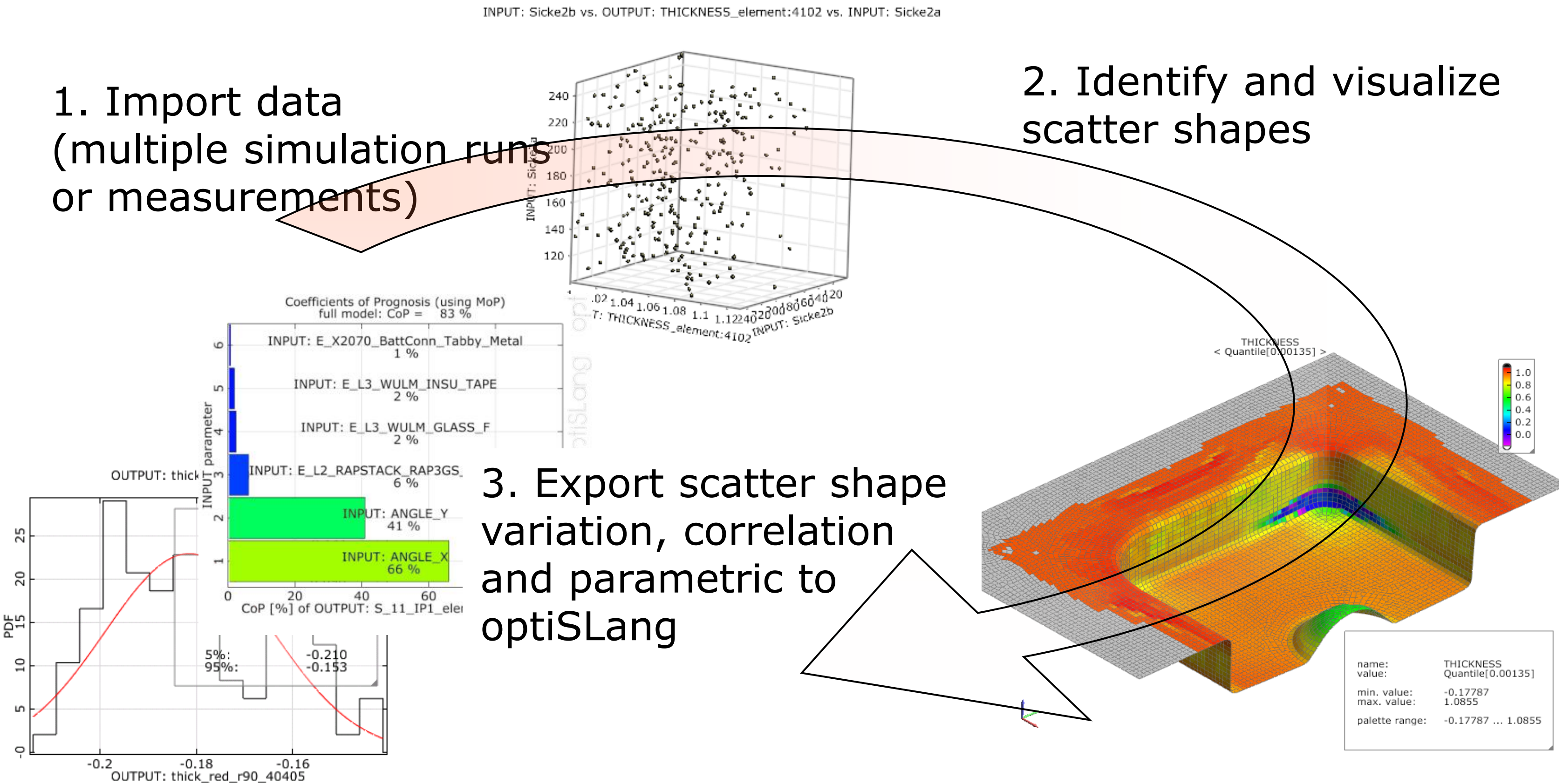


Using SOS to identify scatter shapes

1. Import data (multiple simulation runs or measurements)

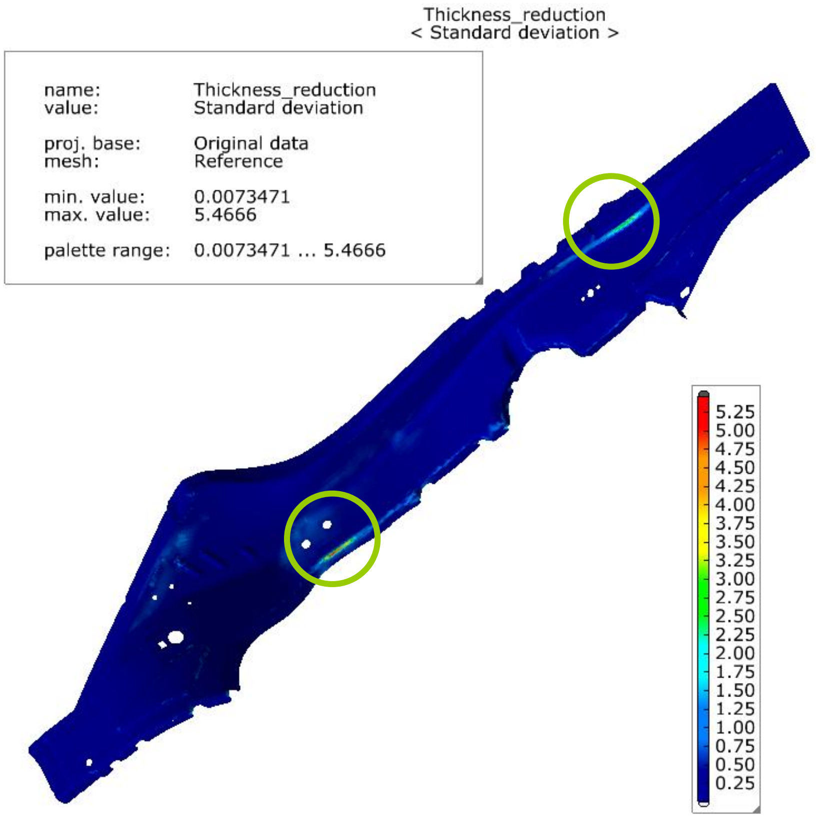
2. Identify and visualize scatter shapes

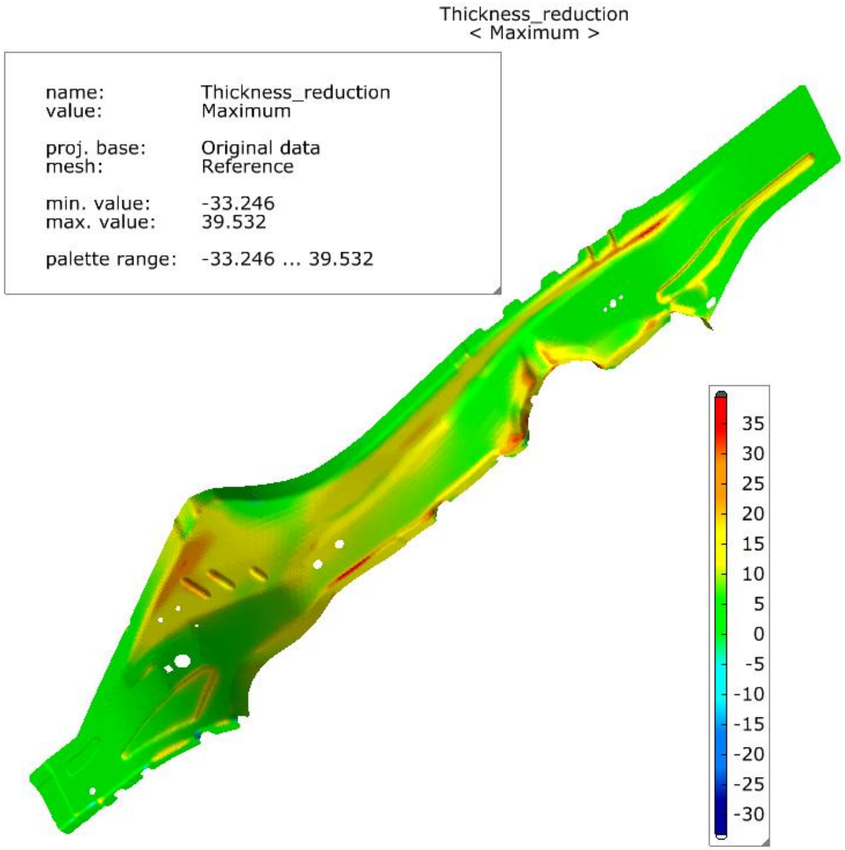
3. Export scatter shape variation, correlation and parametric to optiSLang



Example SOS post processing for forming simulation

First step investigate variation: two hot spots of variation can be identified



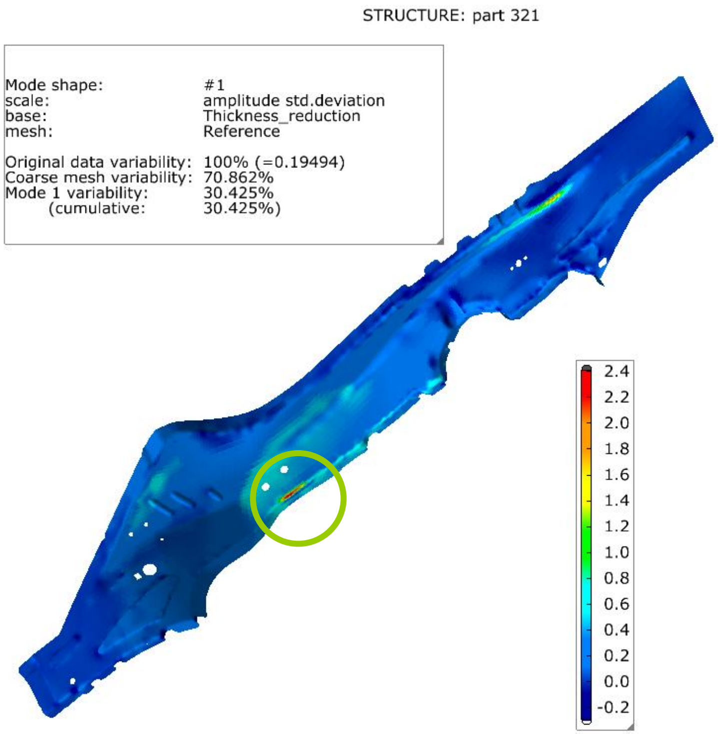


standard deviation thinning

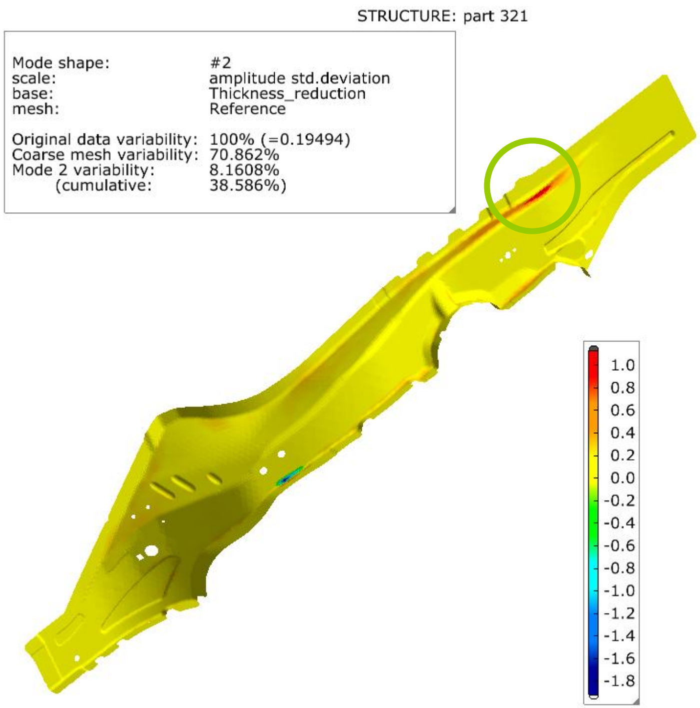
Maximum thinning

Example SOS post processing for forming simulation

Second step decompose variation: decompose total variation into scatter shapes, first scatter shape dominate first hot spot, second scatter shape dominates second hot spot.



