

Variance-based and Probability-based Sequential Robust Design Optimization of Fluid-Structure Interaction Processes.

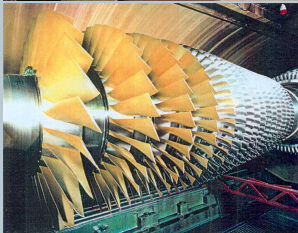
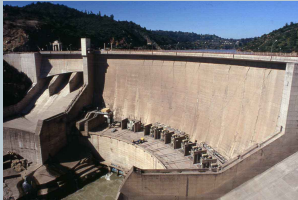
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Niederrhein University of Applied Sciences

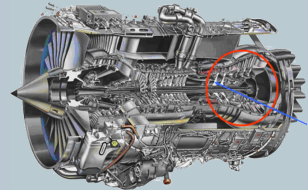
²ANSYS Germany GmbH



Robust Design Optimization

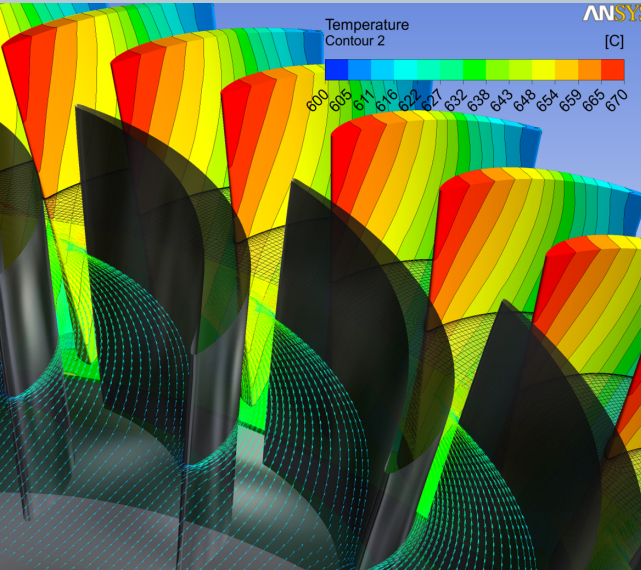


- Power plant 1000 MW, η ca. 50%
- Increasing of **4%** results in additional +80 MW power
- Per person, $P = 1/6$ kW
- Electricity for 80 MW / $1/6$ kW = **480.000 inhabitants**
- Minimal mass, maximal life time
- **Six Sigma Design**
 $P(\mathcal{F}) \leq 3.4 \cdot 10^{-6}$



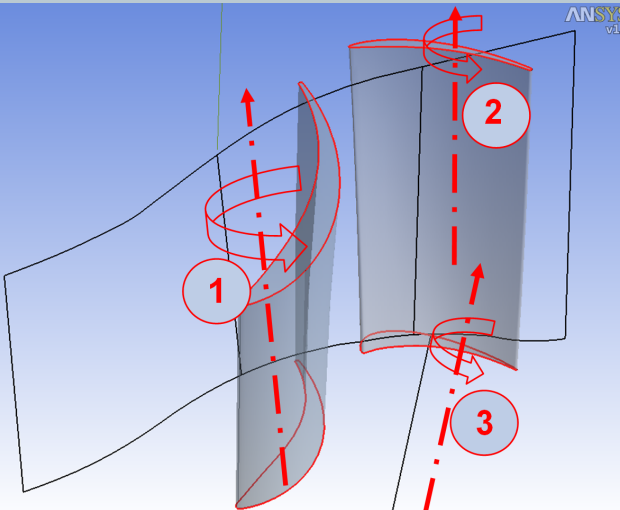
including material, manufacturing uncertainties and process parameters

RDO of an axial turbine blade



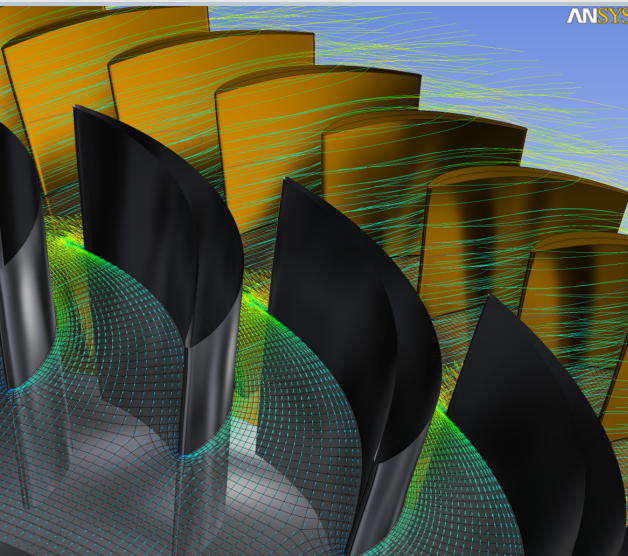
- Structural, thermal and fluid analysis
- CAD- and CAE-based parameterization
- Automatic process integration and meshing using **ANSYS Workbench**

