

DVM Workshop Zuverlässigkeit und Probabilistik  
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# **Varianzbasierte Robustheits- optimierung unter Pareto Kriterien**

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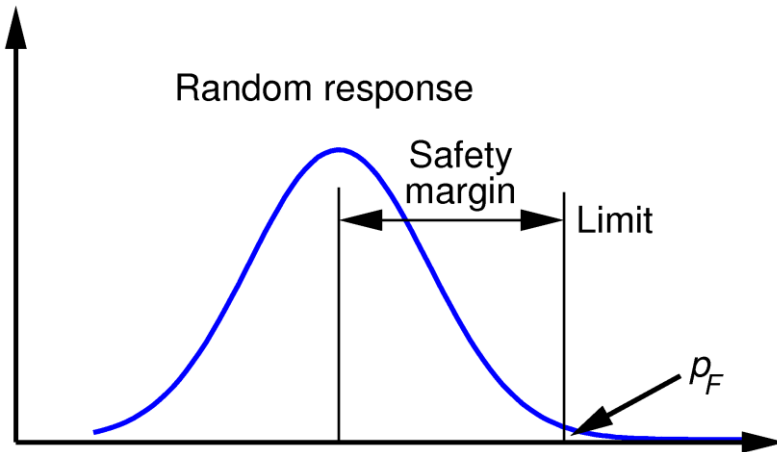
# Robustness Evaluation



## How to Define the 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 $\pm$  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 in terms of constraints



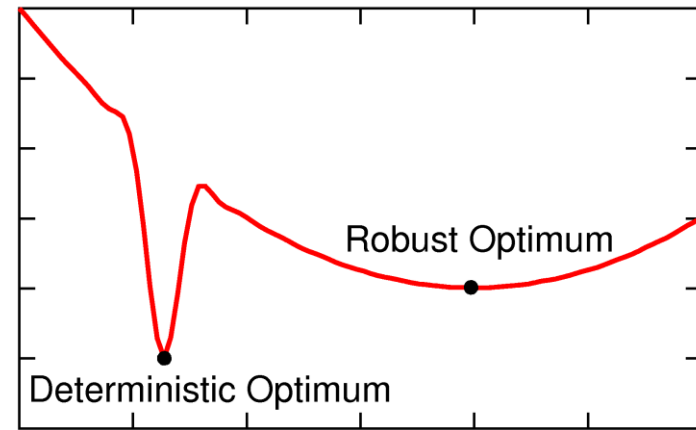
- Safety margin (sigma level) of one or more responses  $y$ :

$$(y_{limit} - \mu_Y) / \sigma_Y \geq a$$

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

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

## Robustness in terms of the objective

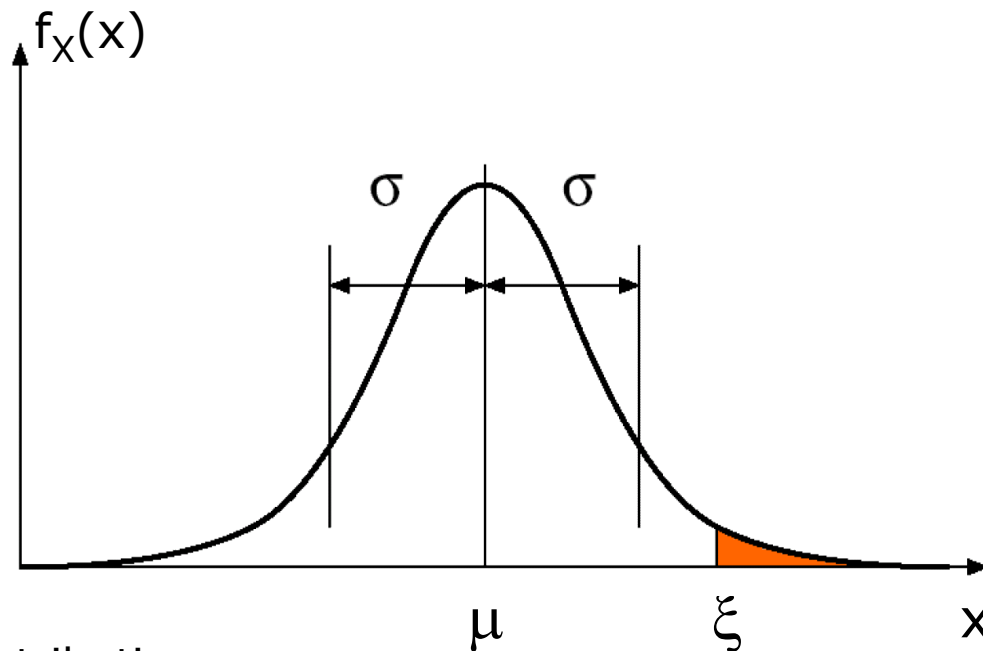


- Performance (objective) of robust optimum is less sensitive to input uncertainties
- Minimization of statistical evaluation of objective function  $f$  (e.g. minimize mean and/or standard deviation):

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

## Exceedance Probability

- Probability of reaching values above a limit



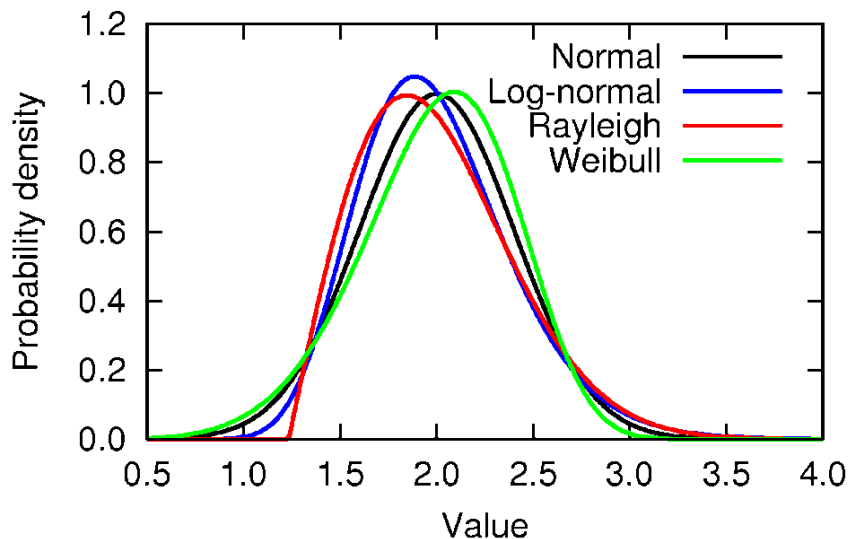
- Gaussian distribution:

$$P_\xi = P[X \geq \xi]$$

$\xi$	$\mu$	$\mu + \sigma$	$\mu + 2\sigma$	$\mu + 3\sigma$	$\mu + 4\sigma$	$\mu + 5\sigma$
$P_\xi$	$5.0 \cdot 10^{-1}$	$1.6 \cdot 10^{-1}$	$2.3 \cdot 10^{-2}$	$1.3 \cdot 10^{-3}$	$3.2 \cdot 10^{-5}$	$2.9 \cdot 10^{-7}$

## Sigma Level vs. Exceedance Probability

- The sigma level can be used to estimate the probability of exceeding a certain response limit
  - Since the distribution type of the response is generally unknown, this estimate may be very inaccurate for small probabilities (sigma levels larger than 3)
  - 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