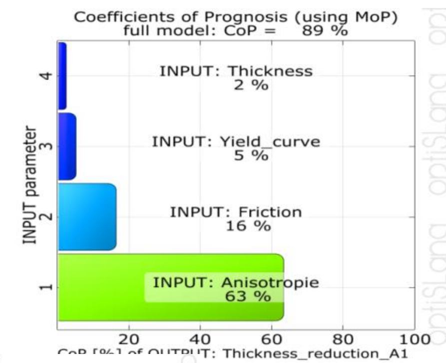
First scatter shape

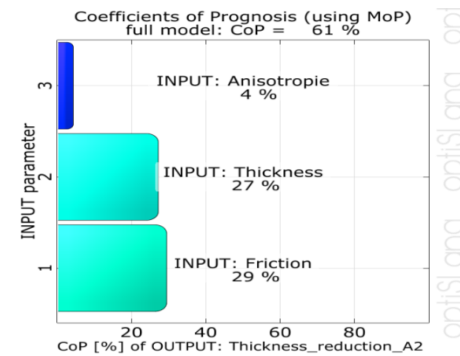


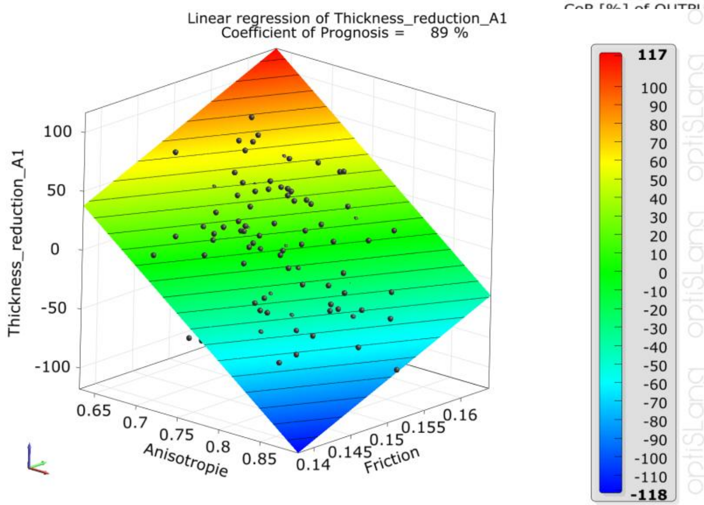
Second scatter shape

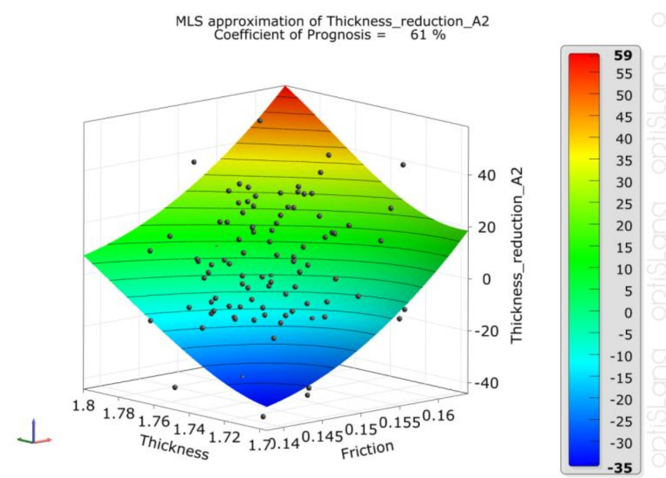
Example SOS post processing for forming simulation

Third step investigate correlations: Scatter of anisotropy dominates scatter of first scatter shape, scatter of friction and thickness dominate scatter of second scatter shape





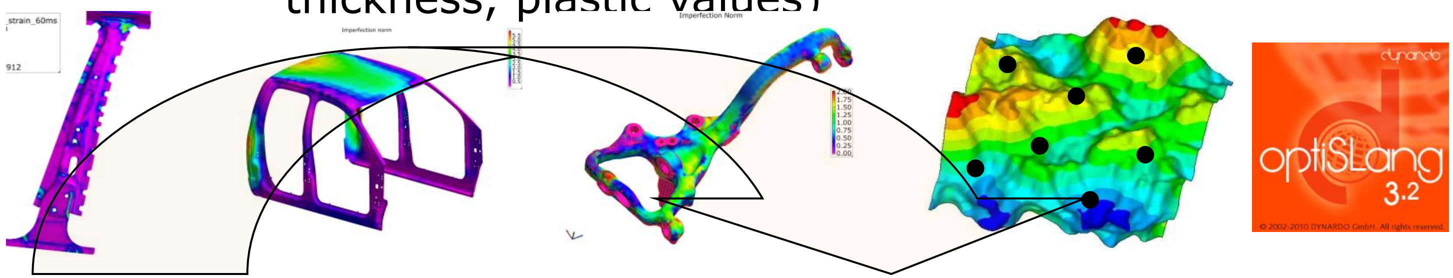




Variation-standard deviation

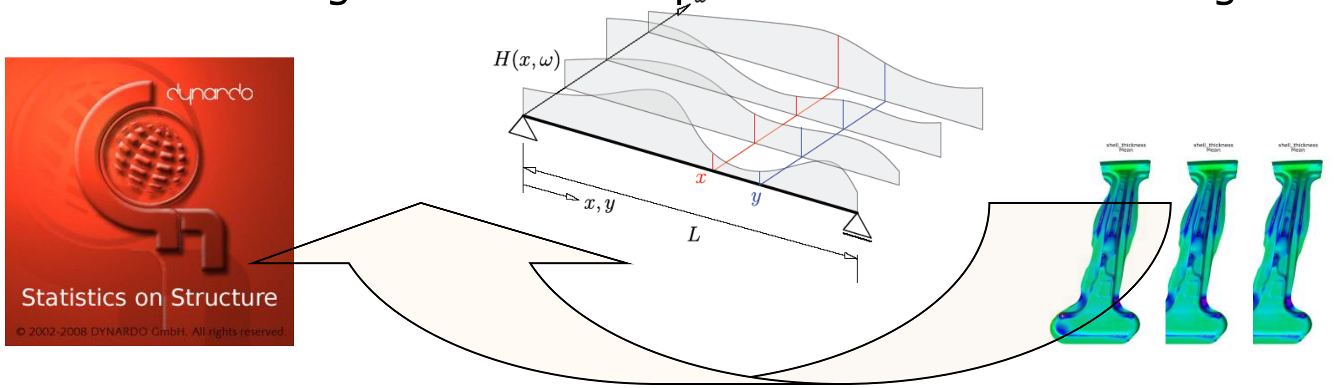
Implementation of Random Field Parametric

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

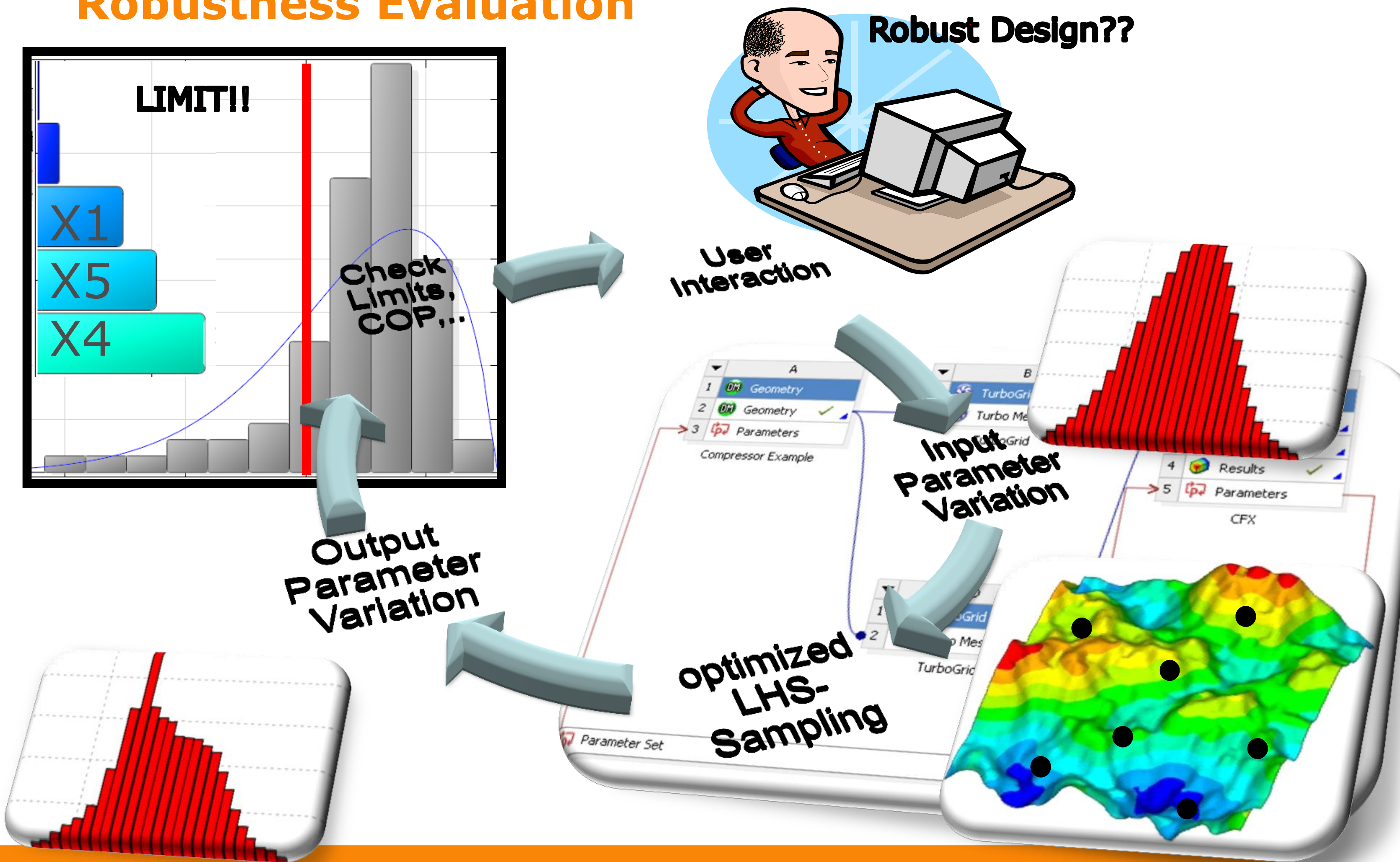


2. Generation of scatter shapes using Random Field parametric, quantify scatter shape importance

1. Input: process simulation or measurements

Variance-based Robustness Analysis

Robustness Evaluation



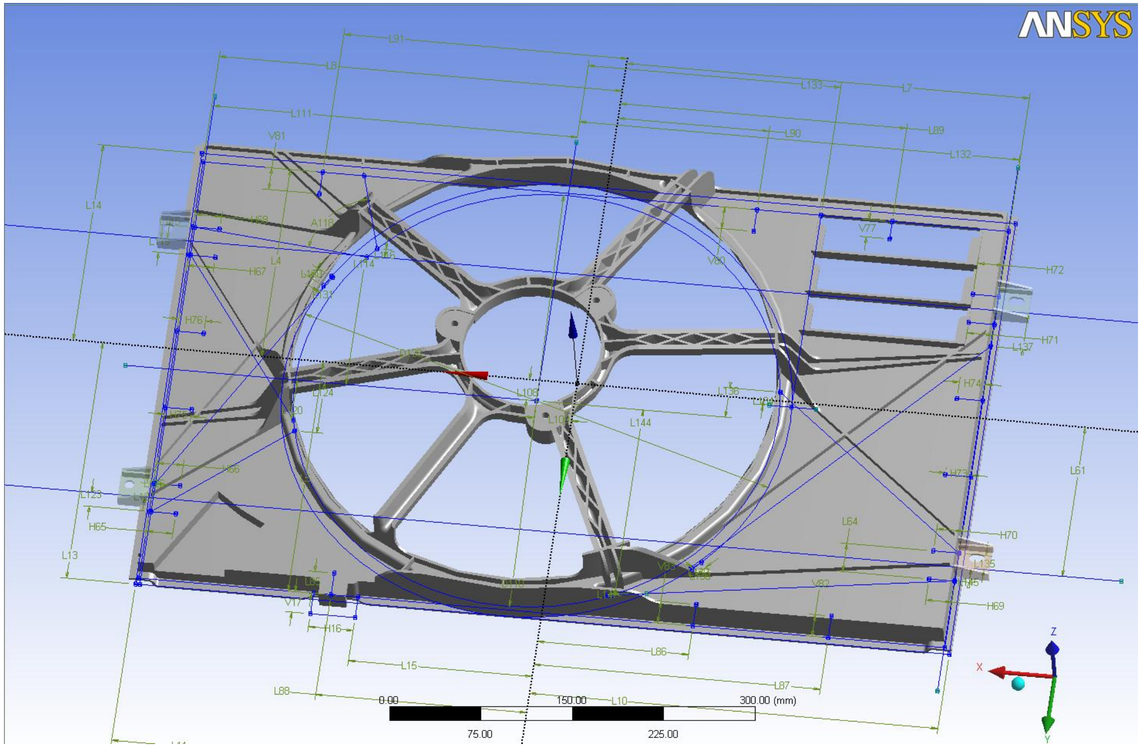
Robustness Check after Optimization

Weight optimization of a cooling system component using 94 CAD-Parameter. With the help of sensitivity study, pre-optimization (ARSM) followed by design improvement (EA) 15% weight reduction was achieved.

Applying variance based Robustness evaluation at the final optimized design using 61 CAD-tolerances and material data scatter the robustness was proven.

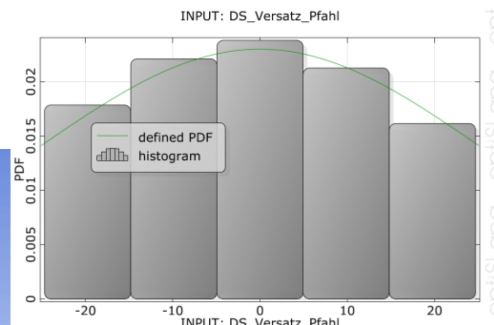
Distance to failure was sufficient large.

