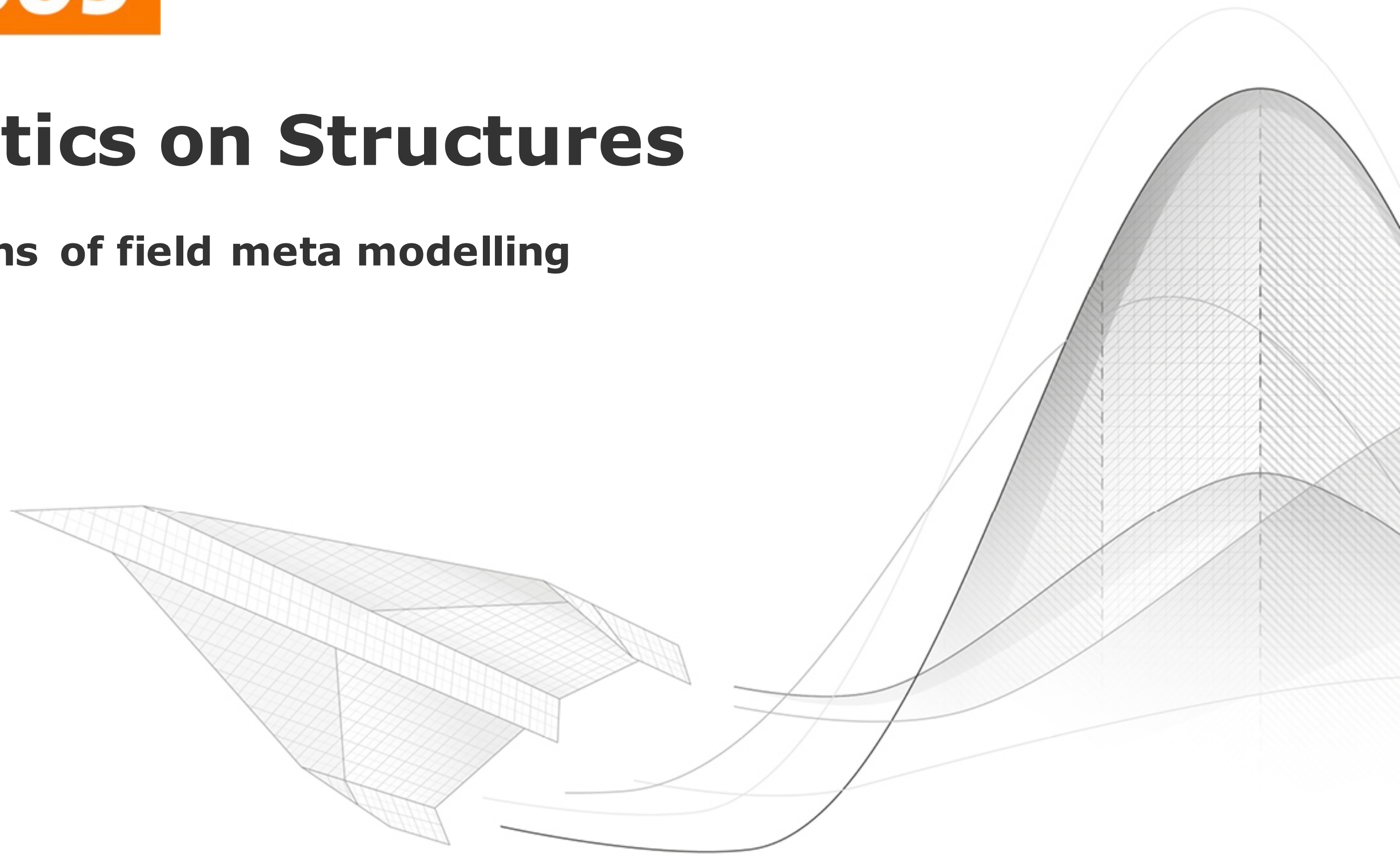
SoS

Statistics on Structures

Applications of field meta modelling



Robust design optimization

1st Sensitivity Analysis

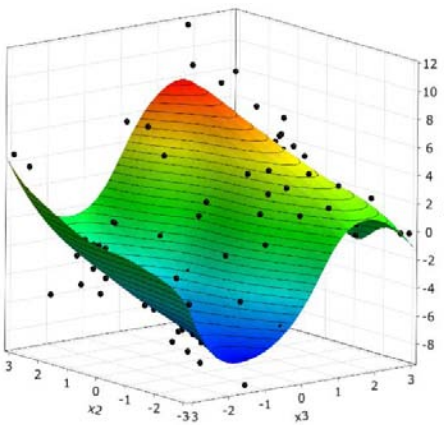
Quantification of parameter importance

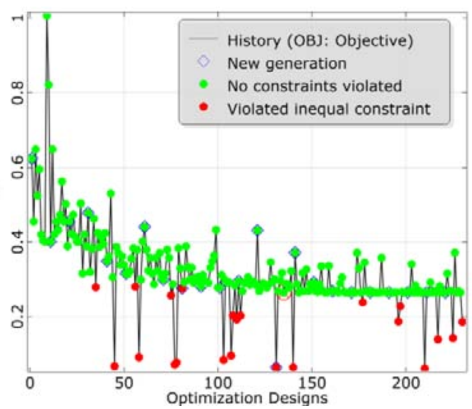
2nd Multidisciplinary Optimization

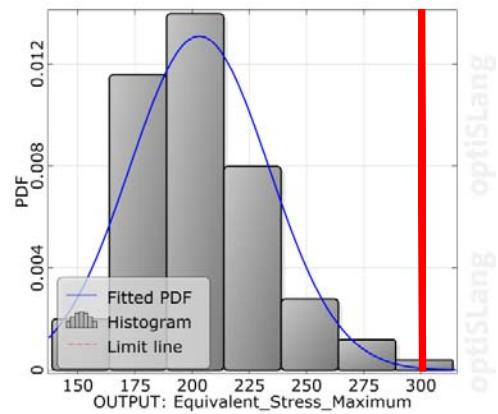
Adaptive Response Surface, Evolutionary Algorithm, Pareto Optimization