Design parameters



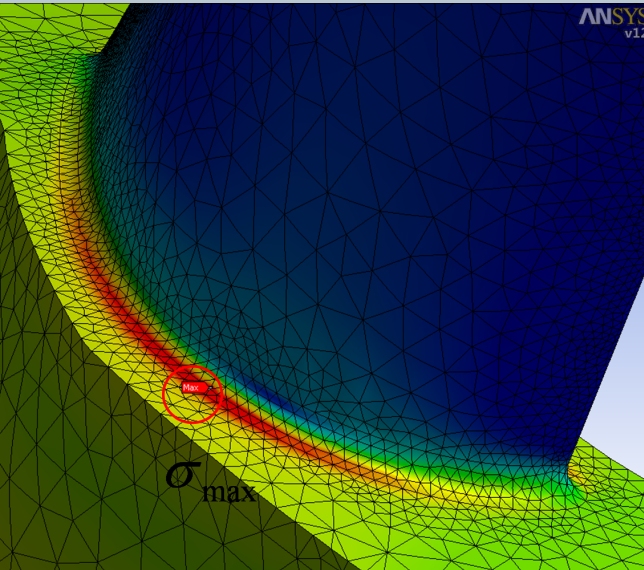
- $n_d = 4 + 3 = 7$
geometry
parameters of the
shroud profile
and guide vane
- Rotational
velocity of the
rotor
- Temperature and
pressure ratio
- Gaussian
distributions

Stochastic objective function



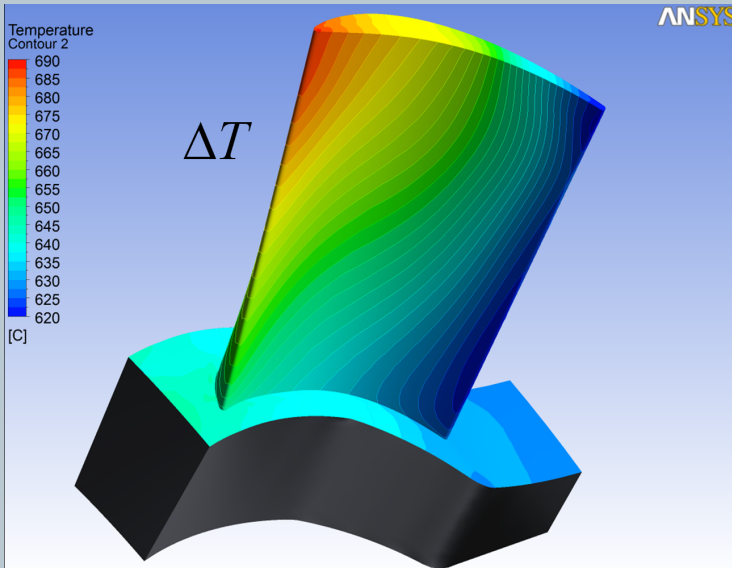
- Random material parameters:
(thermal conductivity of air and steel; mass flow rate, E , v , ρ : steel)
- **Six Sigma Design** criteria
- Maximize
 - isentropic **efficiency**
 - **power** at rotor and
- Minimization of **maximal v. Mises stress**