Design Evaluations: 320
CAE: ANSYS WB
CAD: ANSYS DM

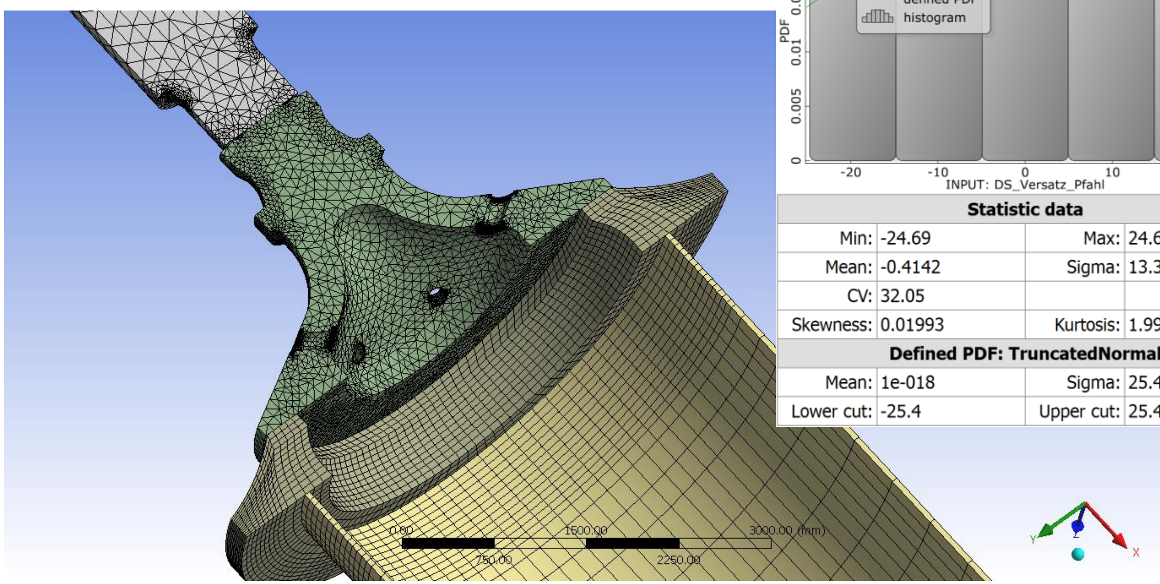


Robustness Check after Optimization

- **With the availability of suitable parametric a robustness check of tolerances and material scatter 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 to safe Money

by courtesy of TIMKEN Where You Turn

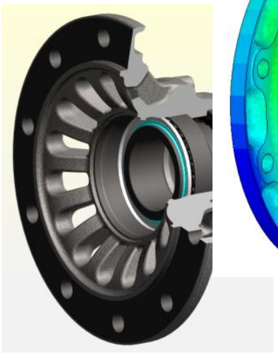
Goal: Tolerance check before any hardware exist!

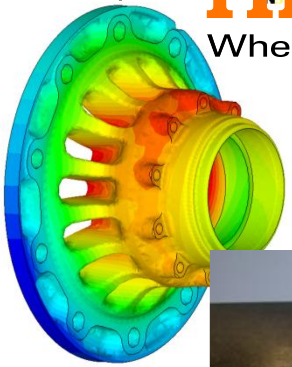
Classical tolerance analysis tend to be very conservative

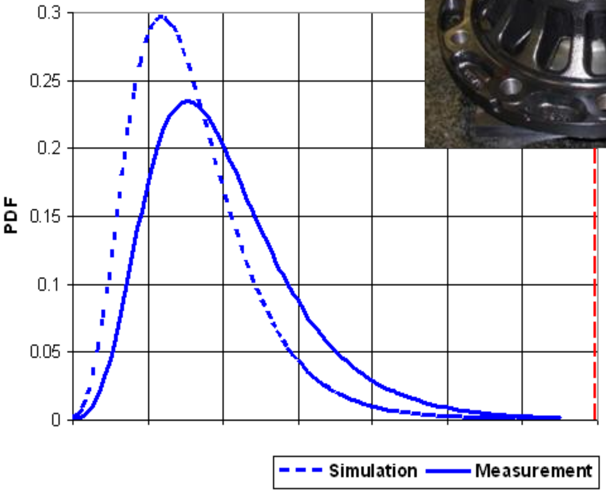
Robustness evaluation against production tolerances and material scatter (43 scattering parameter) shows:

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

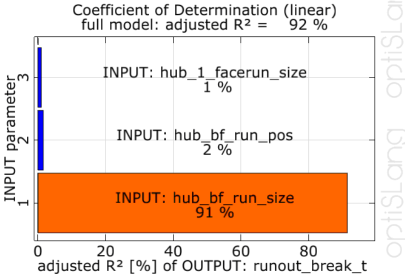
Production shows good agreement!







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

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

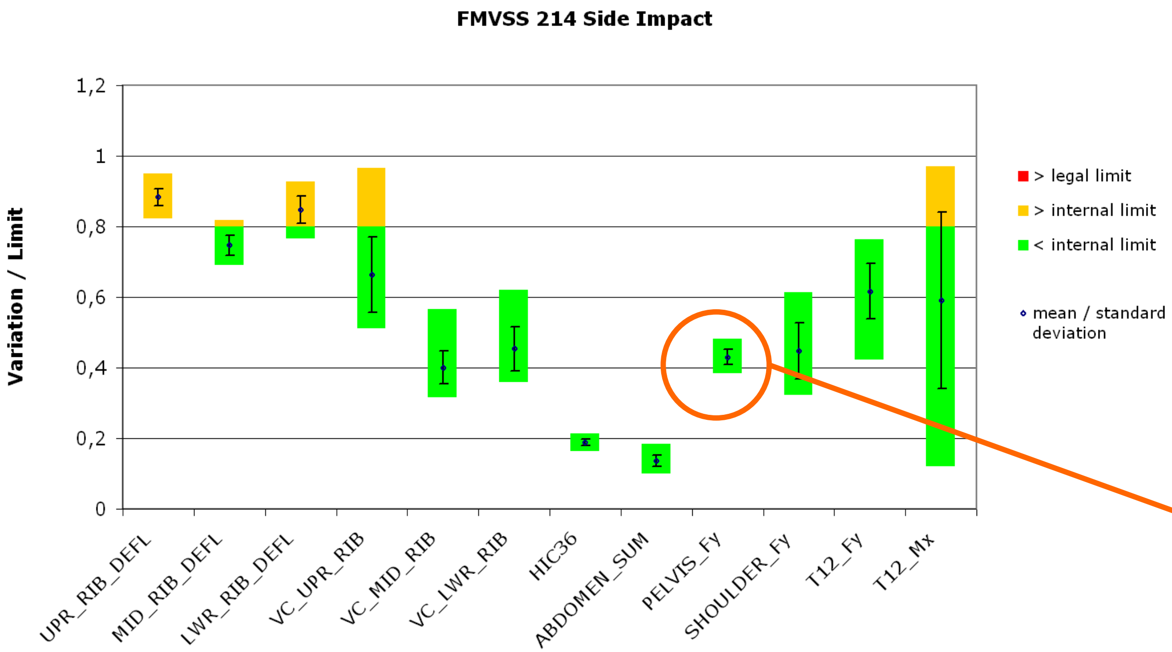
Goal: Ensuring Consumer Ratings and Regulations & Improving the Robustness of a System

by courtesy of

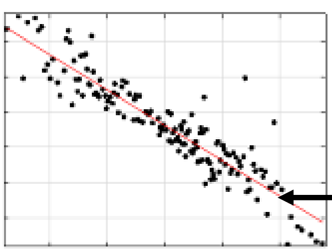
Will, J.; Baldauf, H.: Integration of Computational Robustness Evaluations in Virtual Dimensioning of Passive Passenger Safety at the BMW AG , VDI-Berichte Nr. 1976, 2006, Seite 851-873, www.dynardo.de

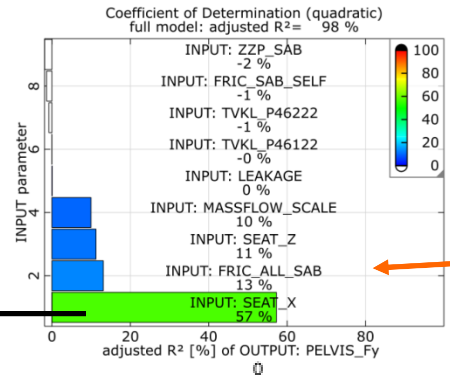
dynardo

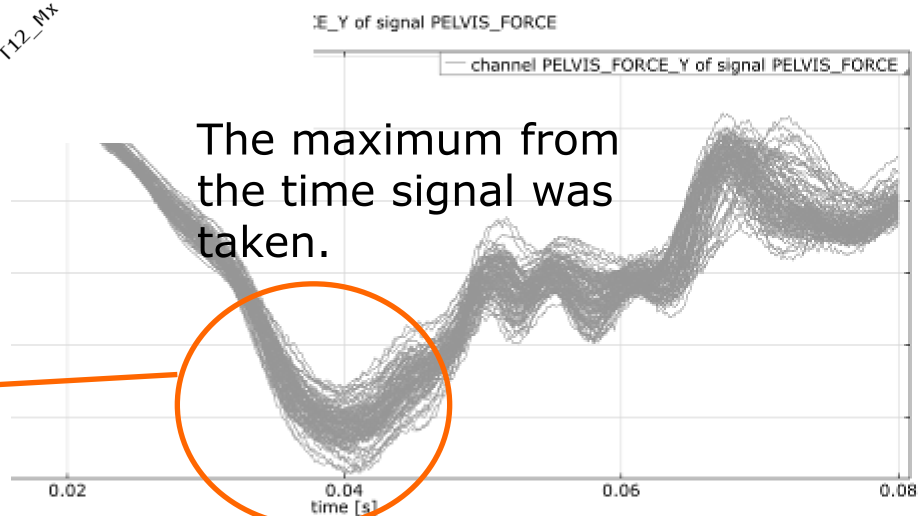
Standardized and Automated Post Processing



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







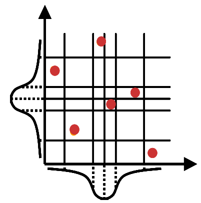
The maximum from the time signal was taken.

Robustness Evaluation of Forming Simulations

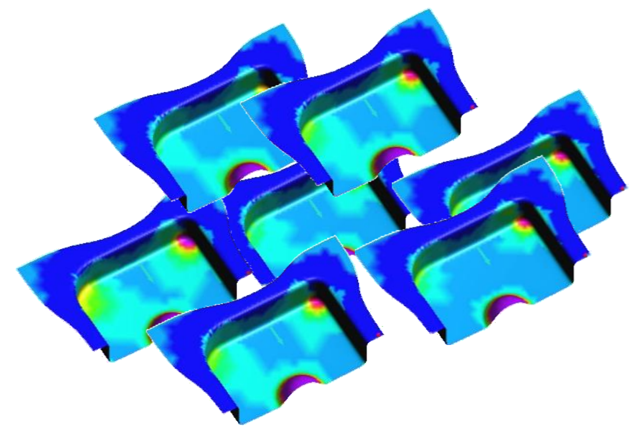
Start in 2004 - since 2006 used for production level

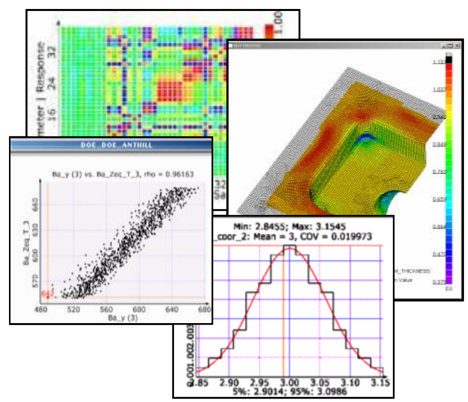
- Consideration of process and material scatter
- Determination of process robustness based on 3-Sigma-values of quality criteria
- **Projection and determination of statistical values on FE-structure necessary**

1. Variation der Eingangsstreuungen mittels geeigneter Samplingverfahren



2. Simulation inkl. Mapping auf einheitliches Netz





3. statistische Auswertung und Robustheitsbewertung

CAE-Solver: LS-DYNA, AUTOFORM and others

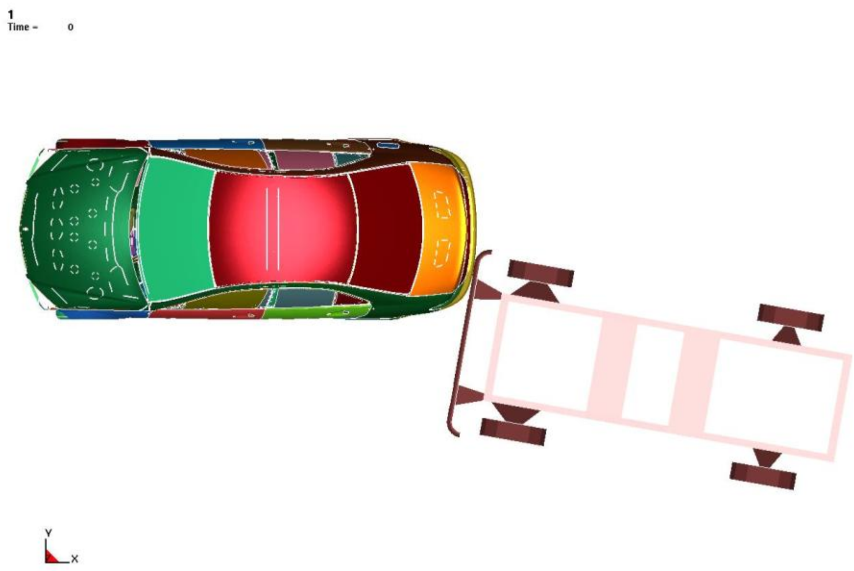
by courtesy of

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 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
- Visualization of hot spots with SoS
- Introduction of forming scatter via Random Fields



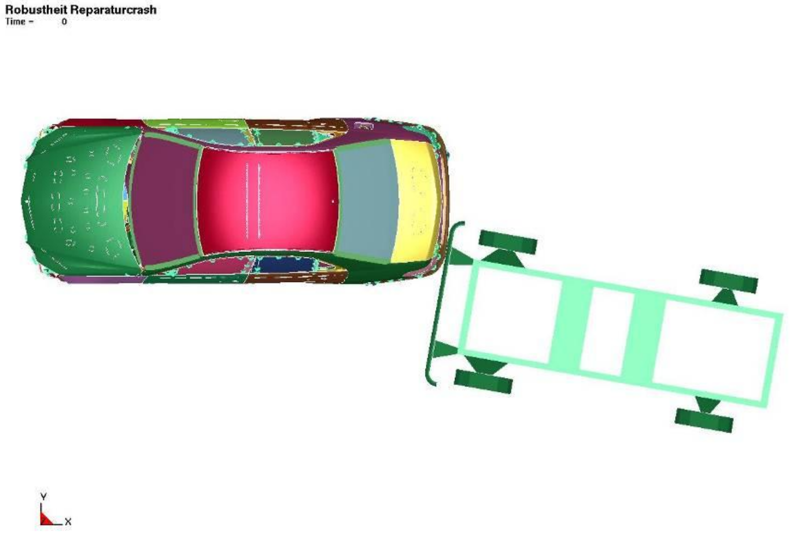
by courtesy of DAIMLER

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

Application Crashworthiness

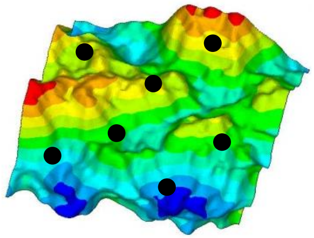
AZT Insurance Crash Load Case

- Scatter definition (40..60 scattering parameter)
  - Velocity, barrier angle and position
  - Friction (Road to Car, Car to Barrier)
  - Yield strength
  - Spatially correlated sheet metal thickness
- Main result: Prognosis of plastic behavior
- CAE-Solver: LS-DYNA

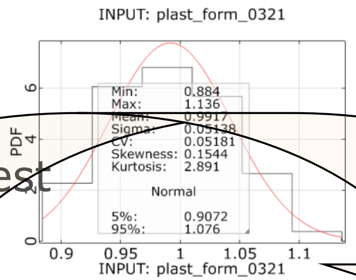


Deterministic analysis show no problems with an AZT load case. Tests frequently show plastic phenomena which Daimler would like to minimize. Motivation for the robustness evaluation was to find the test phenomena in the scatter bands of robustness evaluations, to understand the sources and to improve the robustness of the design.