3rd Robustness Evaluation

Variance based robustness analysis



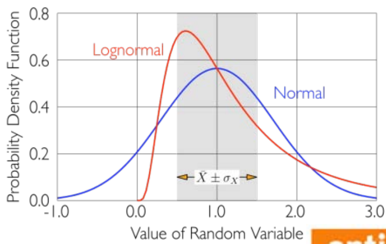


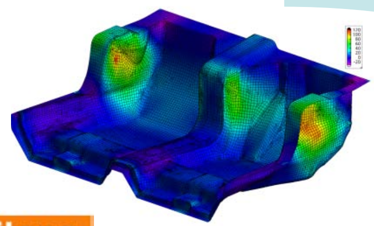


Workflow in variance based robustness analysis

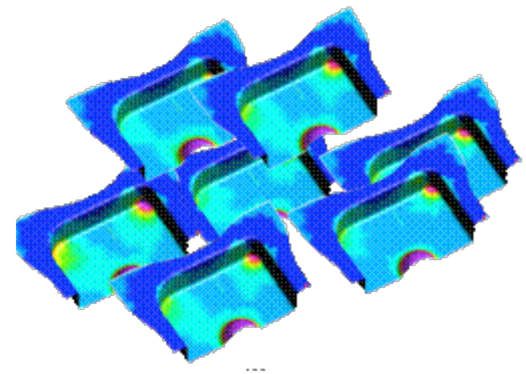
1) Define the robustness space using scatter range, distribution and correlation

2) Sampling: Scan the robustness space by producing and evaluating n designs





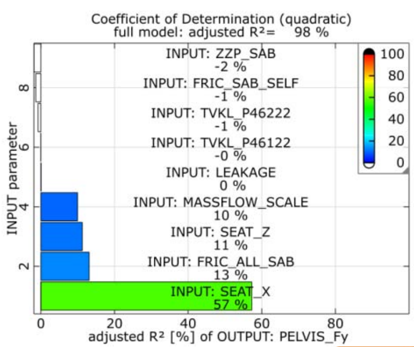
optiSLang



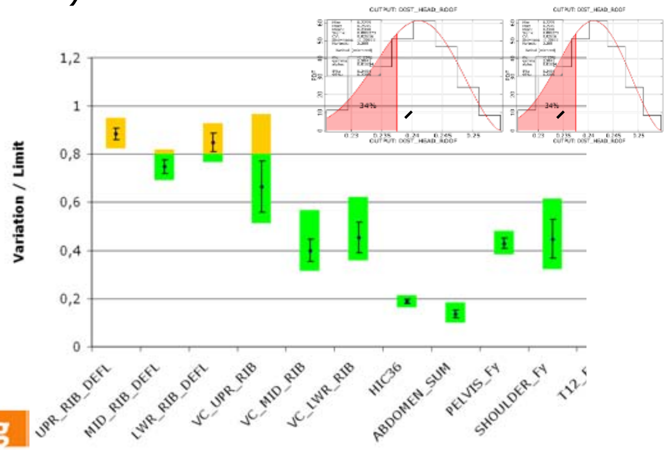
5) Identify the most important scattering variables

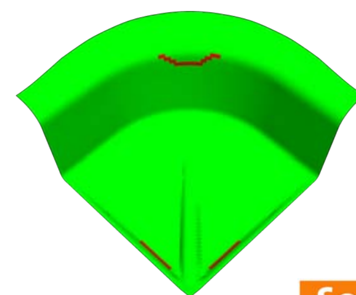
4) Check the variation

3) Identify hot spots



optiSLang



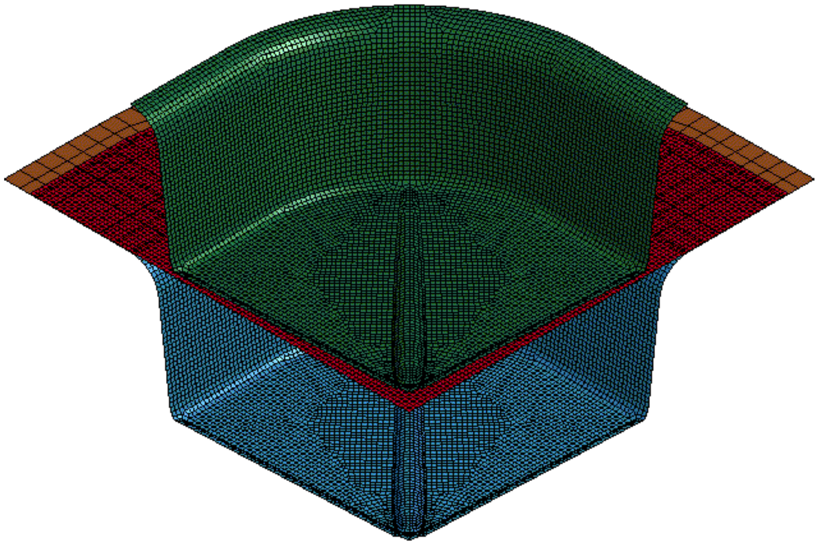


SoS

Why random fields ?

Robustness example
Deep drawing

- Simulation of production process
- Analysis of random variations of production parameters
- Robustness goals: max. pstrain and max. thinning exceed critical thresholds by max. probability p
- Solution using scalar parameters: Analyse statistics of maximum values
- Problem: **Varying position of maximum plastic strain** and maximum thinning
- optiSLang + LS-Dyna, 100 designs