Stochastic responses

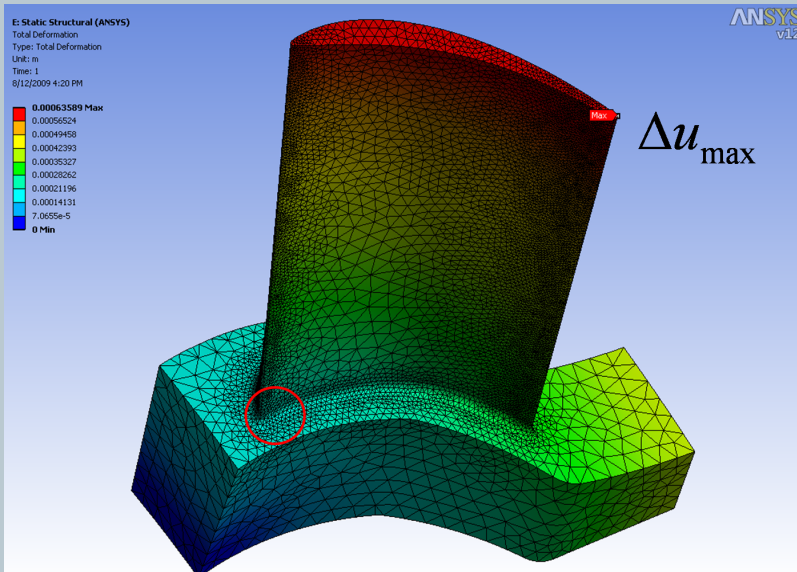


- Location and mesh independency of the v. Mises stress
- Rotor blend radius

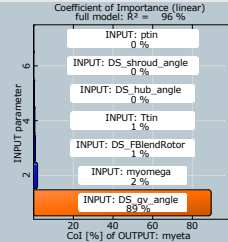
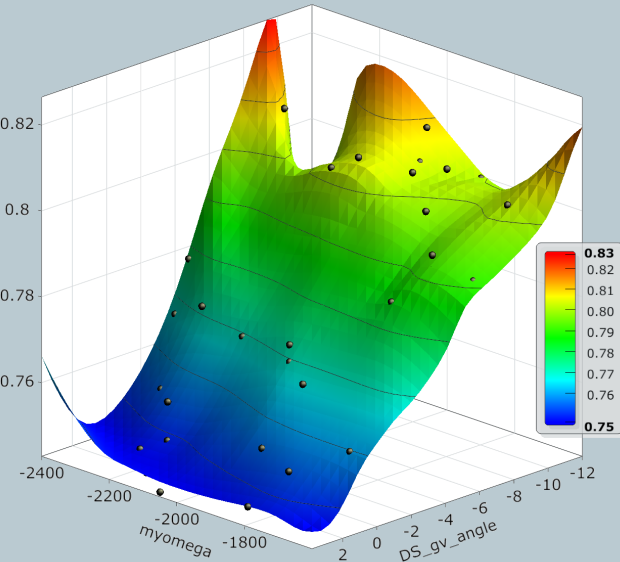
Stochastic constraint: maximal temperature



Stochastic constraint: max. displacement

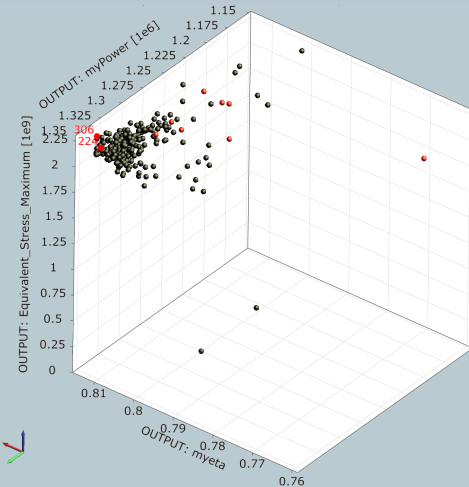


Sensitivity analysis: efficiency

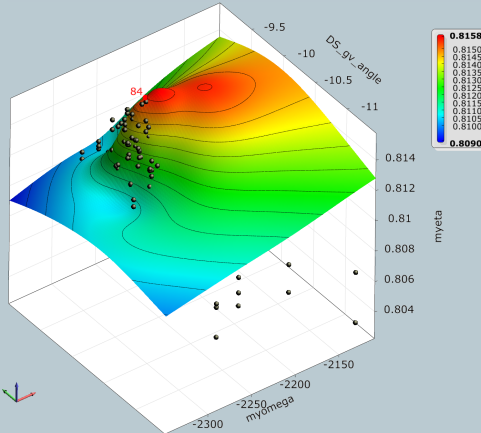


- non-convex objective requires:
- global search strategy (EA) in combination with
- local optimization (ARSM)

Optimization



Evolutionary Algorithm ($N = 224$)



Adaptive RSM ($N = 84$)

No free lunch theorem for optimization

(Wolpert and Macready 1997):

„We show that all algorithms that search for an extremum of a cost function perform exactly the same, when averaged over all possible cost functions.“