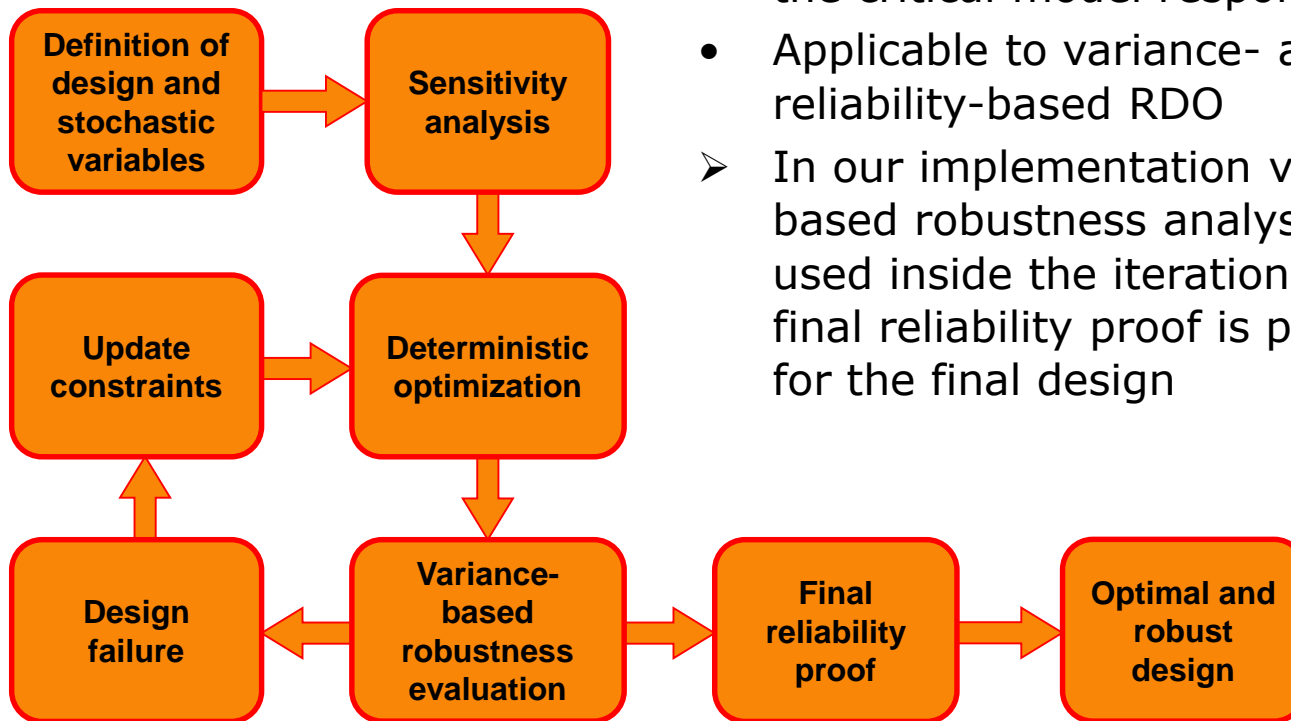
Distribution	Required sigma level (CV=20%)		
	$p_F = 10^{-2}$	$p_F = 10^{-3}$	$p_F = 10^{-6}$
Normal	2.32	3.09	4.75
Log-normal	2.77	4.04	7.57
Rayleigh	2.72	3.76	6.11
Weibull	2.03	2.54	3.49

# Robust Design Optimization



# Iterative Robust Design Optimization

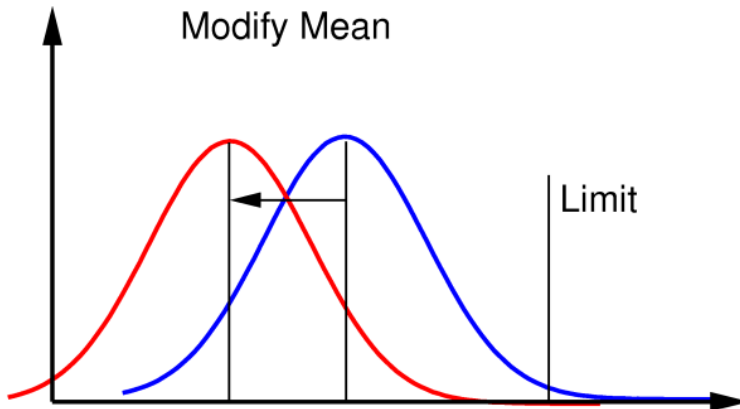
- Decoupled optimization and robustness/reliability analysis
- For each optimization run the safety factors are adjusted for the critical model responses
- Applicable to variance- and reliability-based RDO
- In our implementation variance-based robustness analysis is used inside the iteration and a final reliability proof is performed for the final design





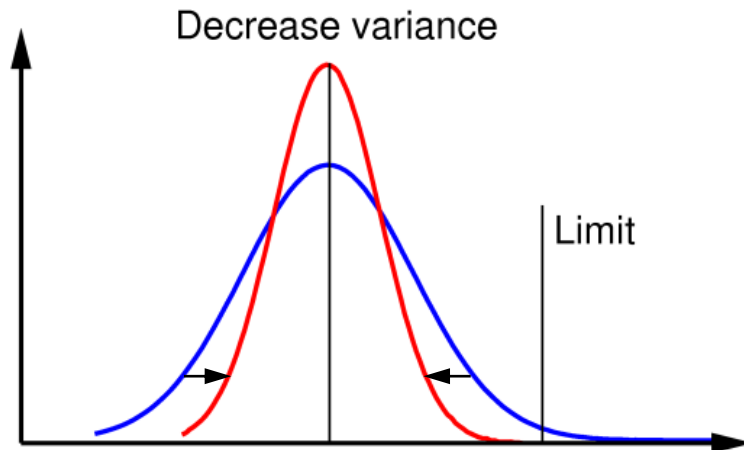
## How to Optimize Robustness

Adapt safety margin (as constraint)

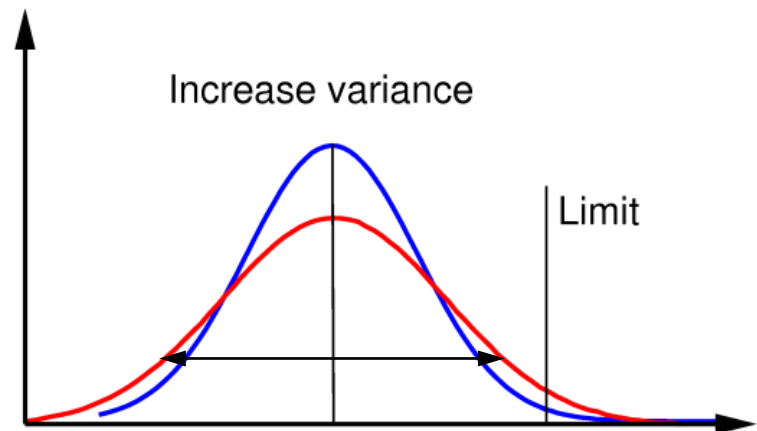


- Shift of mean response from deterministic optimum is possible
- Scatter may vary with different location of the mean

Adapt scatter (in input space)

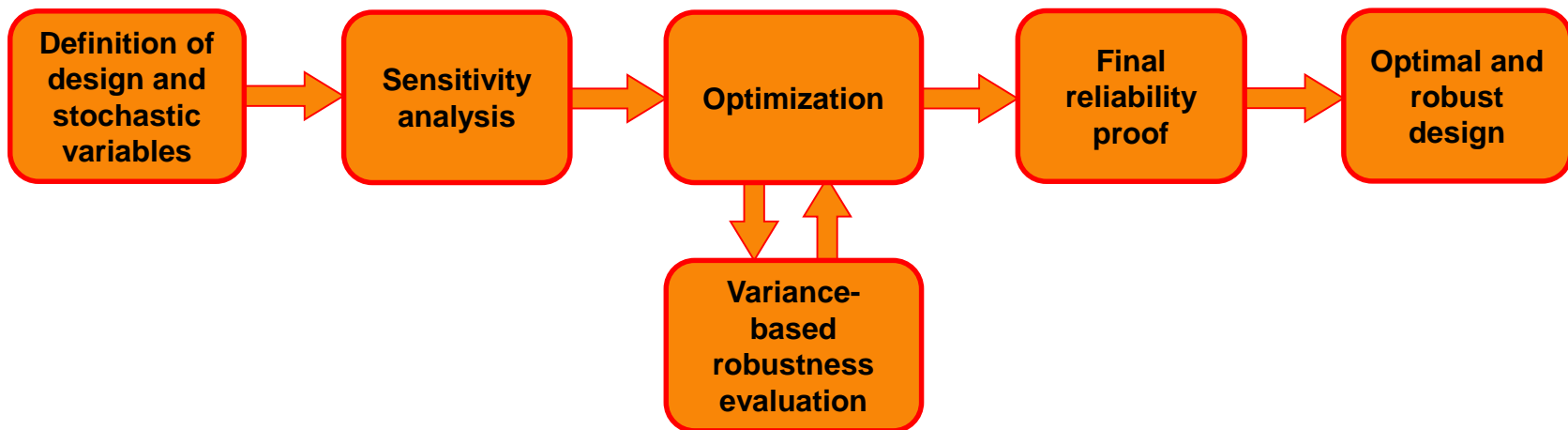


... but avoid "overdesign"