Did You Include All Important Scatter?



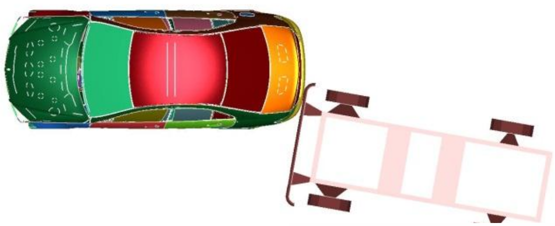
Scatter of uniform sheet thickness (cov=0.05), yield strength, friction, test conditions

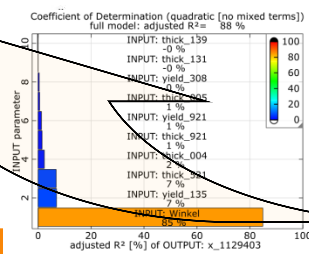


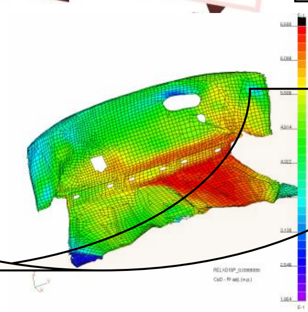
Introduction of sheet metal thickness scatter per part

- 100 LS-DYNA simulation
- Extraction via LS-PREPOST

optiSLang







SoS - post processing Statistics_on_Structure

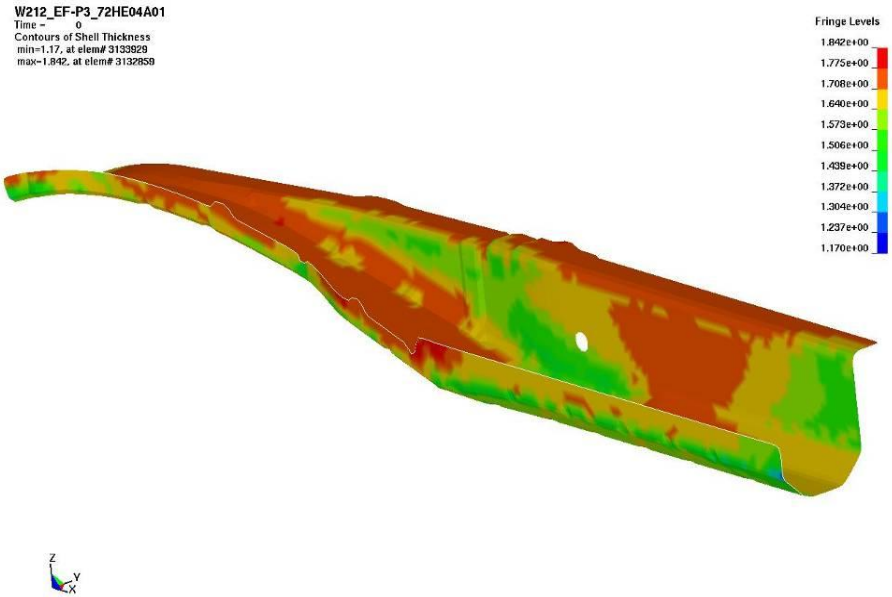
We could not find or explain the test results!

Definition of Scatter is the Essential Input!

Which degree of forming scatter discretization is becomes necessary?

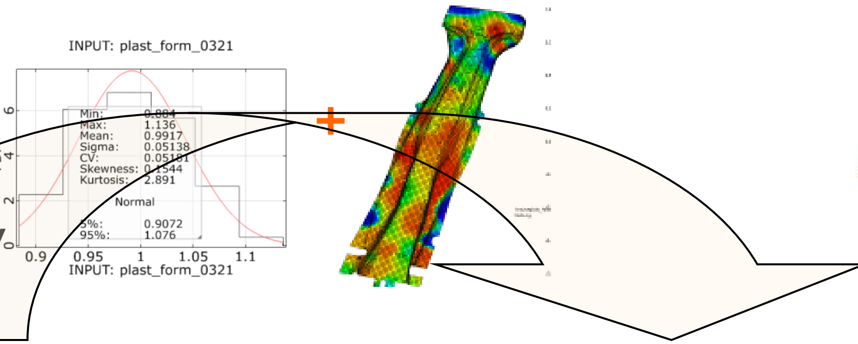
Level 1 - No distribution information: - increase uniform coil thickness scatter cov=0.02 to cov=0.03..0.05

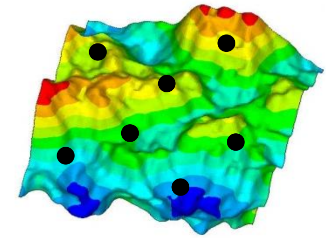
Level 2 - Use deterministic distribution information: - use thickness reduction shape from deterministic forming simulation and superpose coil (cov=0.02) and forming process scatter (cov=0.01..0.03)



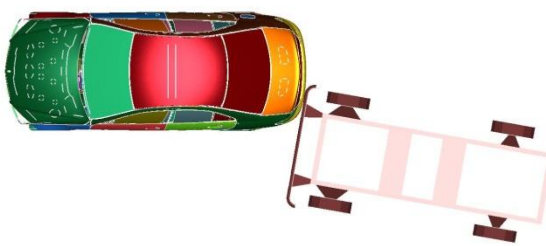
Did You Include All Important Scatter?

Scatter of sheet thickness, forming process scatter covmax=0.05 yield strength, friction, test conditions

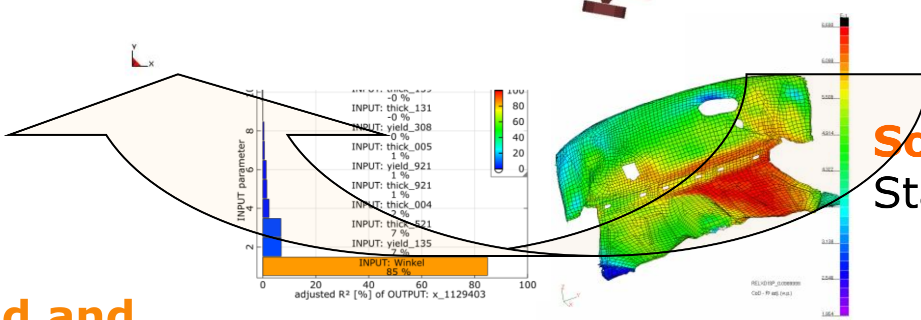




optiSLang



Introduction of spatial correlated forming process scatter
- 100 LS-DYNA simulation
- Extraction via LS-PREPOST



SoS - post prozessing Statistics_on_Structure

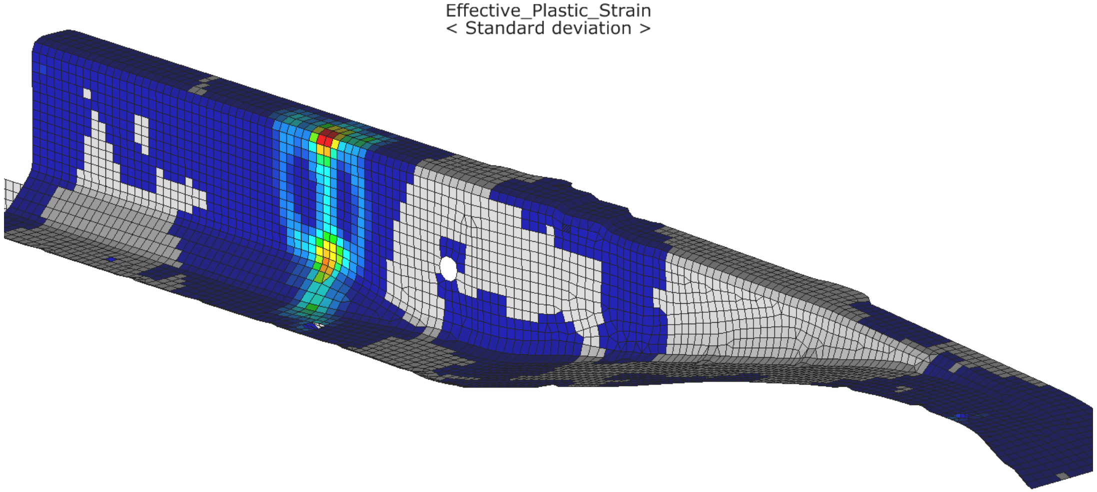
We could find and explain the test results!

SoS for Post Processing of Robustness Evaluations

SoS is the tool to answer the questions:

Where? Locate hot spots of highest variation and/or extreme values, which may cause lack of performance or quality.

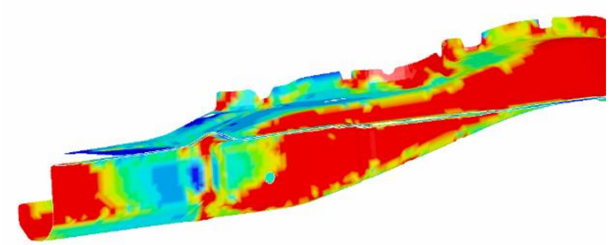
Why? Find the input parameters which cause scatter of the results, by analysing correlation between scattering inputs and scattering results with the help of optiSLang for MoP/CoP analysis.



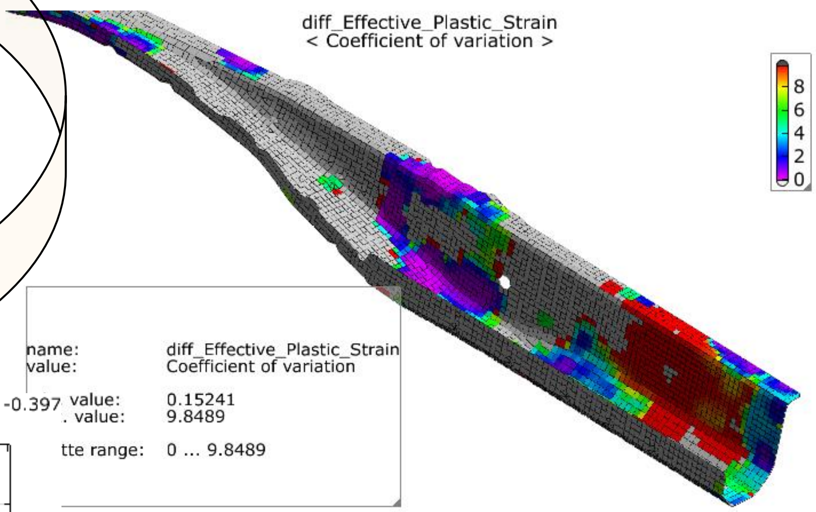
Standardized and Automated Post Processing

Productive Level needs standardized and automated post processing!

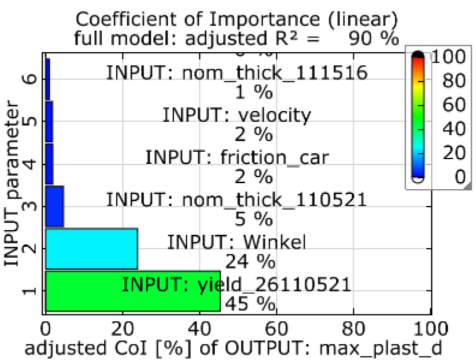
1. Check variation of plasticity, failure, intrusions.