Stochastic optimization problem

$$f(d_1, d_2, \dots, d_{n_d}, \sigma_{X_1}^2, \sigma_{X_2}^2, \dots, \sigma_{X_{n_r}}^2, P(\mathcal{F})) \rightarrow \min$$

$$g_k(d_1, d_2, \dots, d_{n_d}) = 0; k = 1, m_e$$

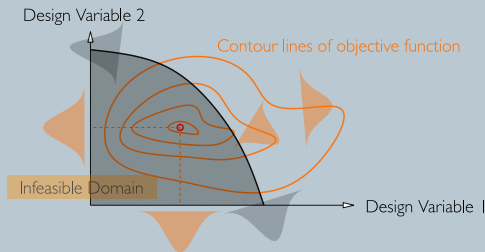
$$h_l(d_1, d_2, \dots, d_{n_d}) \geq 0; l = 1, m_u$$

$$d_i \in [d_l, d_u] \subset \mathbb{R}^{n_d}$$

$$d_l \leq d_i \leq d_u$$

$$d_i = E[X_i]$$

$$\frac{P(\mathcal{F})}{P^t(\mathcal{F})} - 1 \geq 0; \quad \frac{\sigma_L^j}{\sigma_L^t} - 1 \geq 0$$



$$\sigma_{X_i}^2 = \frac{1}{M-1} \sum_{k=1}^M (x_i^k - \mu_{X_i})^2; \quad P(\mathcal{F}) = P[\{\mathbf{X} : g_j(\mathbf{X}) \leq 0\}]$$

Sources of uncertainties

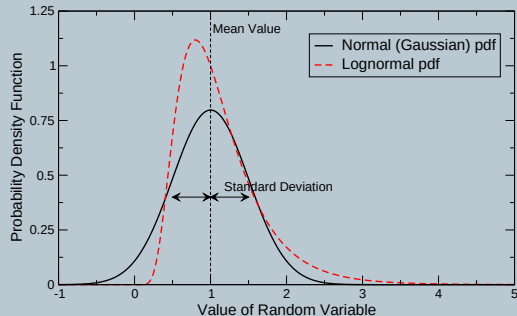
Property	SD/Mean %
Metallic materials, yield	15
Carbon fiber composites, rupture	17
Metallic shells, buckling strength	14
Junction by screws, rivet, welding	8
Bond insert, axial load	12
Honeycomb, tension	16
Honeycomb, shear, compression	10
Honeycomb, face wrinkling	8
Launch vehicle, thrust	5
Transient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



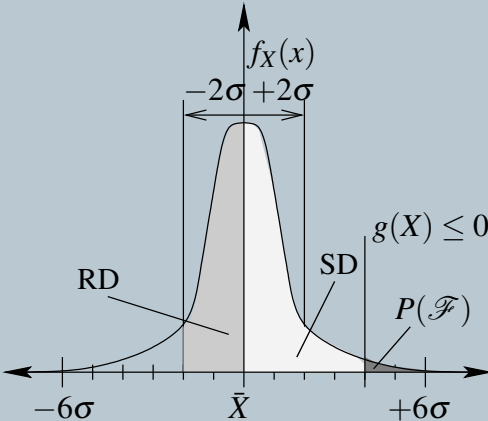
(Source: (Klein, Schuëller, Deymarie, Macke, Courrian, and Capitanio 1994))

Where to get statistical data?

- From lab testing (always best)
- From measurements of suppliers/manufacturers
- From technical references (mostly only mean values provides)
- Estimation - mostly Gaussian or lognormal distribution



Sigma level



Sigma level

$$\sigma_L = \frac{g(X) - \bar{X}}{\sigma_X}$$

specification limit on $2\sigma_X$ and $6\sigma_X$ level. **Robust design** (RD) ($\geq \pm 2\sigma_X$) and **safety design** (SD) ($\geq \pm 6\sigma_X$) depending on specified limit state function $g(X) \leq 0$, e.g. stress limit state.

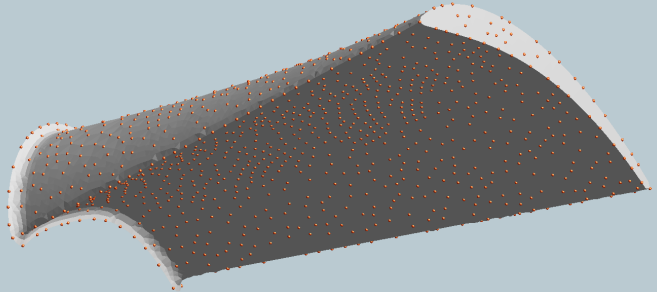
Acceptable probabilities of failure

Values of acceptable annual probabilities of failure $P^t(\mathcal{F})$ and target reliabilities σ_L^t (DNV 1992)¹