## Coupled 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



# Example: Steel Hook



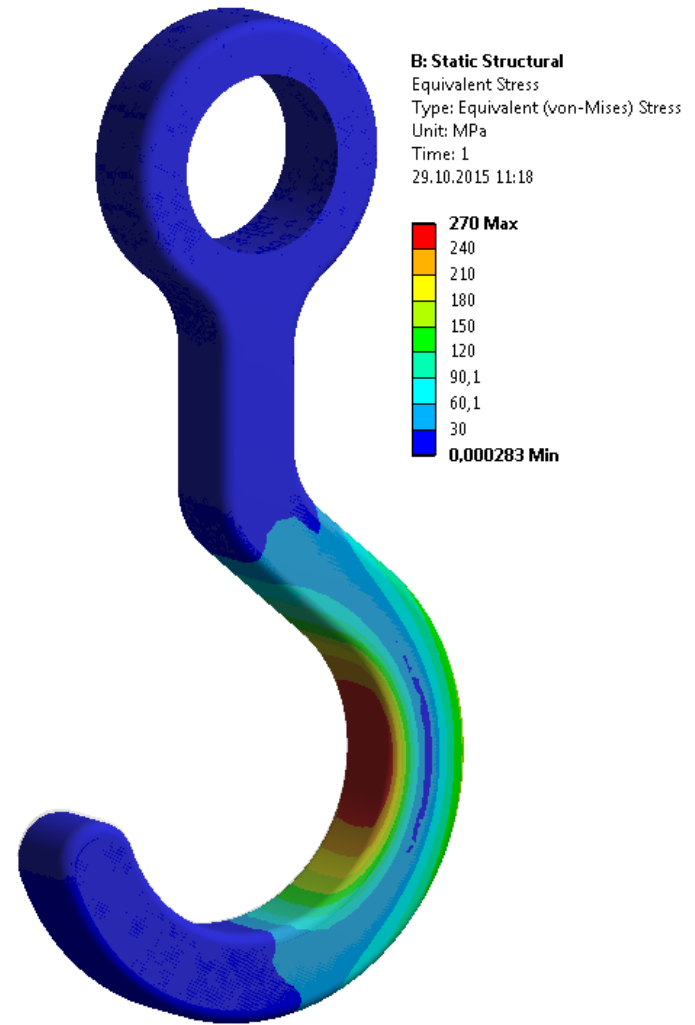
# The Robust Design Optimization Task

## Deterministic Optimization

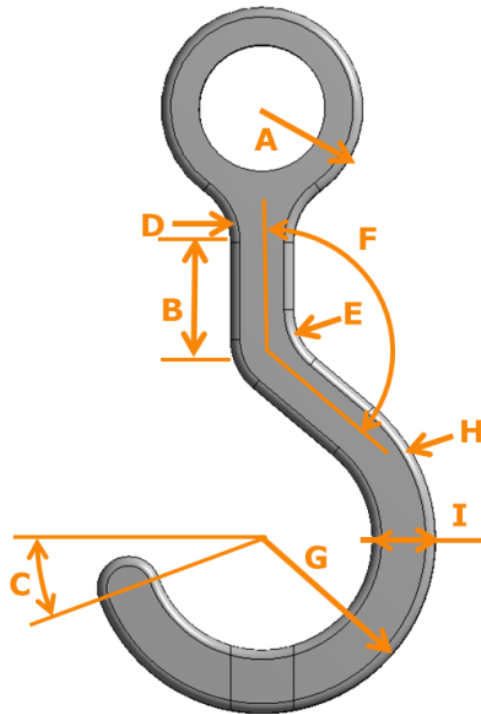
- Minimize the mass
- The maximum stress should not exceed 300 MPa
- 10 geometry parameters are varied for the design variation

## Robustness requirement

- Proof for the optimal design that the failure stress limit is not exceeded with a 4.5 sigma safety margin
- 15 scattering parameters are considered (geometry and material properties and the load components)



## Optimization Parameters; Initial Design



A	Outer_Diameter	28-35 mm
B	Connection_Length	20-50 mm
C	Opening_Angle	10-30 °
D	Upper_Blend_Radius	18-22 mm
E	Lower_Blend_Radius	18-22 mm
F	Connection_Angle	120-150 °
G	Lower_Radius	45-55 mm
H	Fillet_Radius	2-4 mm
I	Thickness	15-25 mm
	Depth	15-25 mm

### Initial nominal values

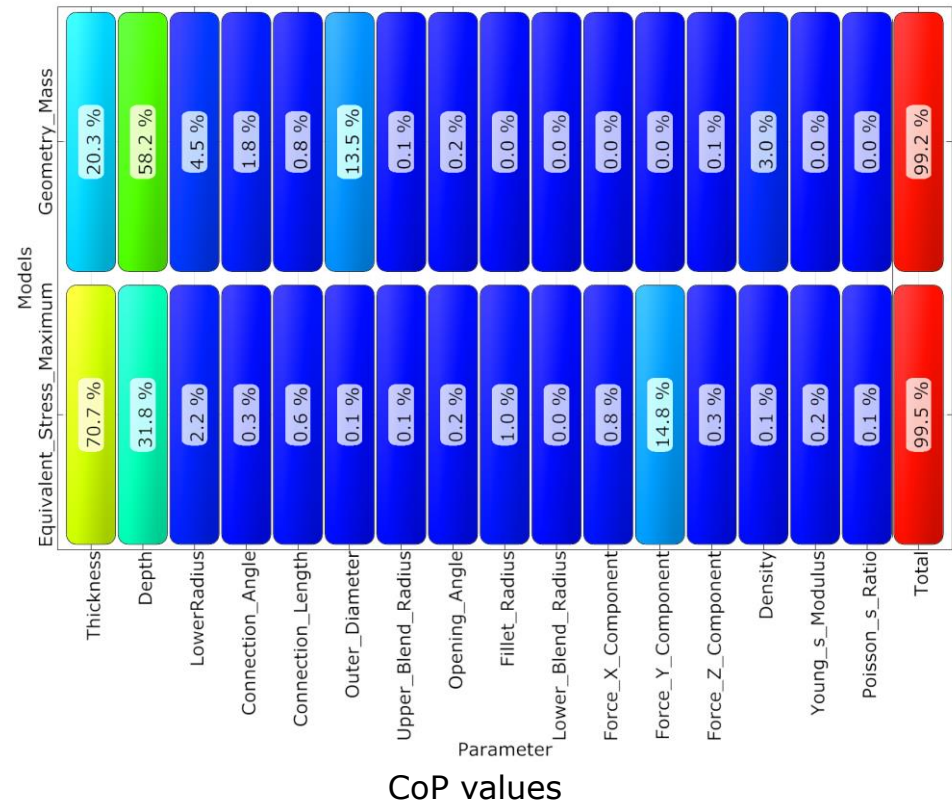
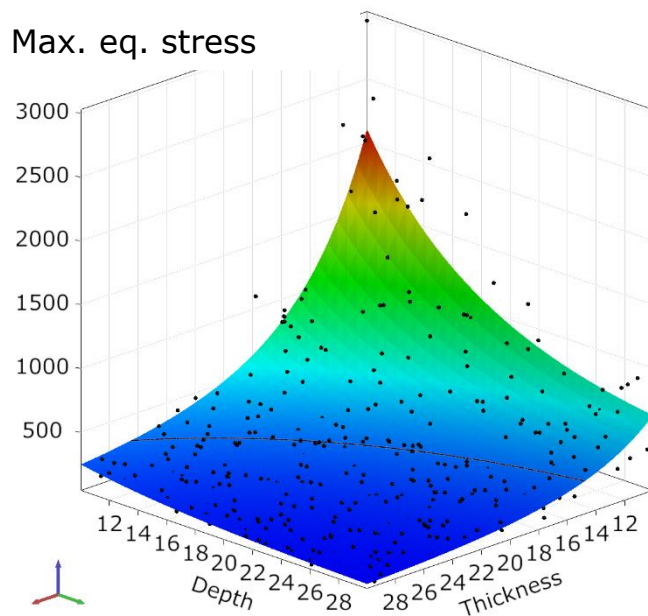
- Mass 1100 g
- Maximum stress 270 MPa
- Slipping height 28 mm
- Opening width 64 mm