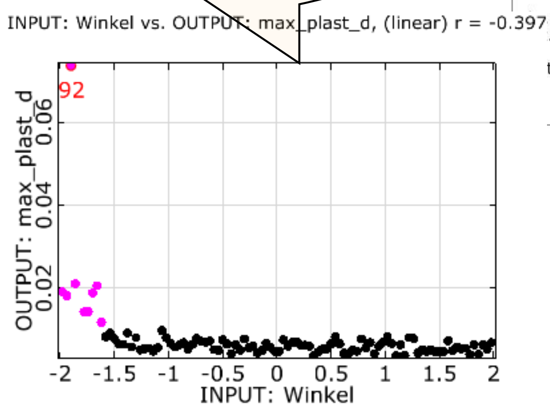


2. Identify the beginning of the phenomena in time and use SoS to identify the source of variation



3. Summarize variation and correlation





Robustness Evaluation for consumer goods

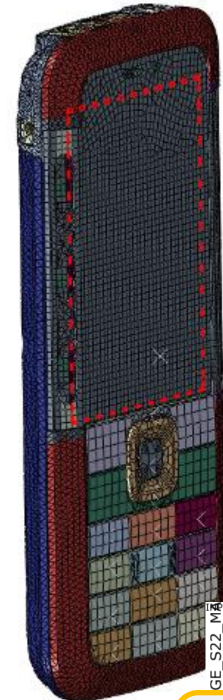
Goal: Check and improve Robustness of a mobile phone against drop test conditions!

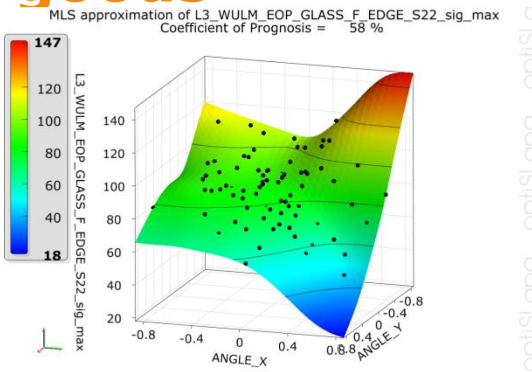
Using sensitivity analysis the worst case drop test position as well as optimization potential out of 51 design variables was identified

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

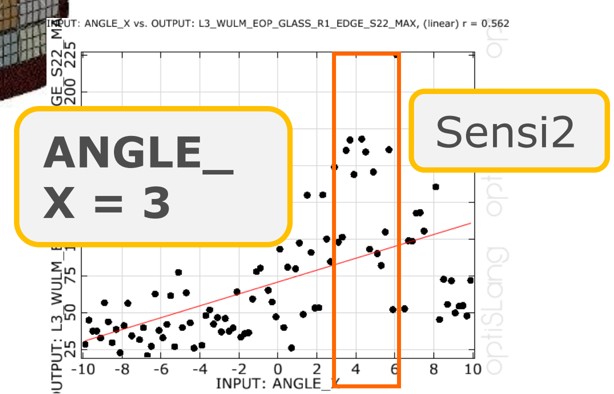
Safety margins are calculated with Robustness evaluation after design improvements

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





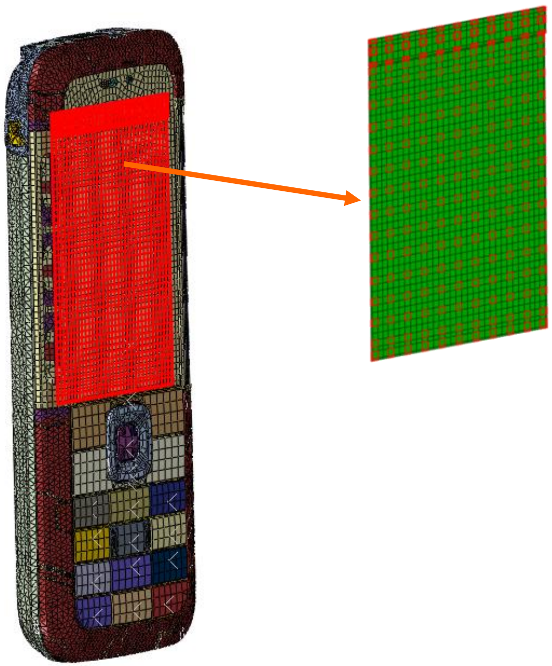
CoD lin adj	CoD quad adj	CoD lin adj Spearman	CoP
48	48	46	58

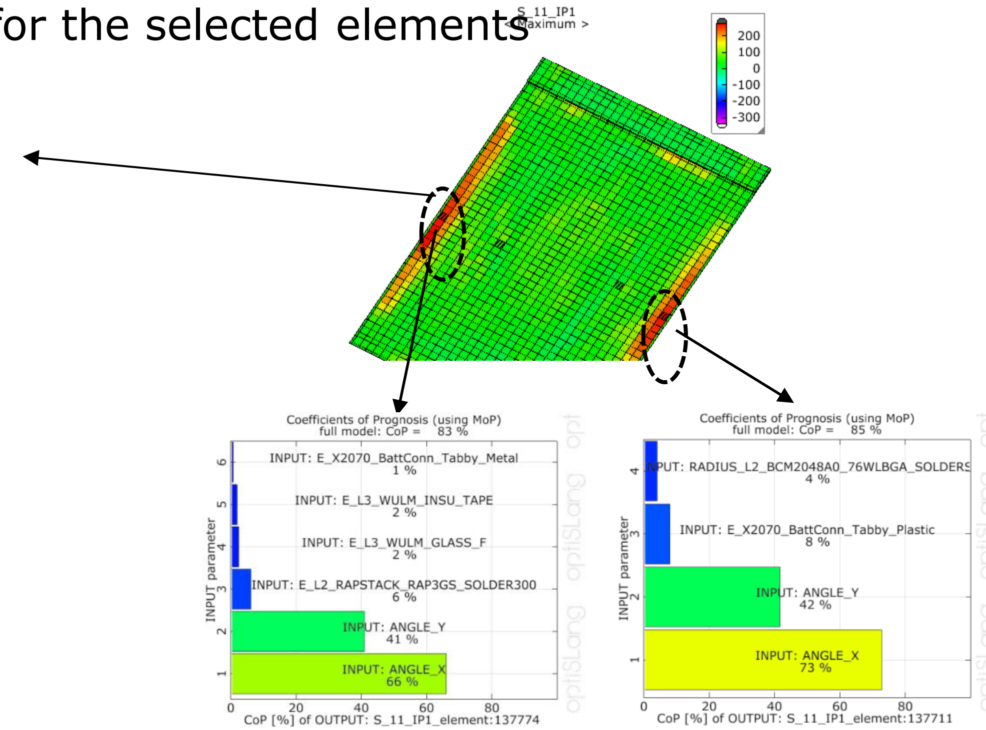


by courtesy of NOKIA

SoS for Post Processing of Robustness Evaluations

- The picture above shows the **maximum** of **S11** (positive - tension)
- In **SoS** it is possible to select elements at hot spots and export to optiSLang
- Use the **result_monotoring** in **optiSLang** to identify local hot spots of variation. The **CoP** plots below show that **ANGLE_X** and **ANGLE_Y** have strongest influence on **S11** for the selected elements





Element sets – all glass element sets

by courtesy of NOKIA

Summary Robustness Evaluation

- optiSLang + SoS have completed the necessary methodology to run CAE – based Robustness Evaluation for real world problems

Success Key:

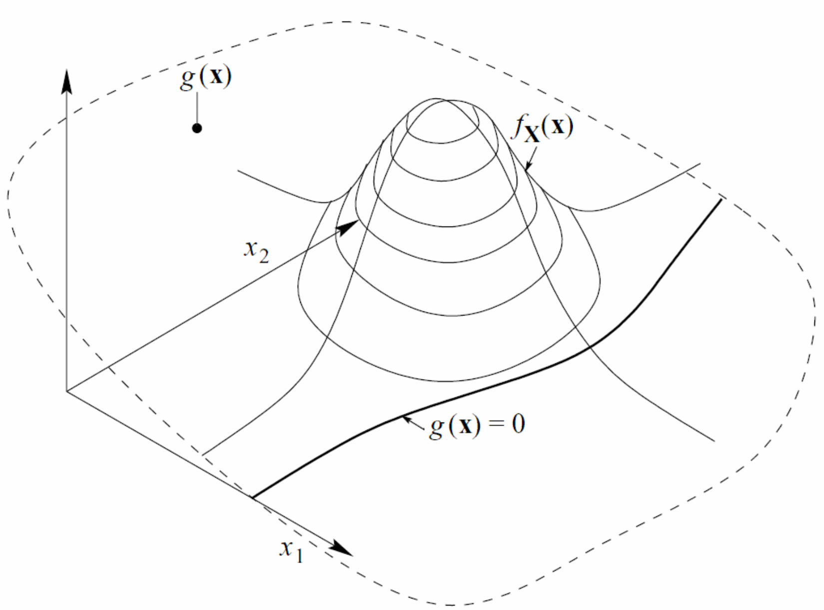
- Necessary distribution types and correlation definitions available
- Optimized LHS sampling
- Reliable measurements of response variation and forecast quality of response variation using optiSLang's COP
- Projection of statistic onto the FE-structure

Customer benefit:

- Identification of problems early in the virtual prototyping stage
- Measure, verify and finally significantly improve the modeling quality (reduce numerical scatter and modeling errors)

Reliability Analysis

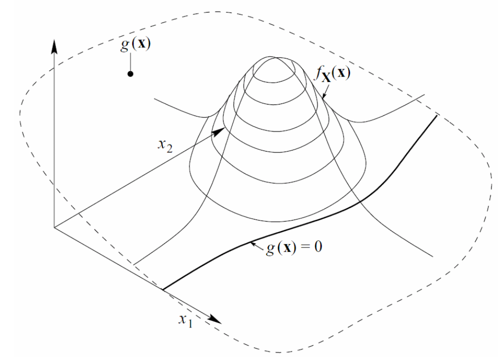
Reliability analysis



$$P_F = P\left[\mathbf{X} : g(\mathbf{X}) \leq 0\right]$$
$$= \int \cdots \int_{g(\mathbf{x}) \leq 0} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$
$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} I\left(g(\mathbf{x})\right) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$

- Limit state function *g(**x**)* divides random variable space **X** in safe domain *g(**x**)*>0 and failure domain *g(**x**)* ≤0
- Multiple failure criteria (limit state functions) are possible
- Failure probability is the probability that at least one failure criteria is violated (at least one limit state function is negative)
- Integration of joint probability density function over failure domain

Reliability Analysis



- Robustness verify relatively high probabilities

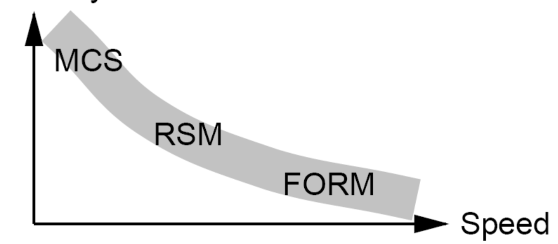
 (±2σ, *like 1% of failure*)

- Reliability analysis <u>verify </u>rare event probabilities

(≥3σ, *smaller then 1 out of 1000)*

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

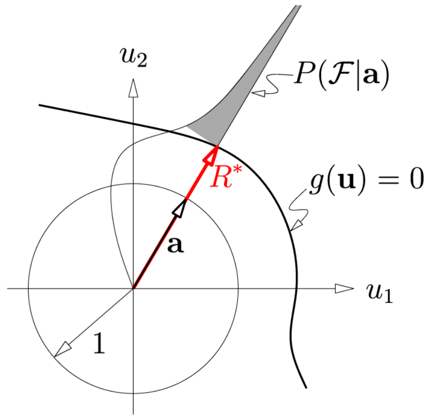
It is recommended to use two different algorithms to verify rare event probabilities



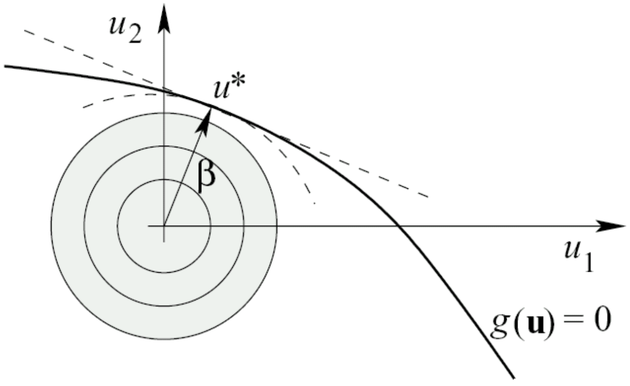
- First order reliability method (FORM), ≥2σ, gradient based
- Importance sampling using design point (ISPUD), ≥ 2σ, n ≤ 10
- Adaptive importance sampling, ≥2σ, n ≤ 10
- Directional sampling, ≥2σ, n ≤ 10
- Monte-Carlo-Simulation, independent of n, but very high effort for ≥2σ
- Latin Hypercube sampling,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

Advanced methods for reliability analysis

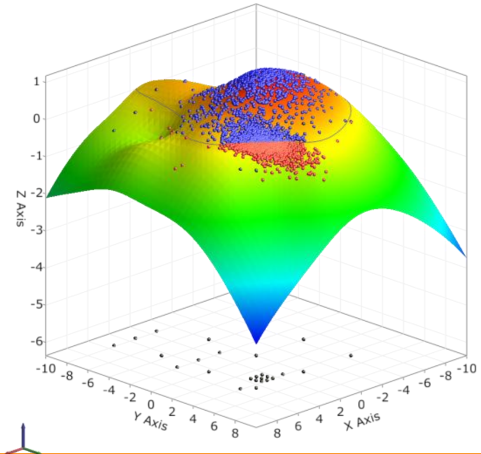
Directional Sampling



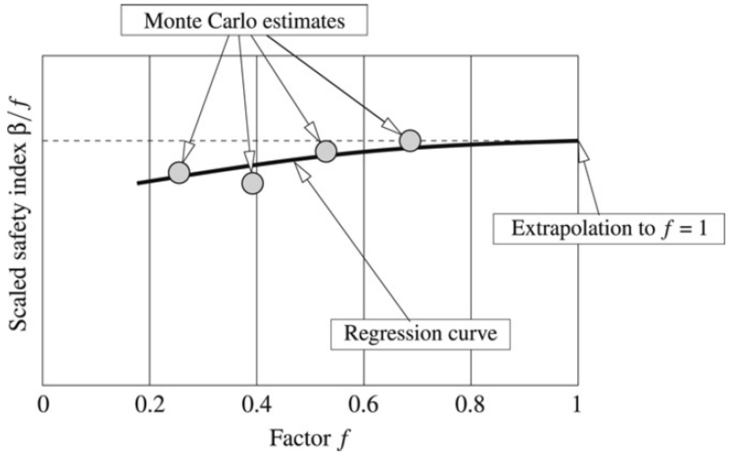
First Order Reliability Method



Adaptive Response Surface Method (Dynardo 2006)