Class of failure	Consequence of failure	
	Less serious	Serious
I - Redundant structure	$P^t(\mathcal{F}) = 10^{-3}$ $\sigma_L^t = 3.09$	$P^t(\mathcal{F}) = 10^{-4}$ $\sigma_L^t = 3.71$
II - Significance warning before the occurrence of failure in a non-redundant structure	$P^t(\mathcal{F}) = 10^{-4}$ $\sigma_L^t = 3.71$	$P^t(\mathcal{F}) = 10^{-5}$ $\sigma_L^t = 4.26$
III - No warning before the occurrence of failure in a non-redundant structure	$P^t(\mathcal{F}) = 10^{-5}$ $\sigma_L^t = 4.26$	$P^t(\mathcal{F}) = 10^{-6}$ $\sigma_L^t = 4.75$

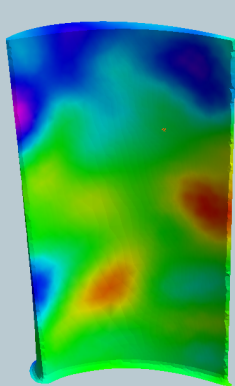
¹Det Norske Veritas (DNV) is an autonomous and independent Foundation with the objective of safeguarding life, property and the environment at sea and ashore.

Measurements of manufacturing tolerances

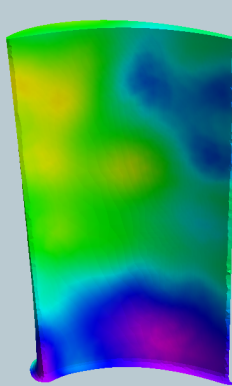
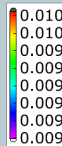


- 3D coordinates (observed with 2 cameras) for **1500 points** (independent of the current geometry)
- **Tolerance interpolation** to different meshes of the multi-physics analysis, **ANSYS Workbench** implementation

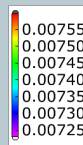
Measurements of manufacturing tolerances



Standard deviation
radial direction y



Standard deviation
tangential direction z



- Mean values and standard deviation of imperfections
- Calculation of the **covariance matrix C_{XX}** of the random field

Modelling of random fields

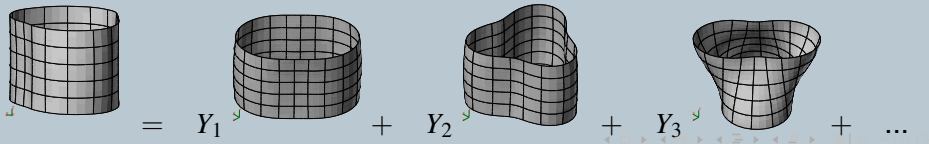
- Decomposition of the covariance matrix:

$$\Psi^T \mathbf{C}_{XX} \Psi = \text{diag}\{\lambda_i\}$$

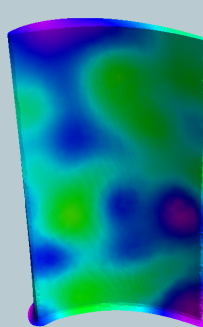
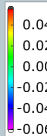
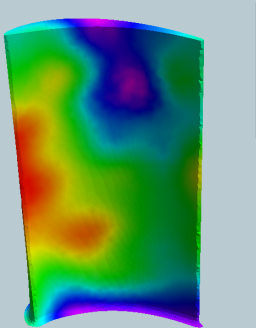
- Simulate **Gaussian** variables $Y_i \sim N(0; \sqrt{\lambda_i})$, $\rho_{i \neq j} = 0$ with variances λ_i
- Transformation between simulated variables $\mathbf{Y}$ and 'real-world'

$$\mathbf{Y} = \Psi^T \mathbf{X} \quad \Leftrightarrow \quad \mathbf{X} = \Psi \mathbf{Y}$$

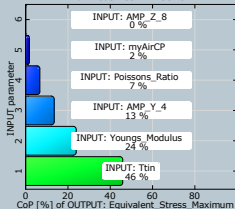
with $\mathbf{Y}$: **matrix of the imperfection modes** (Eigenvectors)



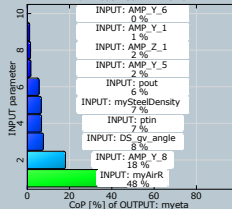
Robustness analysis of an axial turbine



Coefficients of Prognosis (using MoP)
full model: CoP = 96 %



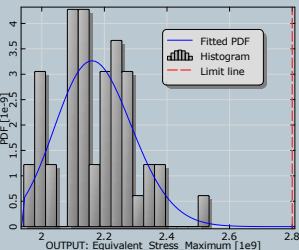
Coefficients of Prognosis (using MoP)
full model: CoP = 75 %