## Random parameters

	Distribution	Mean value	Standard deviation
Outer diameter	normal	nominal	1 mm
Connection length	normal	nominal	1 mm
Opening angle	normal	nominal	2°
Upper blend radius	normal	nominal	1 mm
Lower blend radius	normal	nominal	1 mm
Connection angle	normal	nominal	2°
Lower radius	normal	nominal	1 mm
Fillet radius	normal	nominal	0.2 mm
Thickness	normal	nominal	1 mm
Depth	normal	nominal	1 mm
Young's modulus	log-normal	2e11 N/m <sup>2</sup>	1e10 N/m <sup>2</sup>
Poisson's ratio	log-normal	0.3	0.015
Density	log-normal	7850 kg/m <sup>3</sup>	157 kg/m <sup>3</sup>
Force x-direction	normal	0 N	100 N
Force y-direction	normal	6000 N	600 N
Force z-direction	normal	0 N	1.

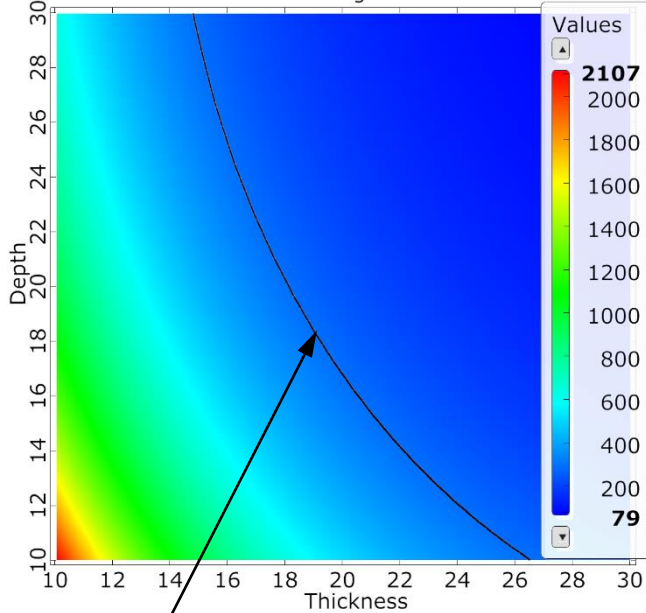
# Metamodel of Optimal Prognosis in RDO Space

- Sampling in RDO space  
Design parameters: Range  $\pm 5\sigma$   
Stochastic variables: Mean  $\pm 5\sigma$
- Advanced Latin Hypercube Sampling with 500 samples
- Global CoP  $\approx 99\%$  for all responses

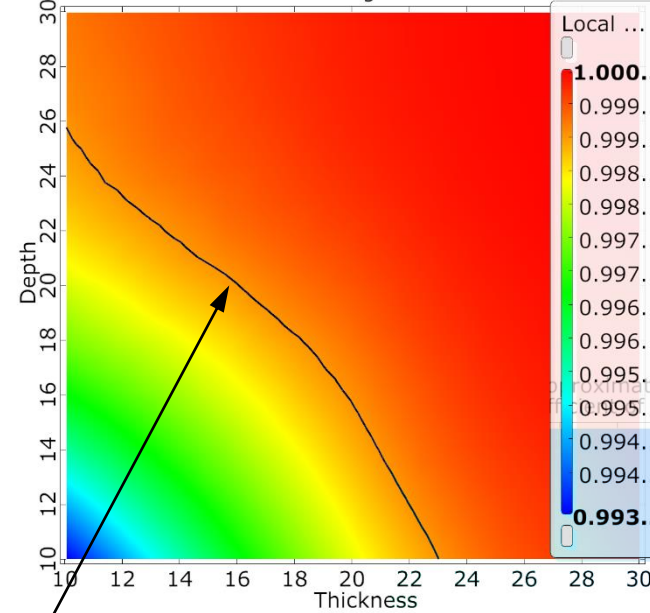


# Metamodel of Optimal Prognosis in RDO Space

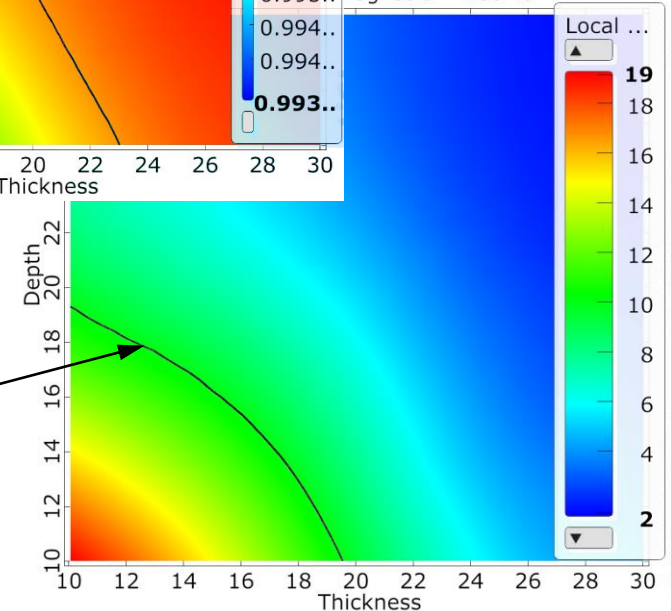
Linear Regression approximation of Equivalent\_Stress\_Maximum  
Coefficient of Prognosis = 100 %



Linear Regression approximation of Equivalent\_Stress\_Maxim  
Coefficient of Prognosis = 100 %



Linear Regression approximation of Equivalent\_Stress\_Maximum  
Coefficient of Prognosis = 100 %



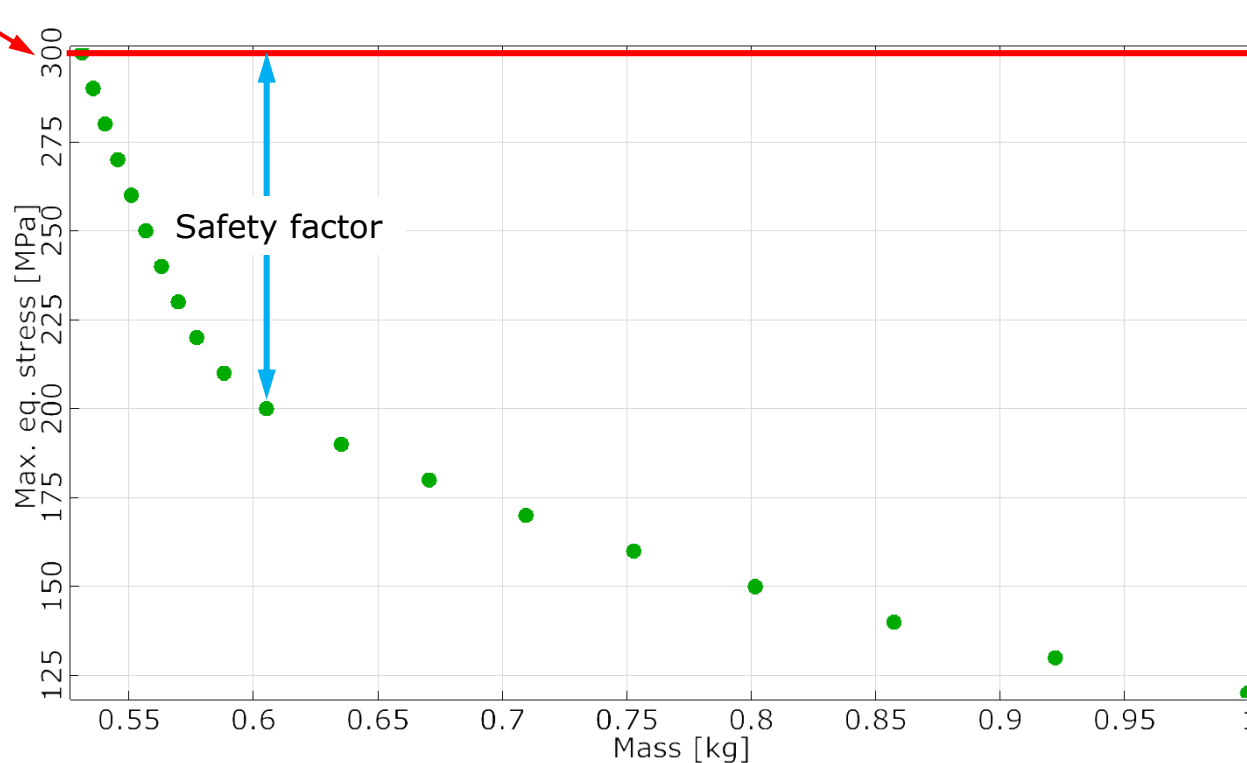
- Equivalent Stress Maximum
- Limit 300 Mpa
- Local CoP 99,9%
- Absolute error 10 MPa