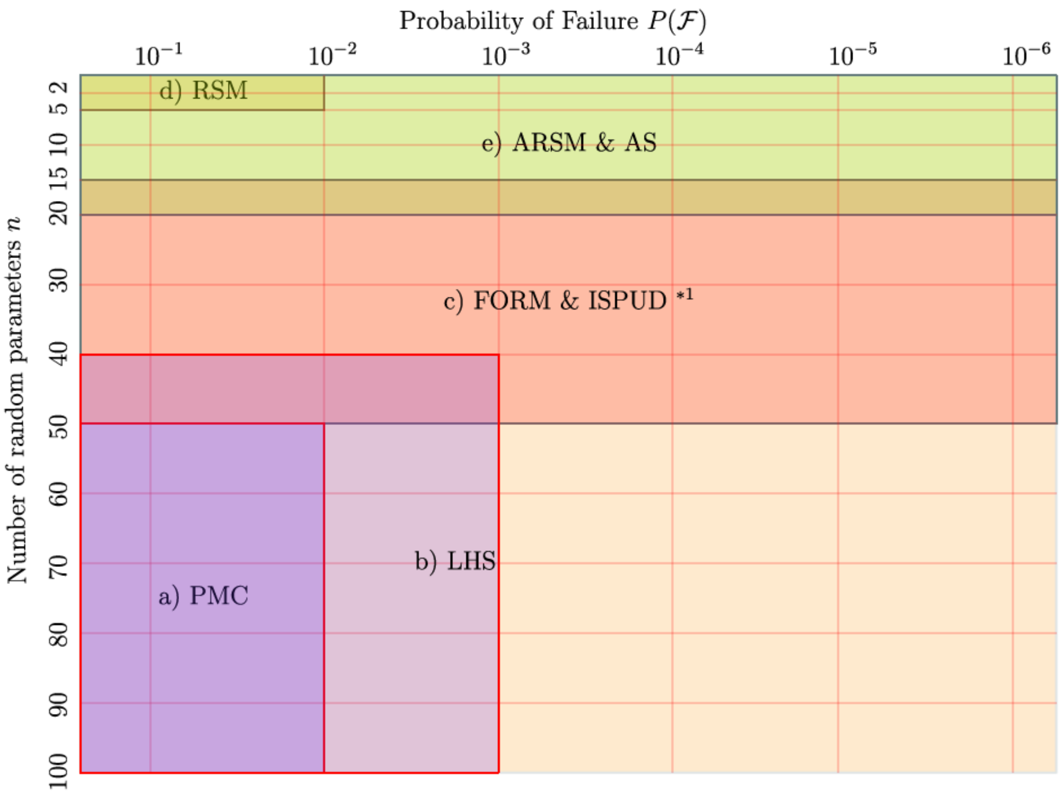


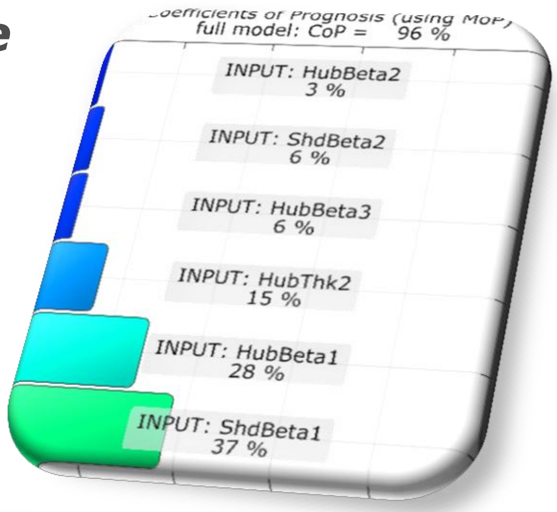
Asymptotic Sampling (Bucher 2009)

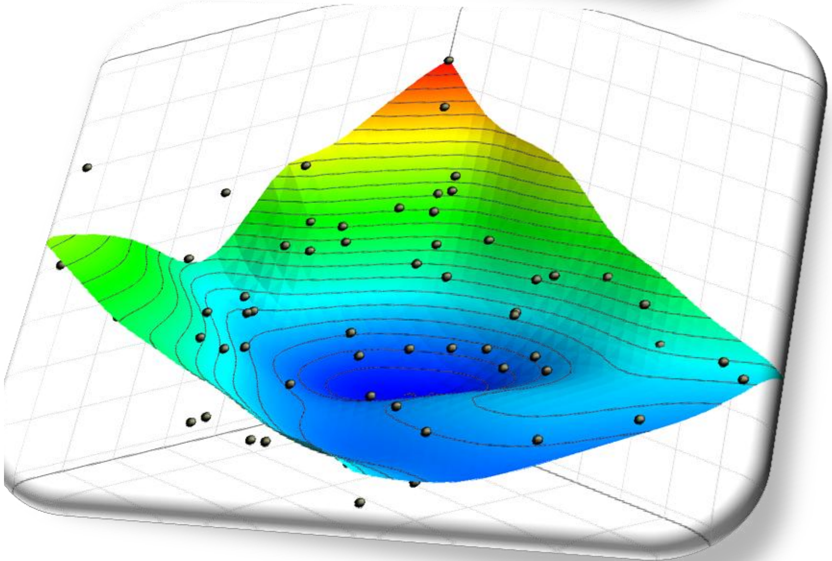


How choosing the right algorithm?

Robustness Analysis provide the knowledge to choose the appropriate algorithm



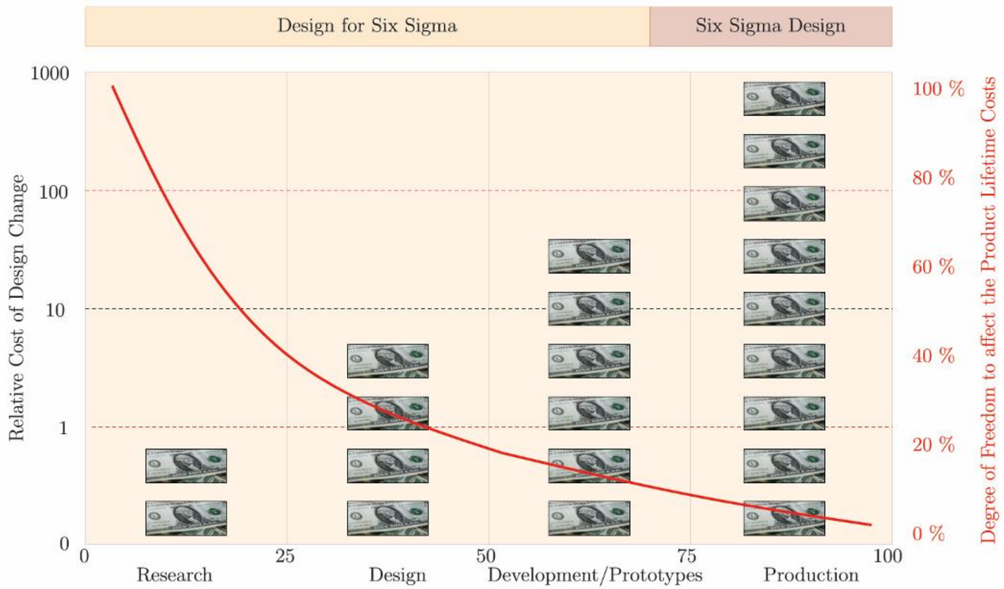




Robustness & Reliability Algorithms

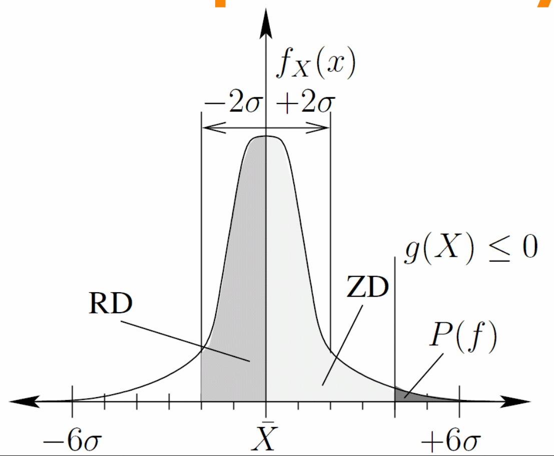
Robust Design Optimization

Design for Six Sigma and RDO



- 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 (RDO)

Failure probability for Six Sigma design



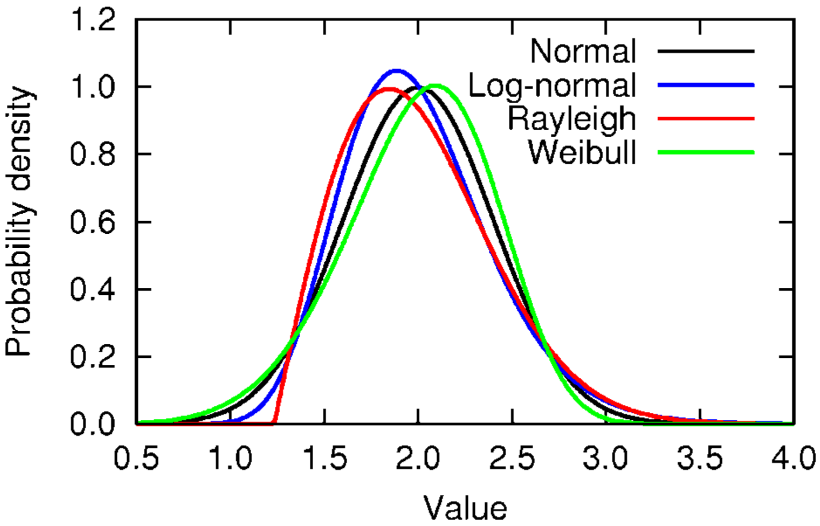
The statement six sigma results in 3.4 defects out of a million introduces a "safety distance" of 1.5 sigma shift for long term effects

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**

Sigma level vs. failure probability

- The sigma level can be used to estimate the probability of exceeding a certain response value
- Since the distribution type is often unknown, this estimate may be very inaccurate for small probabilities
- The sigma level deals with single limit values, whereas the failure probability quantifies the event, that any of several limits is exceeded

➢ Reliability analysis should be applied to proof the required safety level



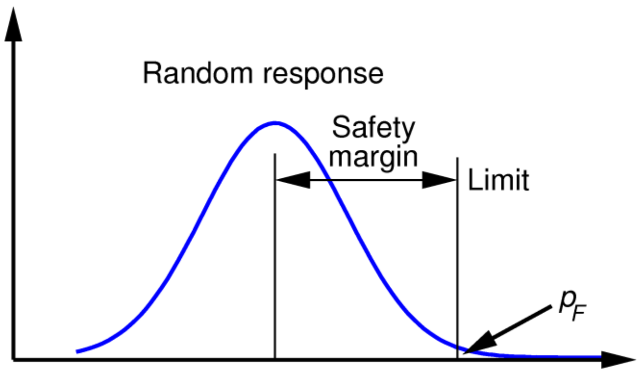
Distribution	Required sigma level (CV=20%)		
	$p_F = 10^{-2}$	$p_F = 10^{-3}$	$p_F = 10^{-6}$
Normal	2.32	3.09	4.75
Log-normal	2.77	4.04	7.57
Rayleigh	2.72	3.76	6.11
Weibull	2.03	2.54	3.49

Methods for Robust Design Optimization

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

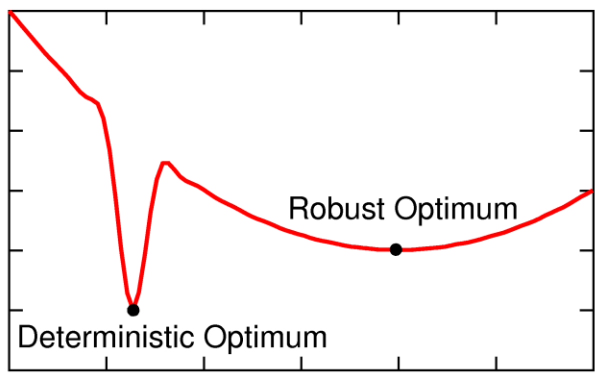
- Failure probability with respect to given limit states is smaller as required value