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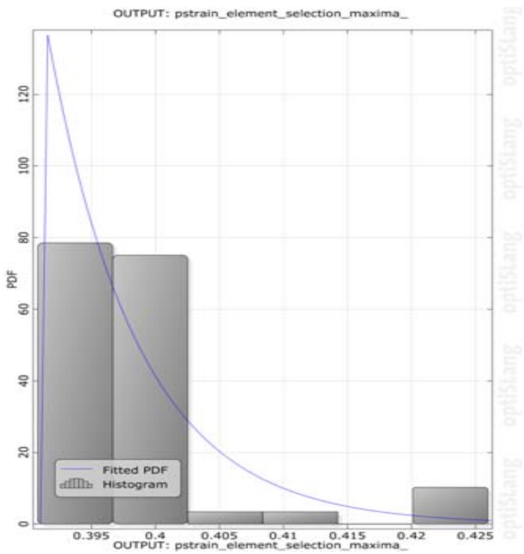
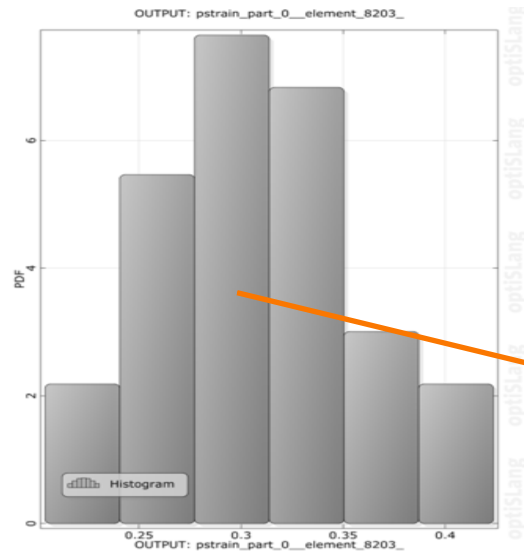
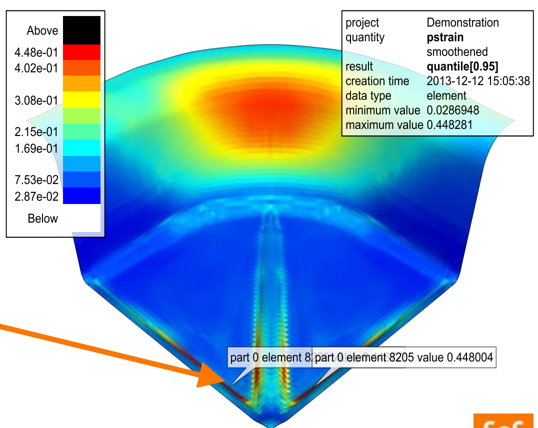
Robustness example
Effect of varying location

- Statistical analysis of

  maximum plastic strain vs. plastic strain at hot spots







SoS

- Sensitivity analysis: Meta model of Optimal Prognosis in optiSLang

  CoP(Total)=86% CoP(Total)=98%

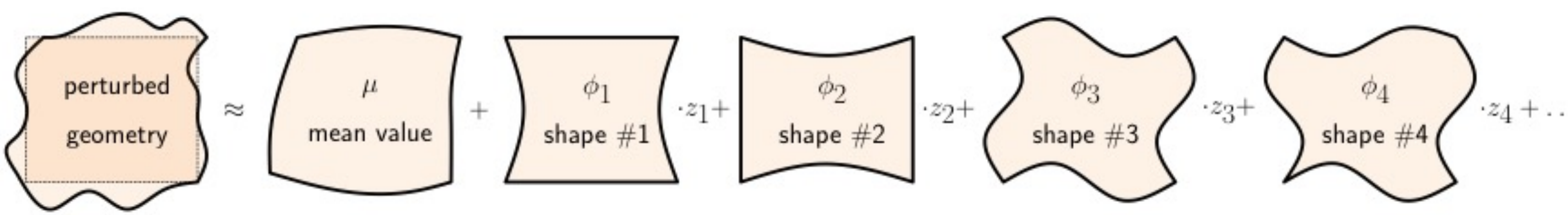
- **Improved accuracy at hot spot instead of maximum value!**

Random fields in space
Karhunen-Loeve expansion for discrete fields

- Karhunen-Loeve expansion: Modal analysis of the covariance matrix
- Spectral representation

$$\mathbf{H} = \mathbf{\Phi z} + \mu_{\mathbf{H}}$$

- Phi: Eigen vectors of covariance matrix (“mode shapes”, “scatter shapes”)
- z: vector of reduced set of uncorrelated random numbers (“amplitudes”)

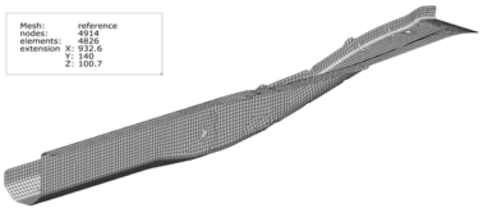


Random fields
Overview on applications

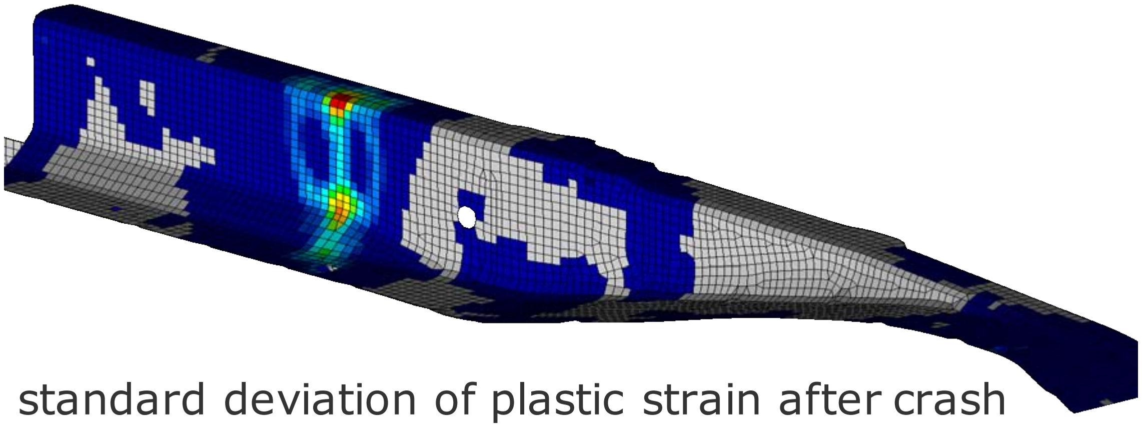
- 1D: signal variations (e.g. time, frequency, load-displacement curves)
- 3D: spatial variations
- **Use random fields as INPUTS or RESPONSES**
- Random fields:
  - **Automatically find optimal parametric to describe field variations**
  - Generate random designs (e.g. random signals – random distribution of temperature profiles in time, or uncertain load-displacement curves)
  - Predict field responses (meta models for signals and 3D fields)
  - Sensitivity analysis of distributed quantities (signals and 3D fields)
  - Statistical smoothening
  - Data reconstruction