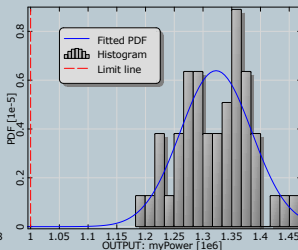
- Identification of $n_r = 9$ random parameters with large prognosis according limit state conditions $g_i, i = 1, \dots, 3$
- Material an process parameters
- 4th and 8th imperfection mode radial direction y
- Angle of the guide vane

Robustness analysis ($\sigma_L \geq 4.5$, $P(\mathcal{F}) \leq 3.4 \cdot 10^{-6}$)

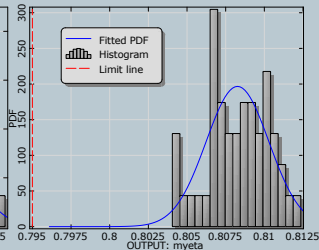
OUTPUT: Equivalent_Stress_Maximum



OUTPUT: myPower



OUTPUT: myeta



Statistic data

Mn:	1.942e+09	Max:	2.535e+09
Mean:	2.171e+09	Sigma:	1.227e+08
CV:	0.0565		
Skew ness:	0.3893	Kurtosis:	3.235

Fitted PDF: Log-Normal

Mean:	2.171e+09	Sigma:	1.227e+08
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Limit x = 2.8e+09

P_rel =	1	P_fit =	0.999997
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Probability P(X<=) = 0.95

x_rel =	2.37151e+09	x_fit =	2.37861e+09
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Statistic data

Mn:	1.183e+06	Max:	1.467e+06
Mean:	1.323e+06	Sigma:	6.246e+04
CV:	0.04722		
Skew ness:	-0.03409	Kurtosis:	2.646

Fitted PDF: Normal

Mean:	1.323e+06	Sigma:	6.246e+04
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Limit x = 1e+06

P_rel =	0	P_fit =	1.19045e-07
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Probability P(X<=) = 0.95

x_rel =	1.43062e+06	x_fit =	1.42543e+06
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Statistic data

Mn:	0.8041	Max:	0.8124
Mean:	0.8083	Sigma:	0.002028
CV:	0.002509		
Skew ness:	-0.1842	Kurtosis:	2.345

Fitted PDF: Normal

Mean:	0.8083	Sigma:	0.002028
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Limit x = 0.795

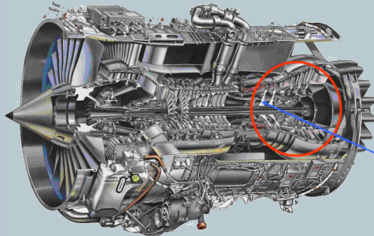
P_rel =	0	P_fit =	3.07755e-11
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Probability P(X<=) = 0.95

x_rel =	0.811073	x_fit =	0.811601
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$$\sigma_L \approx 5.1, P(\mathcal{F}) \approx 5 \cdot 10^{-7} \neq 3 \cdot 10^{-6}, \sigma_L \approx 5.2, \sigma_L \approx 6.6$$

Six sigma analysis & Reliability analysis



- Probabilistic Aerothermal Design of Compressor Airfoils (Garzon 2003)
- Impact of Geometric Variability on Axial Compressor Performance (Garzon and Darmofal 2003)
- Multidisciplinary optimization and reliability analysis of a Two-Stage Turbine (Parchem and Meissner 2009) shows:
- Stochastic analysis should include material, manufacturing uncertainties and process parameters and has to support all sigma levels $\sigma_L^t \leq 4.5...6$