# 1<sup>st</sup> Study: Deterministic Pareto Optimization

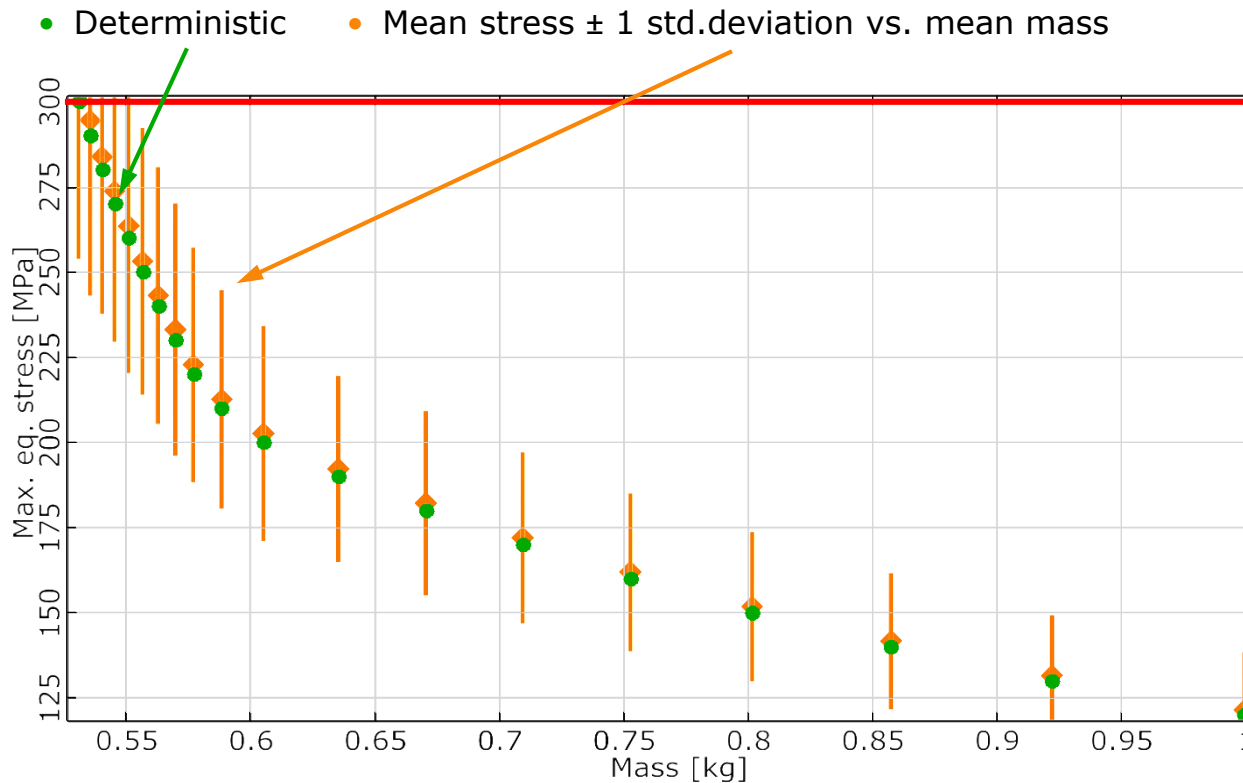
- Criteria: minimize mass and max. stress simultaneously
- Obvious contradiction between mass and max. stress
- Each point is a valid optimum: choose safety distance

Stress limit



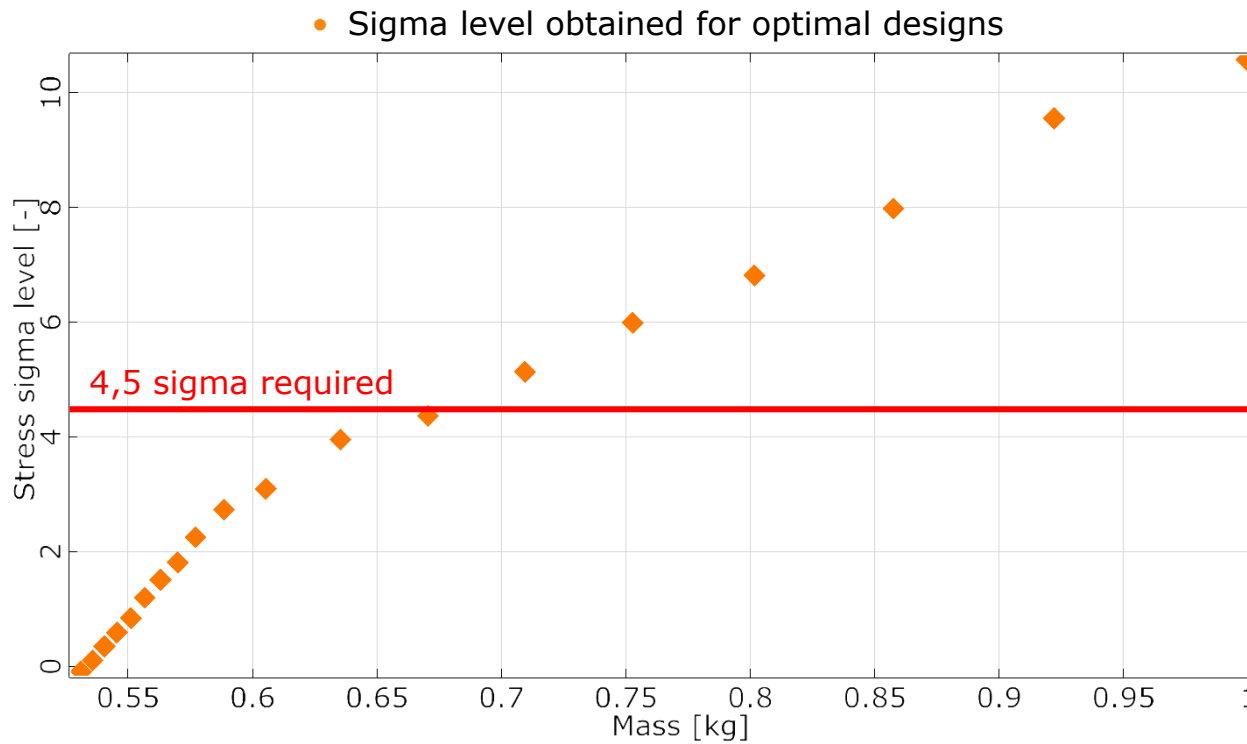
## 2<sup>nd</sup> Study: Robustness of Pareto Designs

- Apply stochastic sampling centered at each pareto-optimal design
- Evaluate means and standard deviations of mass and stress
- ➔ Non-constant scatter over the observed range
- ➔ Observable shift of mean stress w.r.t. deterministic result