Analysis of distributed effects
Example: Nonlinear buckling shapes

- Stringer in a car body subject to crash simulation



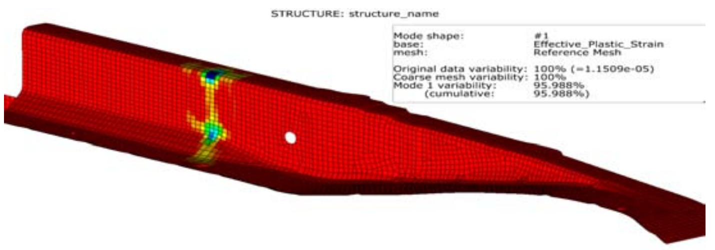
- Hardware experiment: observation of plastic buckling
- Deterministic simulation: plastic effects not reproducible
- Stochastic simulation: DoE and robustness evaluation with optiSLang



standard deviation of plastic strain after crash

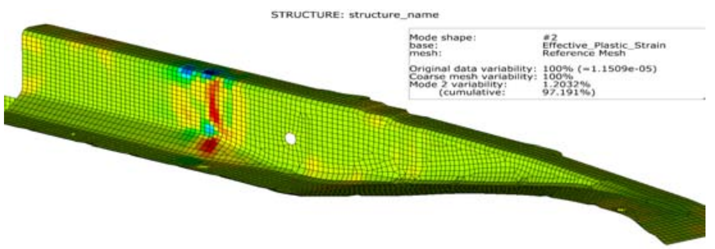
Source: Bayer, Random fields in Statistics on Structures (SoS), WOST 2009

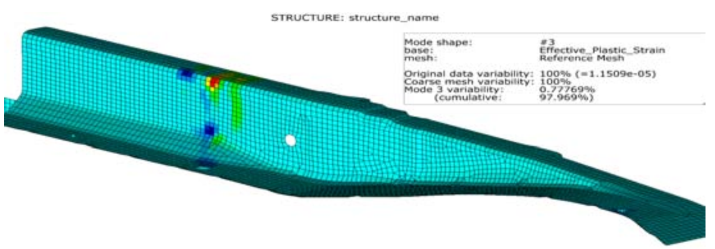
Analysis of distributed effects
Example: Nonlinear buckling shapes



- How to analyse failure sources ? Buckling shape is distributed!

- Decomposition of plastic strain random field into uncorrelated scatter shapes
- Right: 1st three scatter shapes
- Only 3 parameters explain 98% of total variation (compared with original 4826 parameters, one for each element)
- 1st shape (96% of total scatter) explains most of the effects observed in standard deviation



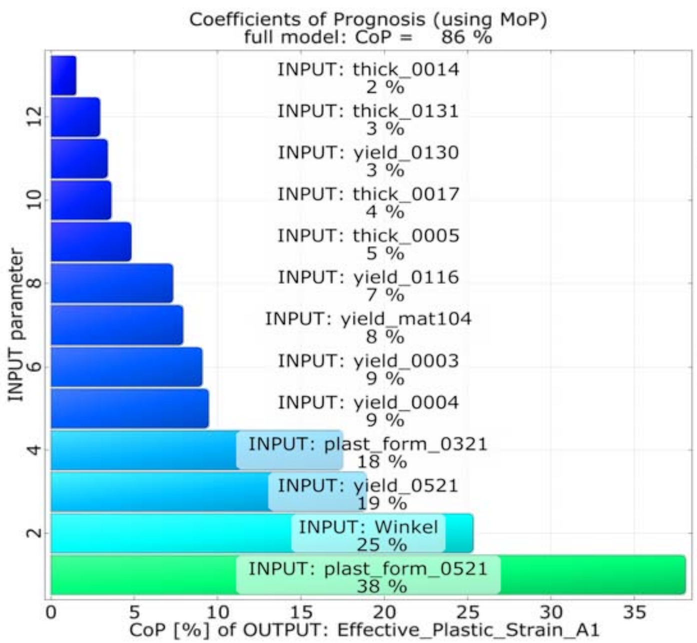


- This strategy is always interesting since typically input parameters affect several locations at same time

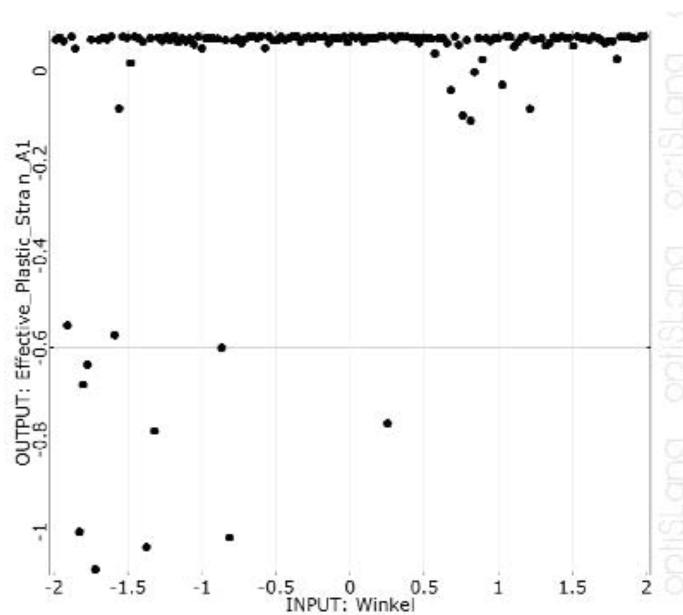
Source: Bayer, Random fields in Statistics on Structures (SoS), WOST 2009

Analysis of distributed effects
Example: Nonlinear buckling shapes

- Solution: 13 of 55 input variables with significant effect on 1st amplitude; These are the initial plastic strains due to manufacturing (forming), the barrier angle and the yield stress