Formula of the failure probability $P(\mathcal{F})$

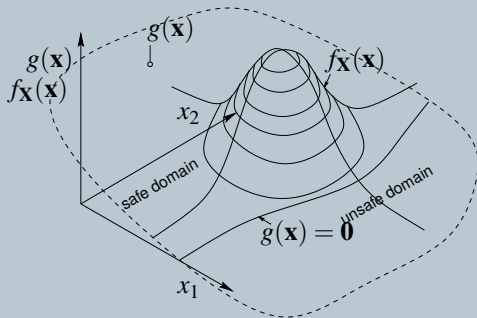
State function of response

$$g(\mathbf{x})$$

Failure state condition:
limit state function

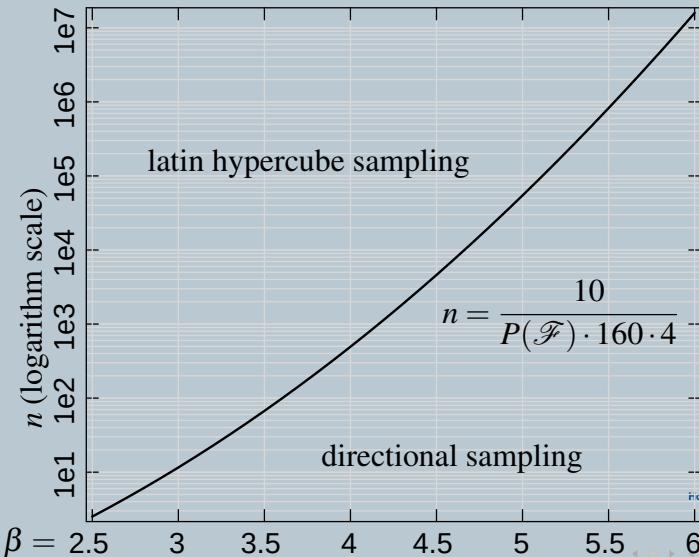
$$g(\mathbf{x}) = g(x_1, x_2, \dots, x_n) \leq 0$$

Joint probability density function $f_{\mathbf{X}}(\mathbf{x})$



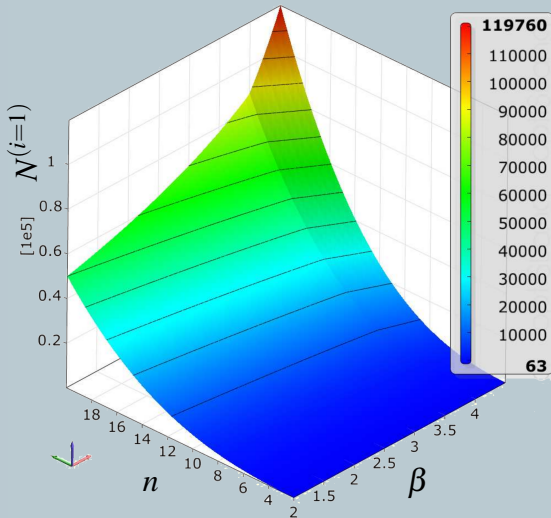
$$P(\mathcal{F}) = P[\mathbf{X} : g(\mathbf{X}) \leq 0] = \int_{g(\mathbf{x}) \leq 0} \dots \int f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$

Directional sampling vs. latin hypercube sampling



- (Bjerager 1988; Ditlevsen and Bjerager 1989)
- limited application area

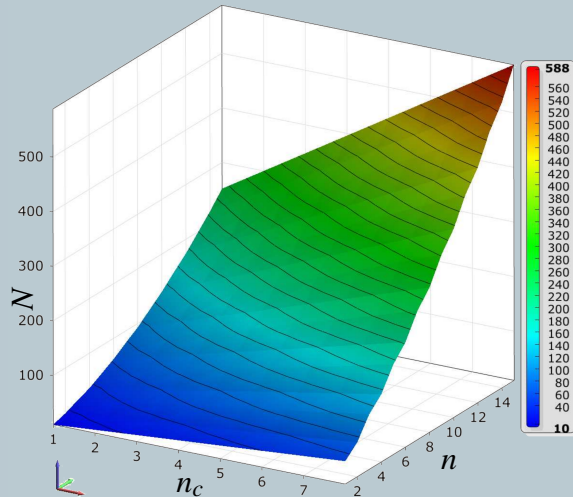
Adaptive importance sampling



- (Bucher 1988)
- minimal initial sample size $N^{(i=1)}$ depending on the
- expected β and the
- number of random variables n
- statistical error:

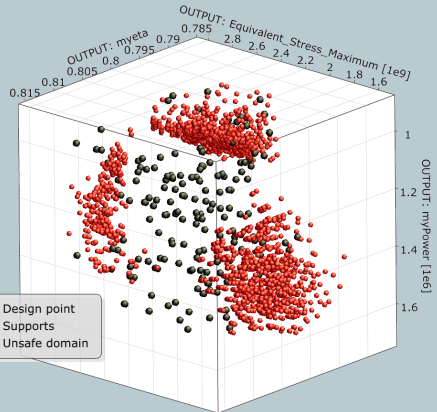
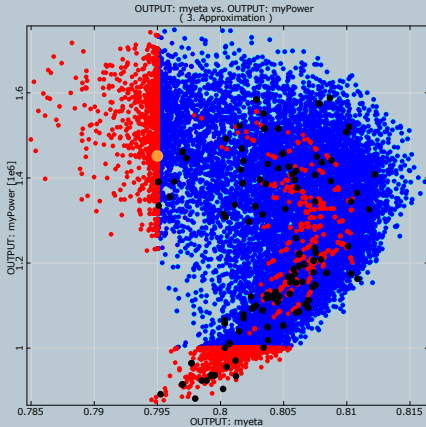
$$\frac{\sigma_{\bar{P}(\mathcal{F})}}{E[\bar{P}(\mathcal{F})]} = 10\%$$