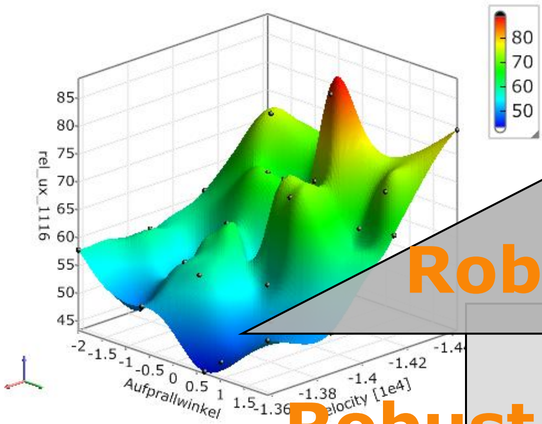
$$p_F \leq p_F^{target}$$

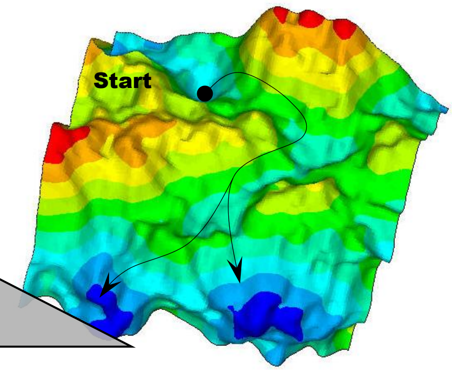
Taguchi-based RDO

- Taguchi loss functions
- Modified objective function

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







Robust Design Optimization

Robust Design

Variance based

Probability based (Reliability analysis)

Taguchi based

Optimization

Sensitivity Study

Single & Multi objective (Pareto) optimization

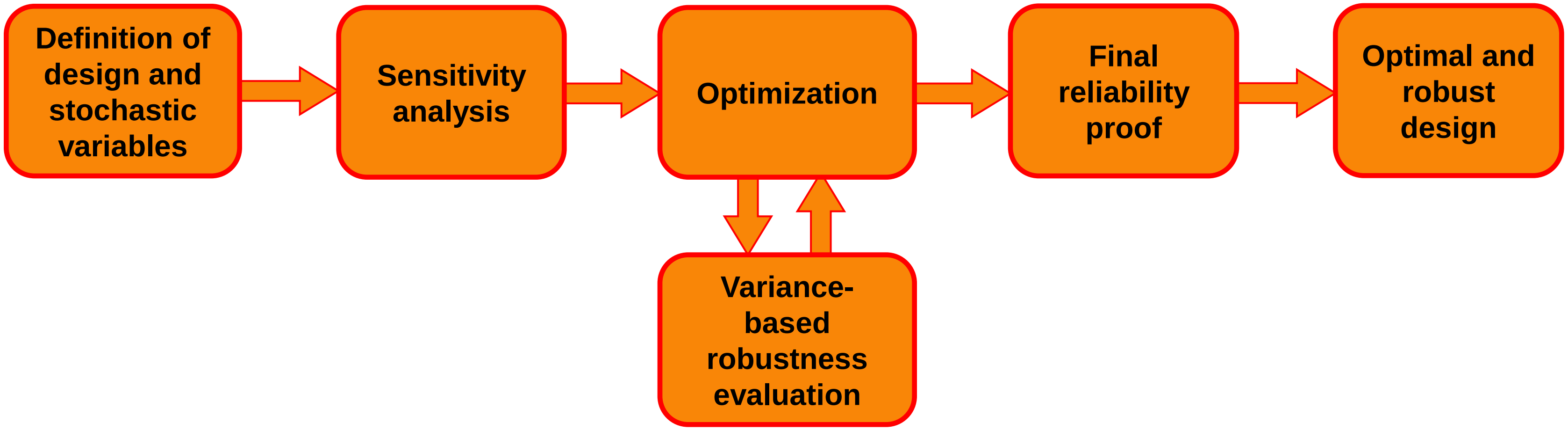
CAE process (FEM, CFD, MBD, Excel, Matlab, etc.)

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

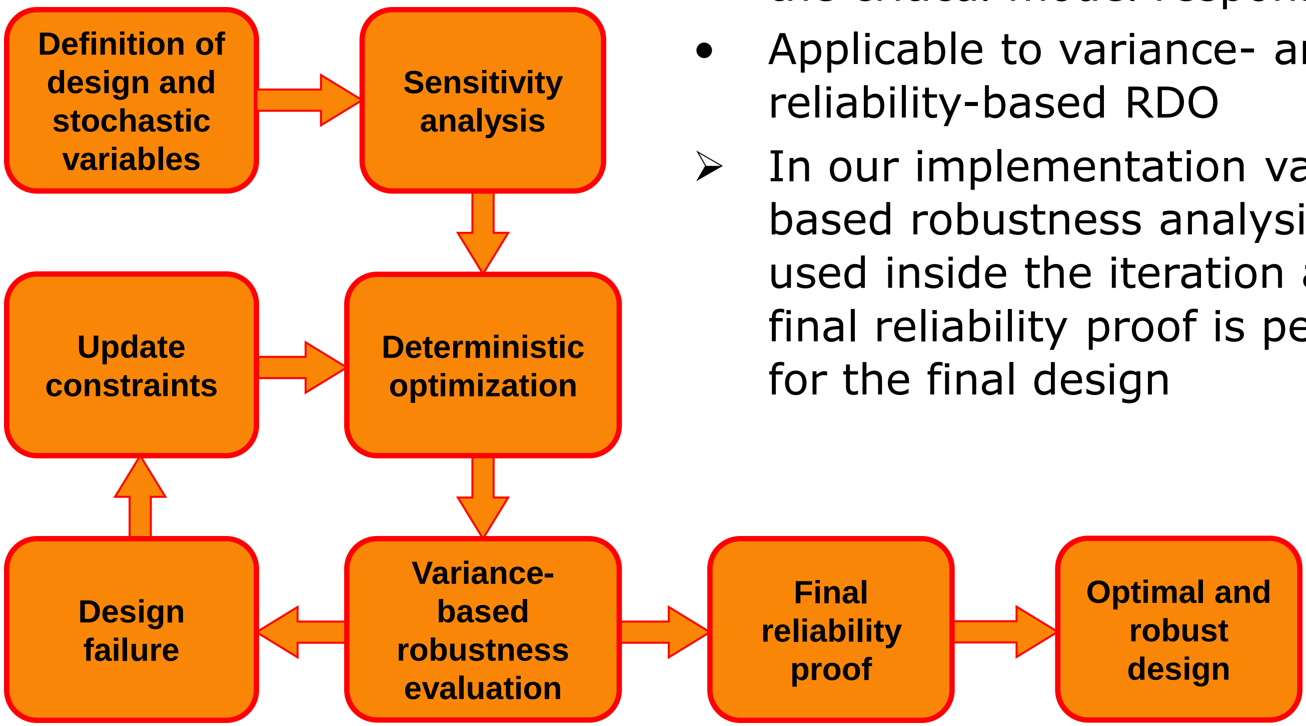
➢ Our efficient implementation uses small sample variance-based robustness measures during the optimization and a final (more accurate) reliability proof

➢ But still the procedure is often not applicable to complex CAE models



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

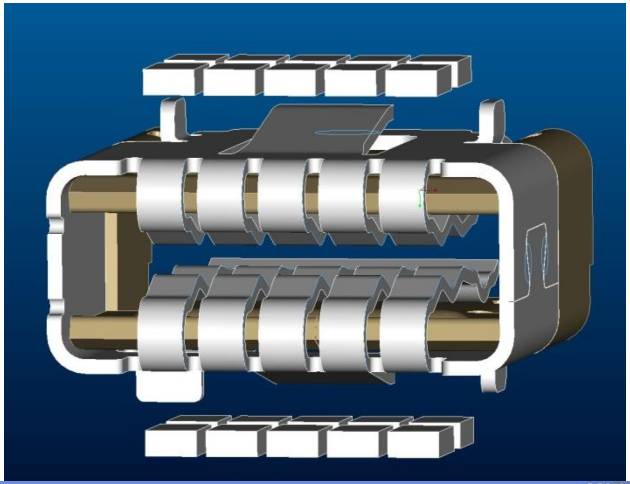


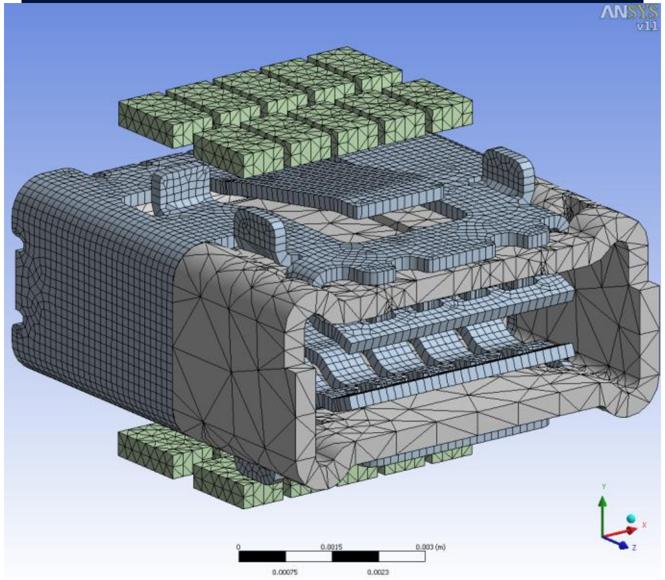
Summary

- 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

dynardo

Iterative RDO Application Connector





Goal: high safety level of connector

10 contact forces have to be checked,

failure may happen if N< 1 N

The failure probability of single contact should be lower than 10%

System Failure probability, the conditional failure of 5 contacts should be less than 1 out 4.300.000. (6 Sigma Design)

→ Status quo: pre optimized design using ANSYS DX and 5 optimization parameter

Question:

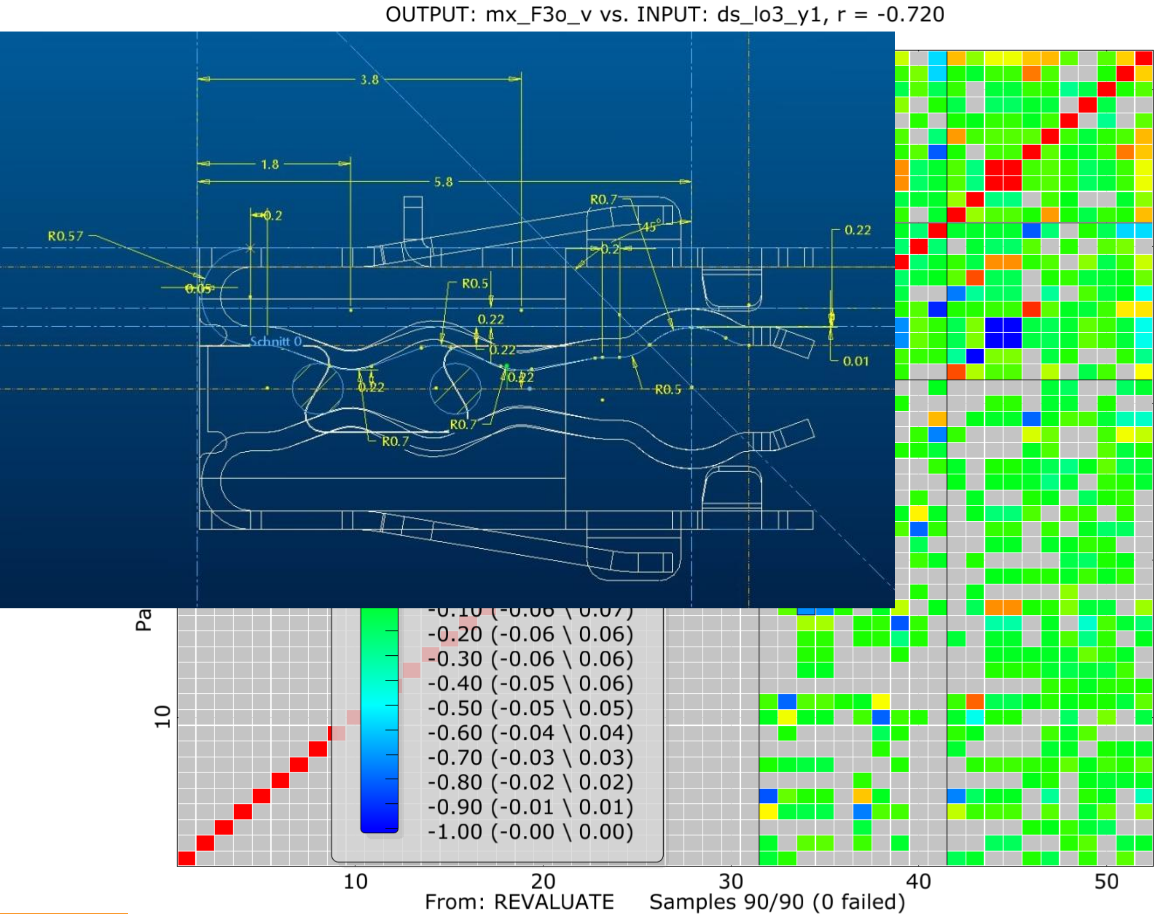
How optimal and robust is the design

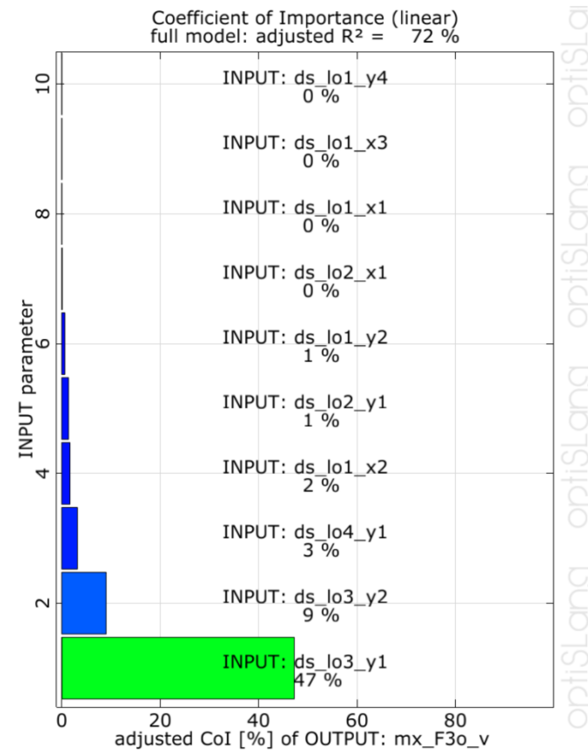
Solver: ANSYS Workbench

by courtesy of Tyco Electronics

Step 1 - Sensitivity analysis

The Sensitivity Analysis id done in the design space of 31 potential CAD (ProE) design parameters





Identification of n=15 most important design parameters

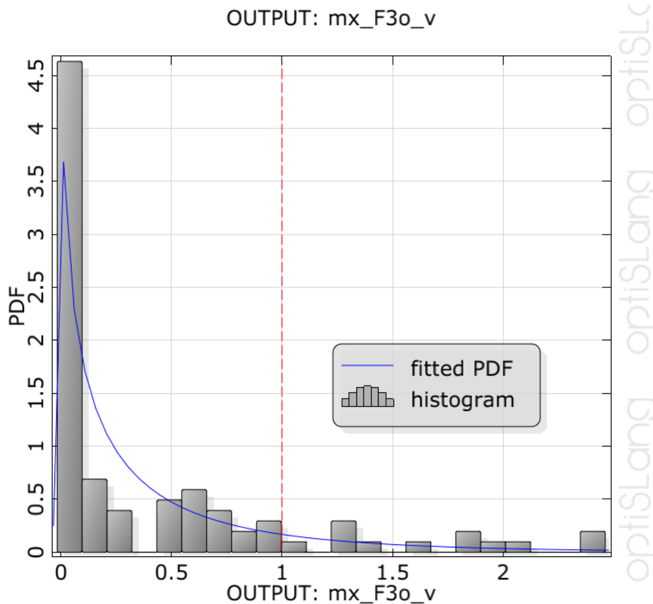
by courtesy of Tyco Electronics

Step 2 - Robustness analysis

The failure probability of single contact failure is checked with Robustness evaluation.