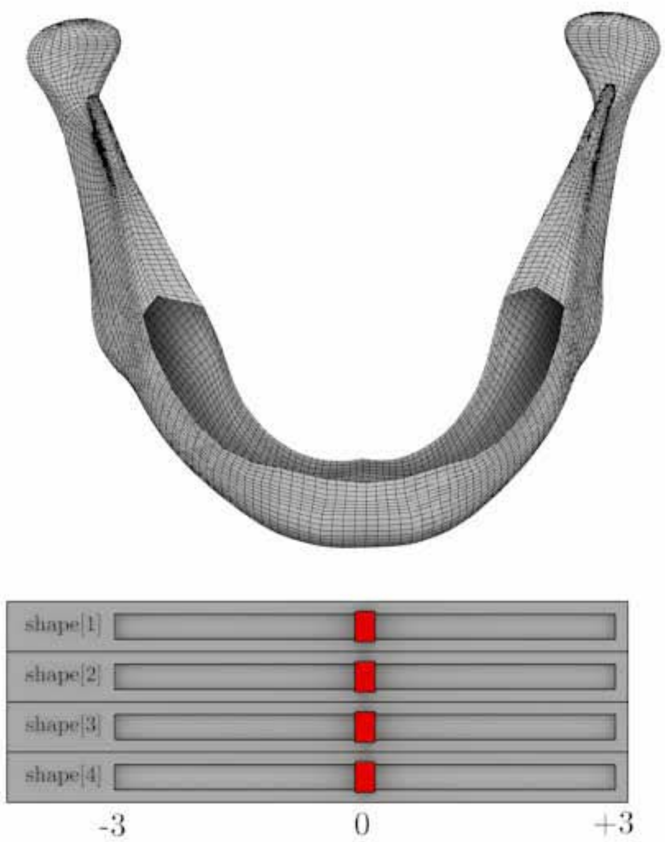
CoP for 1st amplitude



Scatter plot of plastic strain (vert.) over barrier angle (horiz.)

Source: Bayer, Random fields in Statistics on Structures (SoS), WOST 2009

Parameterization of geometric variations
Statistical shape model of human mandible

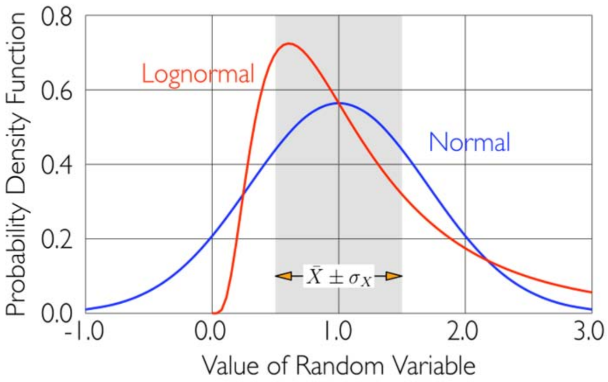


With courtesy of UK Aachen (Source: S. Raith, WOST 2015)

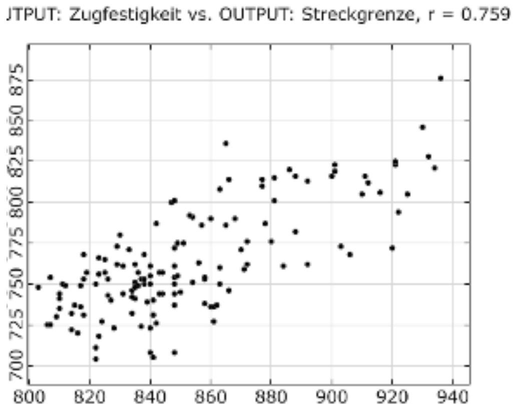
Generation of random designs

Generation of random designs
Definition of uncertainties

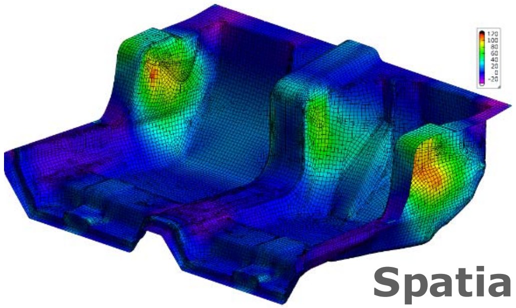
- Translate know-how about uncertainties into proper scatter definition



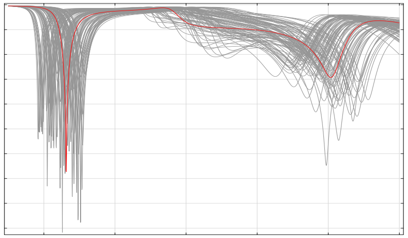
Distribution functions define variable scatter



Correlation is an important characteristic of stochastic variables



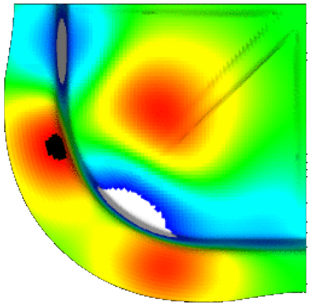
Spatial Correlation random fields



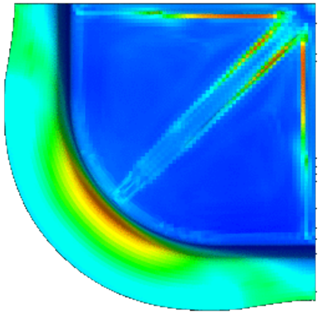
Signal Correlation random fields (in time, freq., etc.)

Generation of random designs
Definition of random fields (1D and 3D)

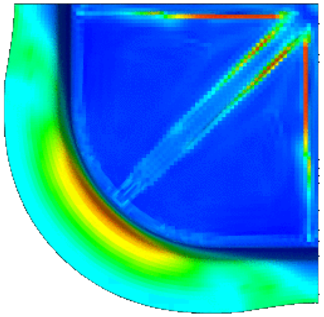
- Depending on available data:
  1. **No/single measurement**:
     assumptions
     (synthetic random field model)



  2. **Few measurements**:
     empirical mean+stddev
     assumed correlation
     (synthetic random field model)



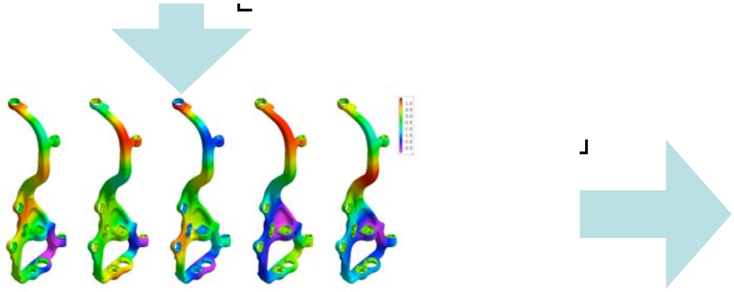
  3. **Many measurements**:
     Empirical random field model
     Anisotropic, inhomogeneous,
     Non-Gaussian