Multi-domain adaptive surrogate models



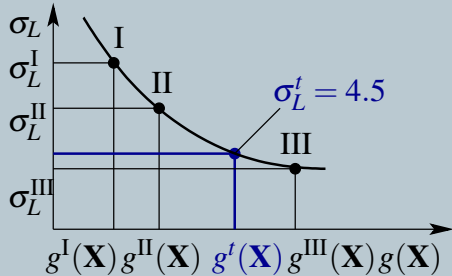
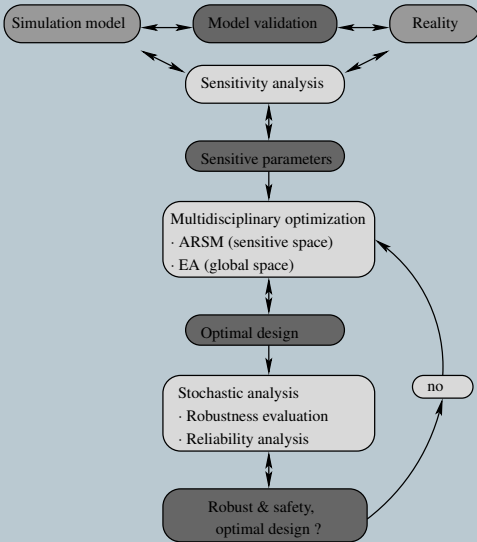
- Simulation method: directional sampling
- **independent** of sigma level ($\sigma_L, P(\mathcal{F})$)
- $P(\mathcal{F}|\mathbf{a})$ -weighted Centroid Cluster Analysis
- D-optimal DOE supports **multiple** failure domains n_c
- (Roos 2011)

Multi-domain adaptive surrogate models



- Number of designs evaluations: $N = 174$
- Six Sigma Design:** $\bar{P}(\mathcal{F}) = 2.6 \cdot 10^{-7} \leq 3.4 \cdot 10^{-6}$
- $\beta = \sigma_L = 5.7 > 4.5$ point: estimation of **partial safety factors**
- FORM: $\bar{P}_\beta(\mathcal{F}) = 7 \cdot 10^{-9}$

Sequential stochastic design optimization



- Within stochastic optimization
- **constrains (including partial safety factors)** $h(\mathbf{X})$ can be formulated as
- **limit state conditions** $g(\mathbf{X})$
- additional optimization effort

Summary

- **Stochastic design optimization**
- Parameters $n = 33$
 - $n_d = 7$ design geometry parameters and process parameters
 - $n_r = 26$ Material parameters and imperfection modes
- Nonlinear multi-physics analysis
- $N = 36 + 224 + 84 + 47 + 2 \cdot (90 + 40) + 174 \approx 800$ design evaluations
- **ANSYS Workbench**: 5 Parallel Tasks
- Calculation time: **48 hours** (2 Intel® Xeon® X5680 Six Core, 3.33 GHz, 12MB Cache)
- **Acknowledgement**: thanks to Ulrike Adams and Daniela Ochsenfahrt of the DYNARDO GmbH (method implementation into the **optiSLang** software package)

Forschungspartner gesucht für

„Robust-Design-Optimierung in der Fluid-Struktur-Analyse von Gasturbinen und Strahltriebwerken unter Berücksichtigung von Fertigungstoleranzen“

- wissenschaftliche Problemstellungen:
 - Effizienzsteigerung der stochastischen Design-Optimierung
 - effiziente Modellierung räumlich korrelierter Oberflächenabweichungen
 - Anwendung auf rechenzeitintensive, komplexe FSI-Simulationen im Turbomaschinenbau
- Projektpartner:
 - Prof. Dr.-Ing. Dirk Roos, IMH (Robust-Design-Optimierung)
 - Prof. Dr.-Ing. Peter Farber, IMH (Strömungsmechanik)
 - Dr.-Ing. Johannes Einzinger, ANSYS Germany GmbH
 - Prof. Dr.-Ing. M. Geller, Institut für Konstruktion und Simulation, Fachhochschule Dortmund (Fluid-Struktur-Interaktion)
 - ???

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