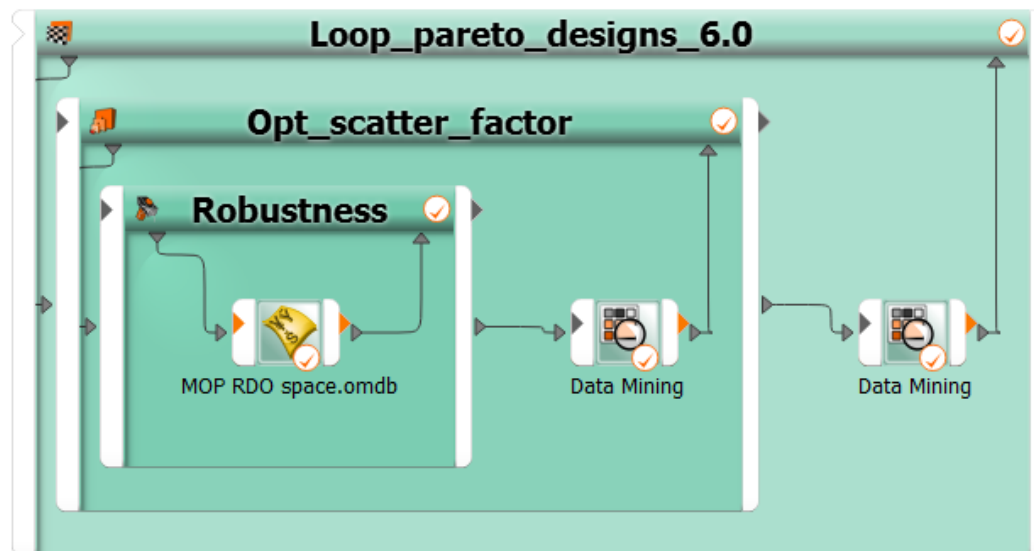
## 2<sup>nd</sup> Study: Robustness of Pareto Designs

- With help of obtained sigma level, a more meaningful safety margin can be chosen
- Stress constraint for deterministic optimization can be derived
- Result not guaranteed due to varying scatter: iteration required



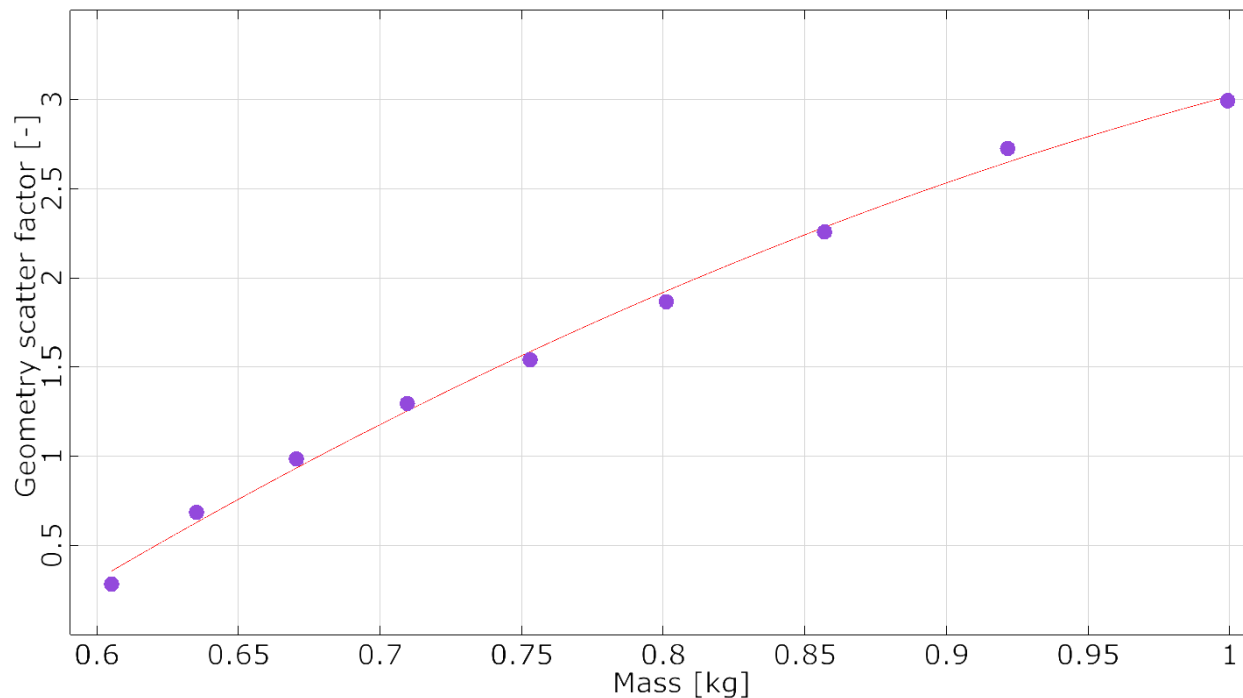
## 4<sup>th</sup> Study: Optimization of Scatter

- Motivation: adaptation of constraints to find robust design changes performance (here: weight)
- Control of input scatter changes costs (manufacturing precision)
- Where is the balance?
- ➔ Introduce scatter factor for geometry parameters (without angles)
- ➔ Optimize scatter factor to given sigma level

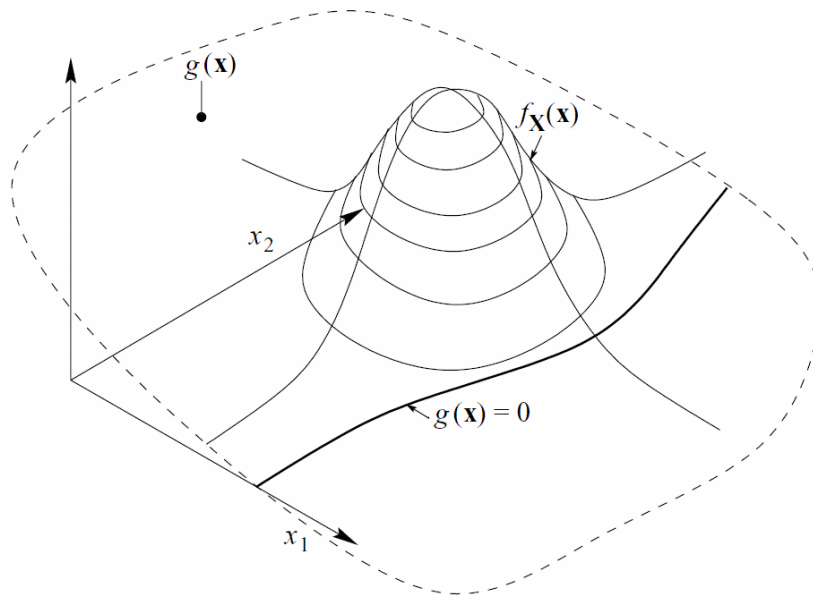


## 4<sup>th</sup> Study: Optimization of Scatter

- Optimized scatter factors for geometry parameters (without angles)
- For each deterministic pareto design
- Required sigma level: 4.5
- ➔ Conflict between mass and scatter



# Reliability Analysis

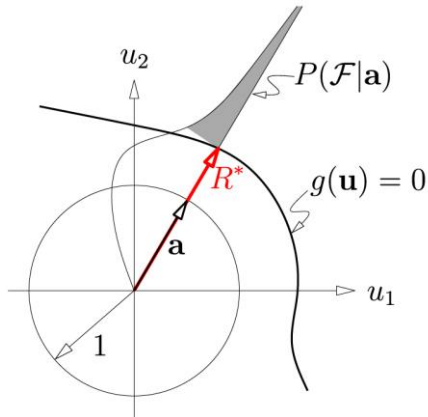


$$\begin{aligned}
 P_F &= P[\mathbf{X} : g(\mathbf{X}) \leq 0] \\
 &= \int_{g(\mathbf{x}) \leq 0} \cdots \int f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} \\
 &= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} I(g(\mathbf{x})) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}
 \end{aligned}$$