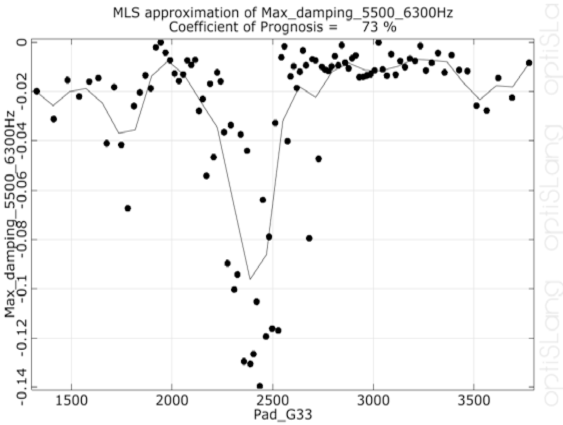
Generation of random designs
Example: Synthetic random fields

- Synthetic random fields: Based on a single or only few measurements
- Spatial correlation defined by numerical model
- Example: Analysis of influence of geometric variations of a knuckle onto frequency of brake squeal noise

difference between measured and modeled geometry of a knuckle



simulation of imperfect geometries



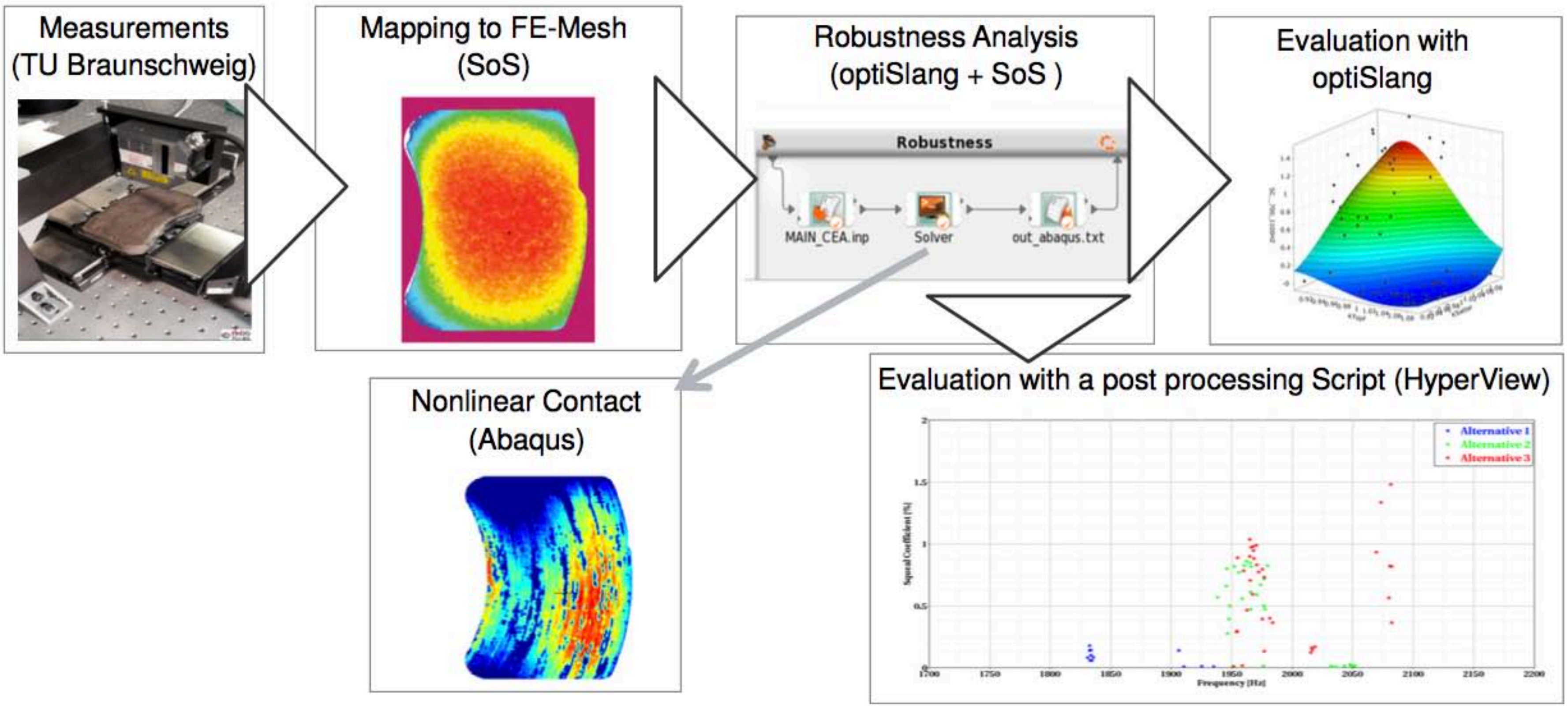
Predict change of Eigen frequencies due to uncertain geometric perturbations

With courtesy of DAIMLER (Sources: Nunes e al, WOST 2009; Wolff, RDO-Journal I/2016)