The Robustness Analysis is done in the Robustness space of 36 CAD tolerances

- Global variance-based robustness analysis using Advanced Latin hypercube sampling with 90 design evaluations



Statistic data			
Min:	-0.017	Max:	2.462
Mean:	0.4005	Sigma:	0.6079
CV:	1.518		
Skewness:	1.731	Kurtosis:	5.282
Fitted PDF: Extreme Typ III (Max) Weibull			
Mean:	0.4005	Sigma:	0.6079
Lower cut:	-0.017		
Limit x = 1			
P_rel =	0.8667	P_fit =	0.8893
Probability P(X<x) = 0.95			
x_rel =	1.832	x_fit =	1.56

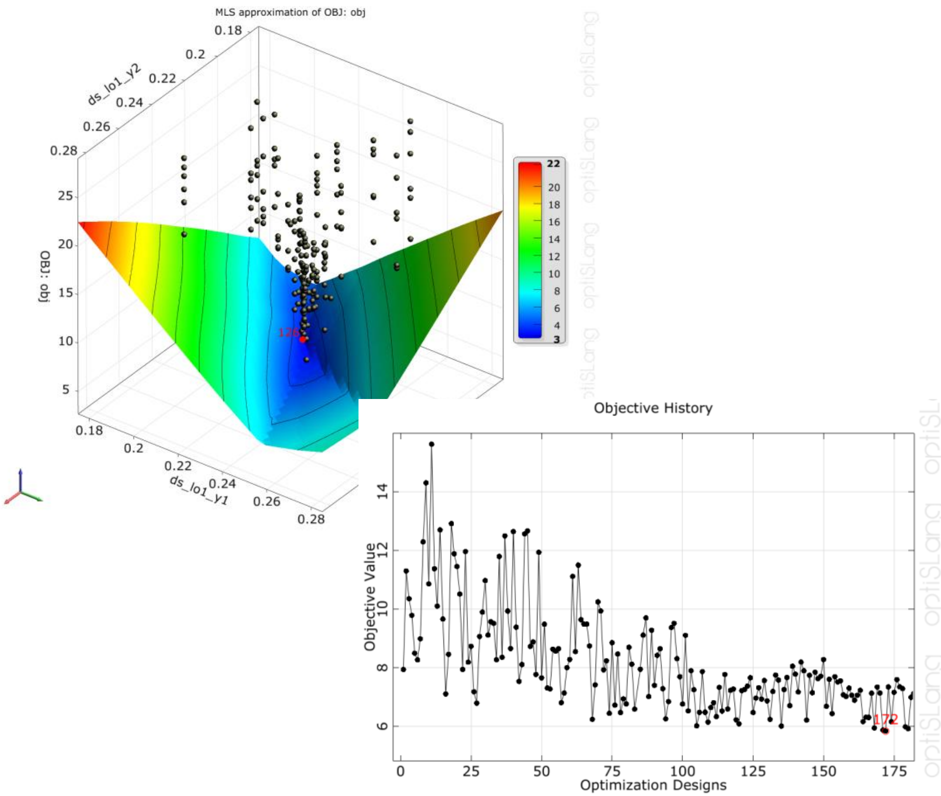
Performance critical contact force F3o_v

With failure probability of **89 %!**

by courtesy of Tyco Electronics

Step 3 - Optimization

- n=15 most important CAD design parameters
- Objective: minimal failure distance of every contact



Step 1: ARSM

- Stagnation after 5 Iterations (126 Design evaluations), contact force F3o_v still violating criteria

Step 2: introducing of additions constraints

Restart of Evolutionary Optimization using best Design_ARSM, stop after 390 Design evaluations with feasible design, but now other contact forces become critical

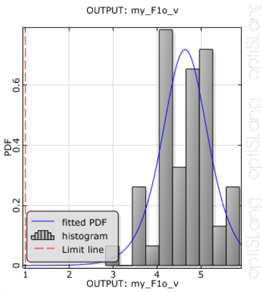
Step 3: modifying the design space range and introducing additional constraints

Restart using ARSM with best Design_EA, stop after 172 Design evaluations

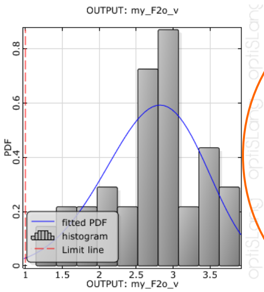
by courtesy of Tyco Electronics

Step 4 Robustness Analysis

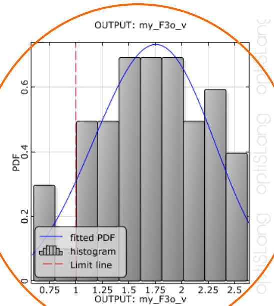
- 36 scattering CAD tolerances
- Global variance-based robustness analysis using Advanced Latin hypercube sampling with N=50 design



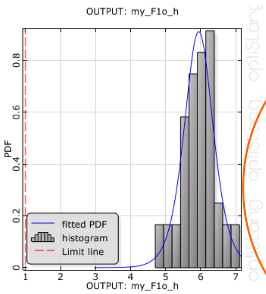
Statistic data			
Min:	2.828	Max:	5.885
Mean:	4.641	Sigma:	0.6302
CV:	0.1358		
Skewness:	-0.3658	Kurtosis:	3.221
Fitted PDF: Logistic			
Mean:	4.641	Sigma:	0.6302
Limit x = 1			
P_rel =	0	P_fit =	2.808e-005
Probability P(X<x) = 0.001			
x_rel =	2.828	x_fit =	2.242



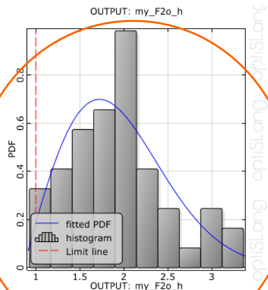
Statistic data			
Min:	1.144	Max:	3.901
Mean:	2.719	Sigma:	0.6628
CV:	0.2437		
Skewness:	-0.4539	Kurtosis:	2.701
Fitted PDF: Weibull (2p)			
Mean:	2.719	Sigma:	0.6628
Limit x = 1			
P_rel =	0	P_fit =	0.006139
Probability P(X<x) = 0.001			
x_rel =	1.144	x_fit =	0.6777



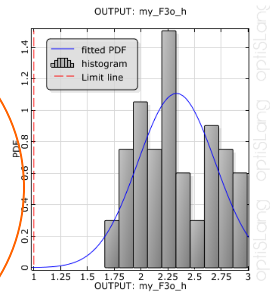
Statistic data			
Min:	0.5997	Max:	2.622
Mean:	1.728	Sigma:	0.525
CV:	0.3038		
Skewness:	-0.2233	Kurtosis:	2.251
Fitted PDF: Weibull (2p)			
Mean:	1.728	Sigma:	0.525
Limit x = 1			
P_rel =	0.08	P_fit =	0.08832
Probability P(X<x) = 0.001			
x_rel =	0.5997	x_fit =	0.2905



Statistic data			
Min:	4.704	Max:	7.11
Mean:	5.944	Sigma:	0.4974
CV:	0.08368		
Skewness:	-0.1861	Kurtosis:	3.271
Fitted PDF: Logistic			
Mean:	5.944	Sigma:	0.4974
Limit x = 1			
P_rel =	0	P_fit =	1.48e-008
Probability P(X<x) = 0.001			
x_rel =	4.704	x_fit =	4.05



Statistic data			
Min:	0.9273	Max:	3.364
Mean:	1.944	Sigma:	0.5676
CV:	0.2919		
Skewness:	0.5921	Kurtosis:	3.084
Fitted PDF: Rayleigh			
Mean:	1.944	Sigma:	0.5676
Limit x = 1			
P_rel =	0.02	P_fit =	0.0133
Probability P(X<x) = 0.001			
x_rel =	0.9273	x_fit =	0.897



Statistic data			
Min:	1.663	Max:	2.991
Mean:	2.332	Sigma:	0.3603
CV:	0.1545		
Skewness:	0.1473	Kurtosis:	1.921
Fitted PDF: Normal			
Mean:	2.332	Sigma:	0.3603
Limit x = 1			
P_rel =	0	P_fit =	0.0001094
Probability P(X<x) = 0.001			
x_rel =	1.663	x_fit =	1.218

Failure probabilities of two forces higher than 1%

Performance critical contact force F3o_v with failure probability 9 %!

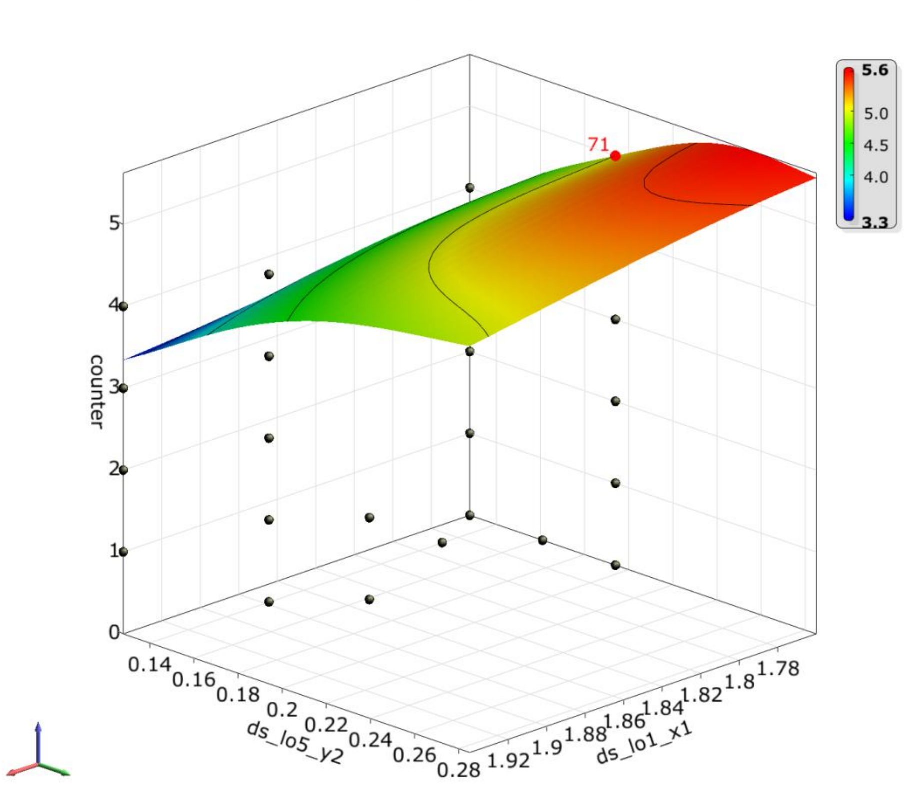
Contact force F2o_h with failure probability 1 %!

by courtesy of Tyco Electronics

Step 5 - Reliability analysis

- Identification of n=12 most important random parameters using coefficients of importance

- Defining the limit state condition for violation more than 50% of the contact forces are lesser than 1N



- Reliability analysis using ARSM with N=137 D-optimal design of experiment
- Adaptive sampling on the MLS surrogate model without samples in the unsafe domain
- Probability of failure is near zero, assumption: normal distributed random parameters
- Optimized design is an Six Sigma Design

Results

- ✓ Variance and probability-based robust design optimization with 31 optimization parameters and 36 scattering parameters
- ✓ Increasing the performance critical contact force F3o_v according failure probability 89% -> 9%
- ✓ Failure probabilities of the other contact forces lesser than 1%
- ✓ System failure probability (more than 50% of the contact forces are lesser than 1) is near zero! (Six Sigma Design)
- ✓ N=950 parallel finite element calculations
- ✓ Total calculation time 1 week

by courtesy of Tyco Electronics