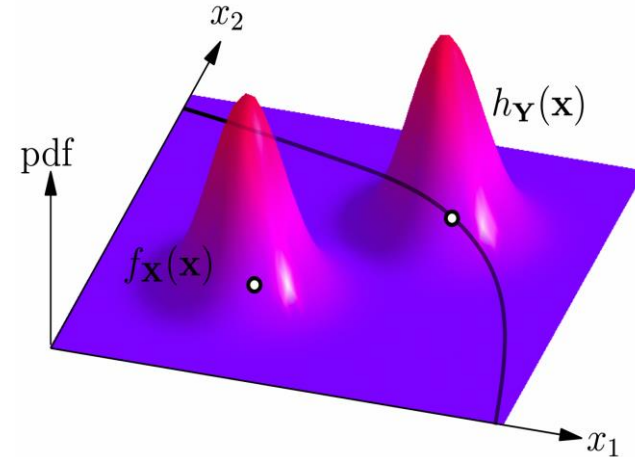
- Limit state function  $g(\mathbf{x})$  divides random variable space  $\mathbf{X}$  in safe domain  $g(\mathbf{x}) > 0$  and failure domain  $g(\mathbf{x}) \leq 0$
- Multiple failure criteria (limit state functions) are possible
- Failure probability is the probability that at least one failure criteria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

# Advanced Methods for Reliability Analysis

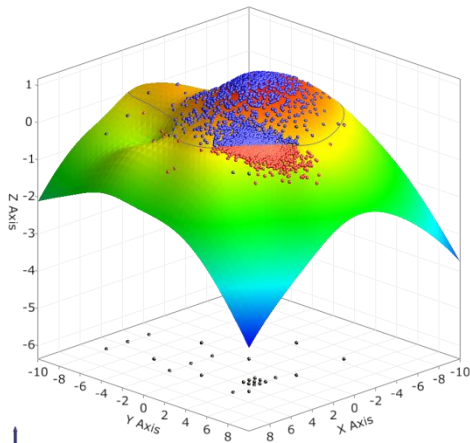
## Directional Sampling



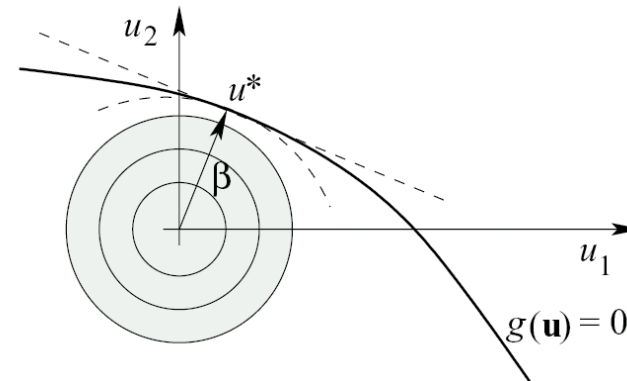
## Importance Sampling



## Adaptive Response Surface Method



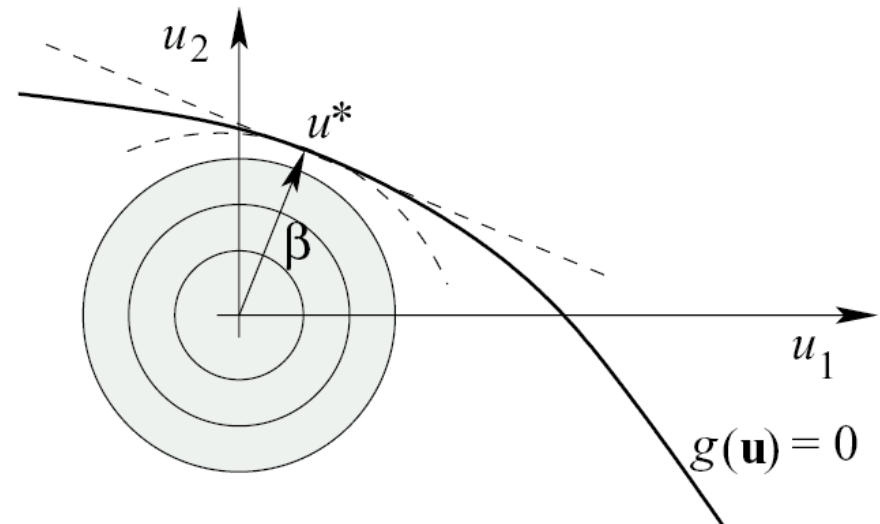
## First Order Reliability Method



## First Order Reliability Method (FORM)

- Operates in the space of standardized Gaussian variables
- Search for failure point with maximum probability density (*design point*)
- Equals the point on the limit state surface with minimal distance to origin
- Default algorithm is gradient-based optimization
- Limit state function is linearized around design point
- Requires continuously differentiable limit state function
- Multiple design points (local minima) are not supported
- Independent search for each limit state may be more robust

$$\mathbf{X} \rightarrow \mathbf{U} \sim \mathcal{N}(0; 1) \quad \rho_{i,j \neq i} = 0$$



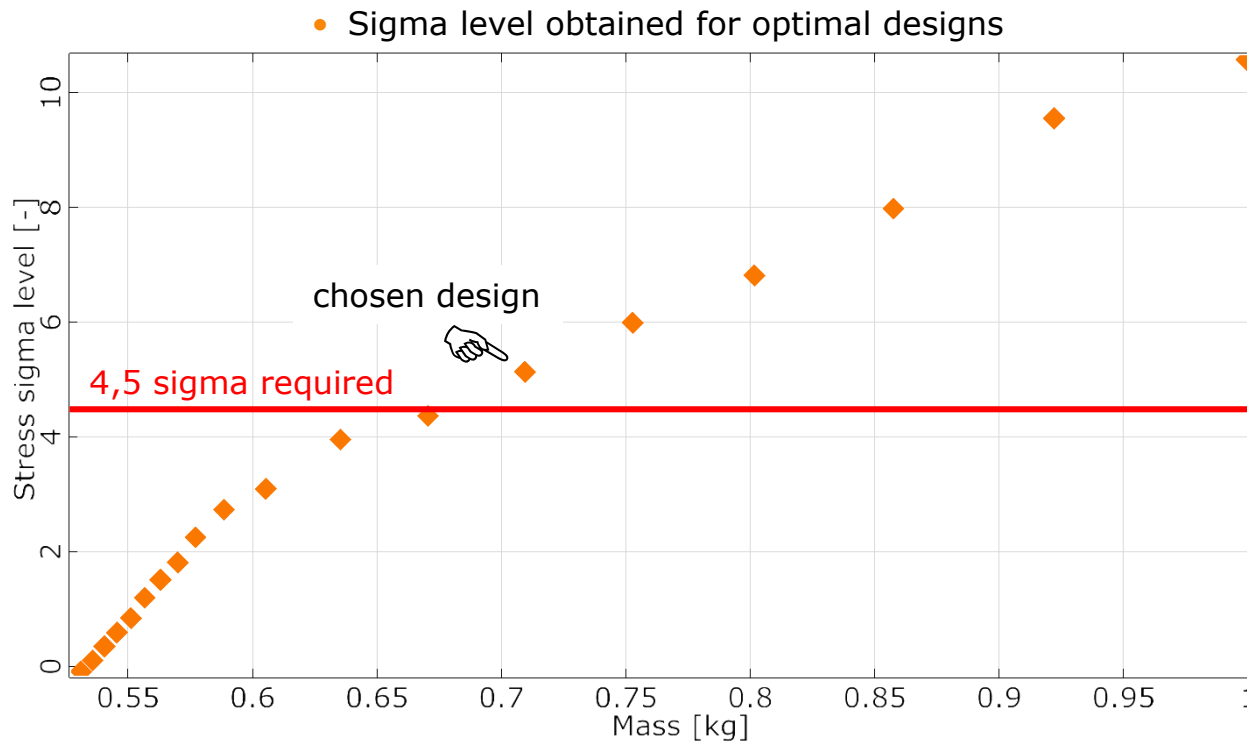
$$\mathbf{u}^* : \frac{1}{2} \mathbf{u}^T \mathbf{u} \rightarrow \min, \quad g(\mathbf{u}) = 0$$