DAIMLER

dynardo

Generation of random designs
Example: Based on measurements

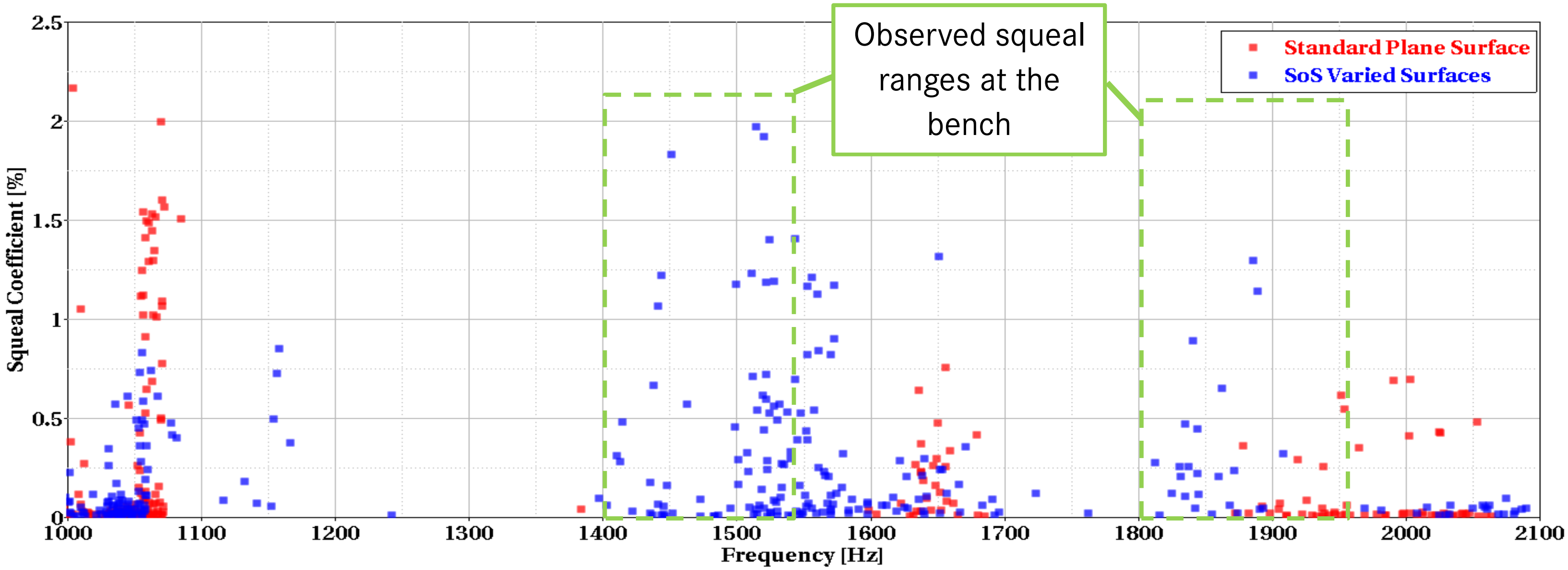


DAIMLER

With courtesy of DAIMLER (Sources: Nunes, WOST 2015; Wolff, RDO-Journal I/2016)

Generation of random designs
Example: Based on measurements (cont.)

- ❑ New Analysis adds random surfaces to the same random designs



→ Higher instabilities occur with a slight change in frequency
→ The frequency at ~1 kHz decreases (→ frequency not observed at bench tests)
→ Mode shapes and contact conditions have to be evaluated carefully

Mercedes-Benz

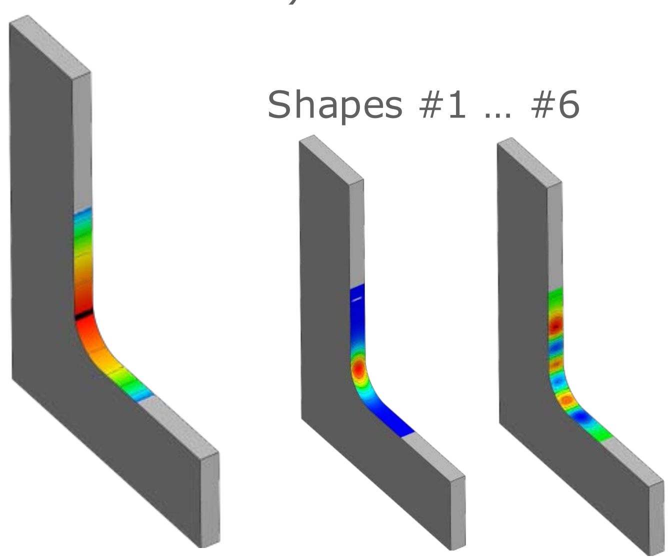
DAIMLER

With courtesy of DAIMLER (Sources: Nunes, WOST 2015; Wolff, RDO-Journal I/2016)

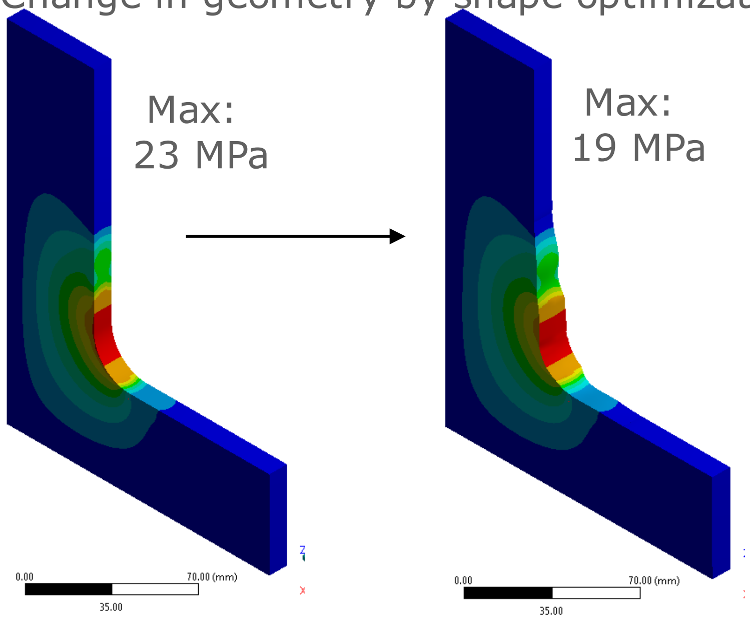
Parameterization of geometries
Shape optimization

- Use synthetic random field model to generate geometric variations on arbitrarily complex geometries
- Example: Shape optimization with ANSYS WB 17 with 6 shapes

Applied variation field
(stddev of random field)



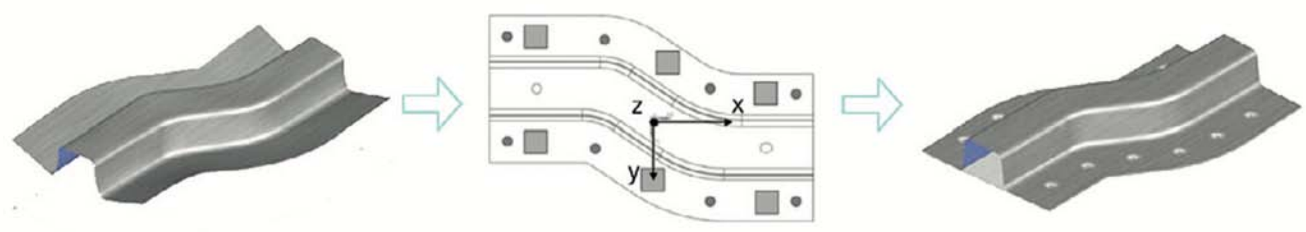
Change in geometry by shape optimization