$$P_f = \Phi(-\beta)$$



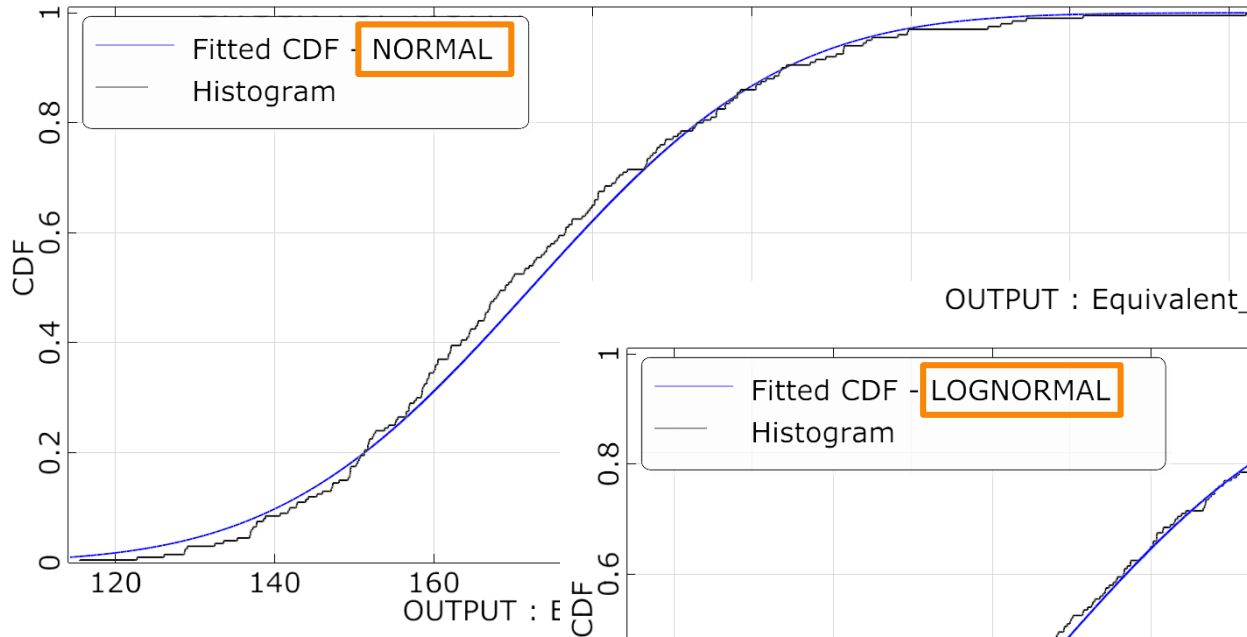
## 5<sup>th</sup> Study: Reliability Analysis of Chosen Design

- Previous studies were performed on an approximation model
- Only variance-based analyses despite high sigma level demand
- ➔ Proof of safety is necessary
- Chosen design: Mass = 7.08kg; Stress sigma level = 5.13

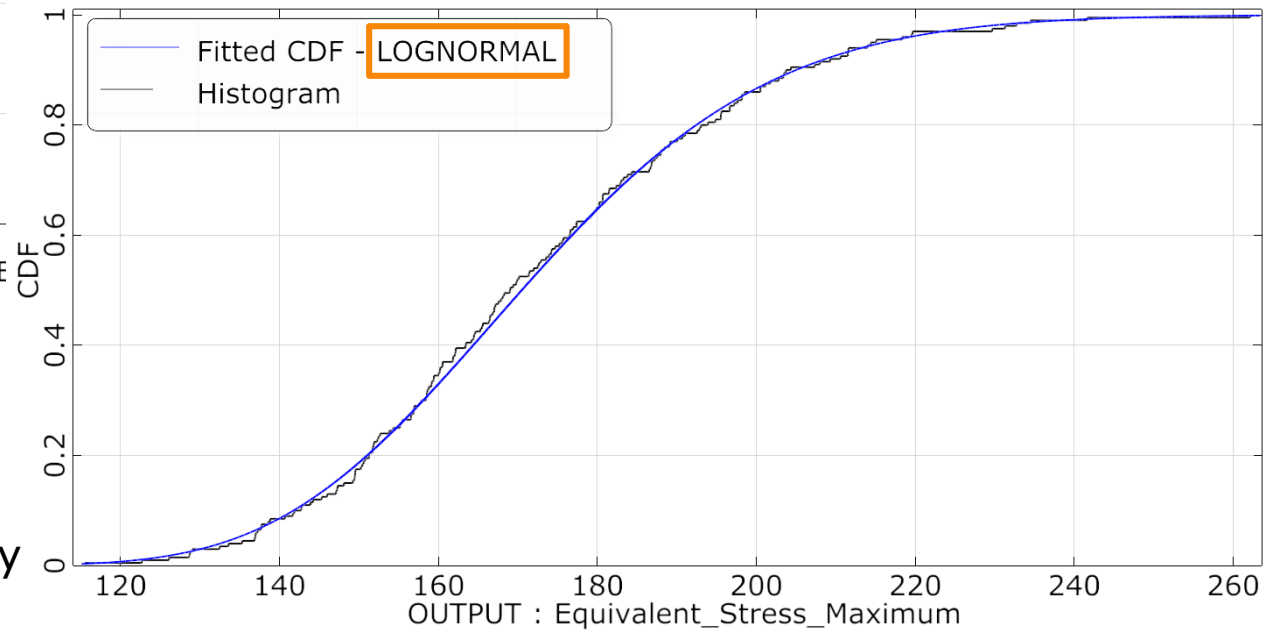


## Check for Normal Distribution

OUTPUT : Equivalent\_Stress\_Maximum



OUTPUT : Equivalent\_Stress\_Maximum

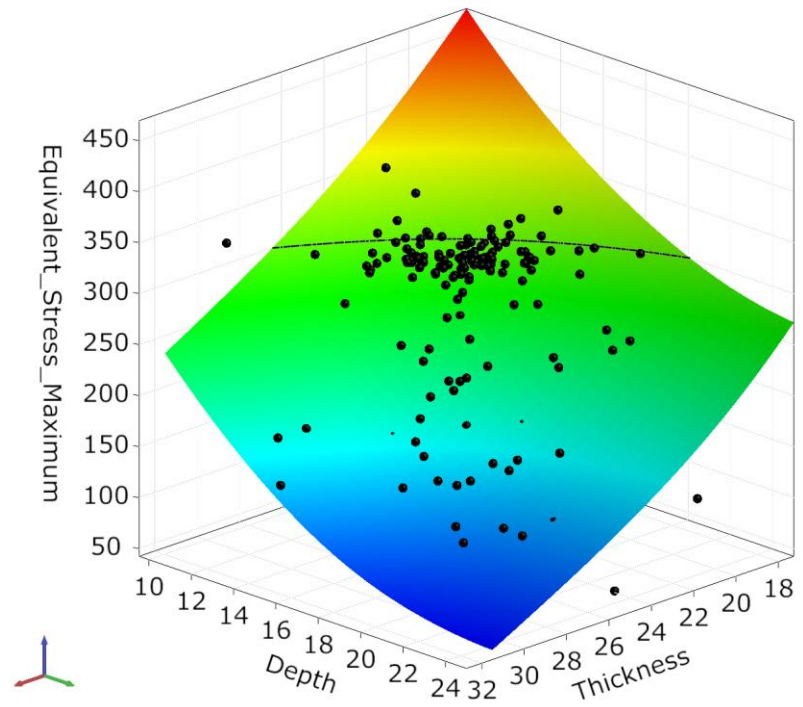


- Log-normal provides best fit
- Correspondence between sigma level and failure probability is in doubt

## Results of Probability-Based Analysis

- Reliability analysis using Adaptive Response Surface Method combined with Directional Sampling (ARSM-DS)
- Limit state function:  $300\text{MPa} - \text{max. eq. stress} = 0$
- 200 solver calls needed
- Failure probability  $P_F = 8\text{E-}6$
- Reliability index  $\beta = 4.3$   
smaller than sigma level 4.5!

Moving Least Squares approximation of Equivalent\_Stress\_Maximum



## Summary and Conclusions

- Robust Design Optimization (RDO) helps to develop designs that
  - Have optimal performance
  - Fulfill reliability (or quality) criteria without "over-design"
- The handles to influence robustness are
  - Optimization constraints (→ mean values of results)
  - Input scatter (→ scatter or sigma level of results)
- The optimal design shall provide a balance between
  - Performance ("product promise")
  - Manufacturing costs (due to precision)
- Presented study was performed on an approximate model (Metamodel of Optimal Prognosis)
  - Fast analyses become possible
  - High demand on model accuracy
  - ➔ For safety requirements: proof by reliability analysis is necessary