Sensitivity analysis and approximation

Field meta model
Calibrate model parameters to match geometry

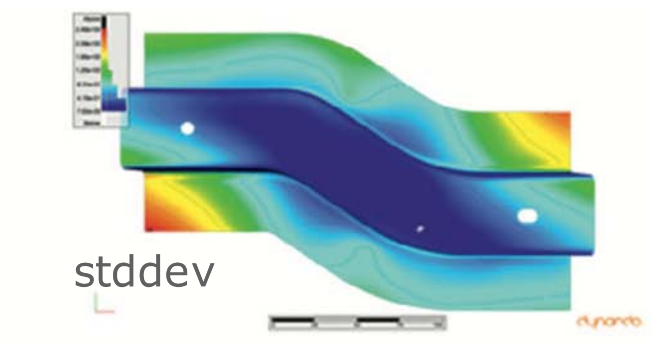
- Task:
  - Calibrate model parameters of a joining process (after deep drawing) to minimize the error between the resulting geometry and the desired CAD0 geometry
  - Identify important joining parameters
  - Estimate maximum geometric deviations



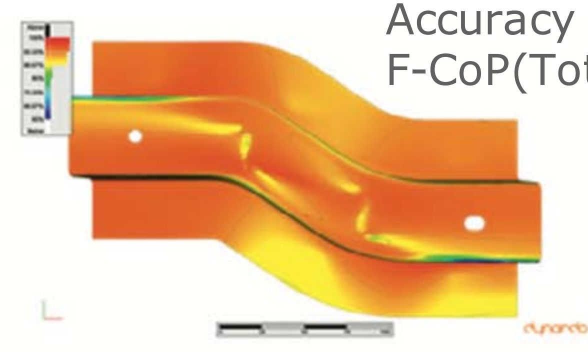
DAIMLER
With courtesy of DAIMLER (Sources: Konrad, WOST 2015; Wolff, RDO-Journal I/2016)

Field meta model
Sensitivity analysis of joining parameters

- Validate field meta model:

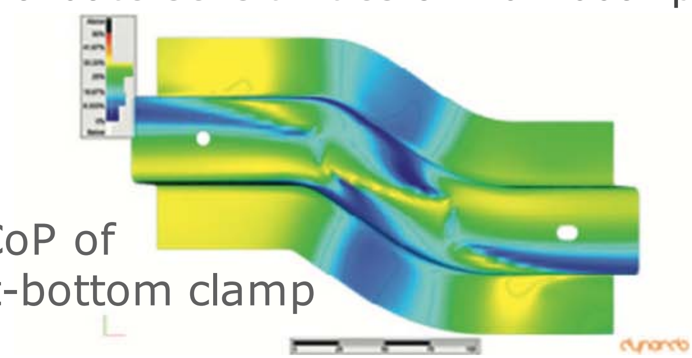


stddev

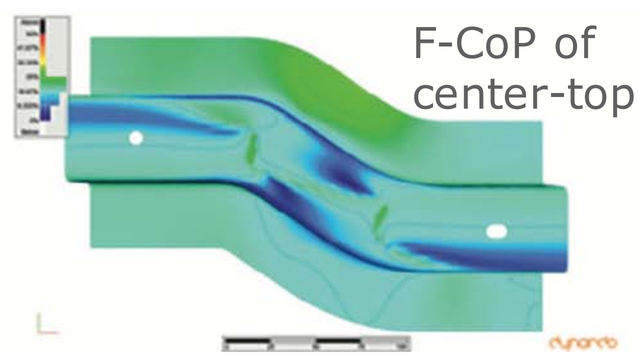


Accuracy of model
F-CoP(Total)

- Validate sensitivities of individual parameters:



F-CoP of
left-bottom clamp

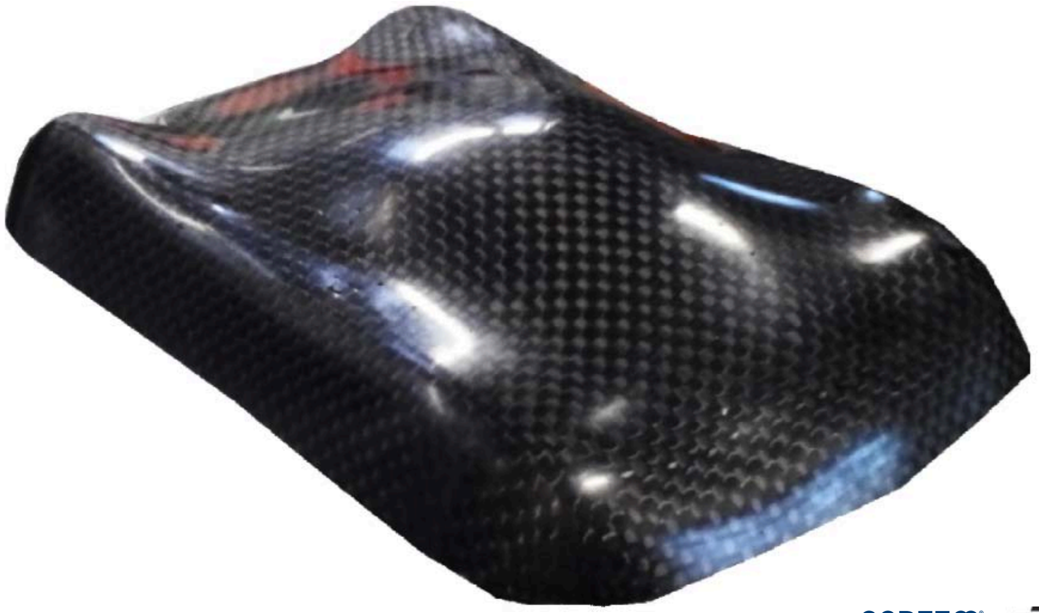


F-CoP of
center-top clamp

DAIMLER
With courtesy of DAIMLER (Sources: Konrad, WOST 2015; Wolff, RDO-Journal I/2016)

Field meta model of fibre angles (composites)
Calibrate draping process parameters

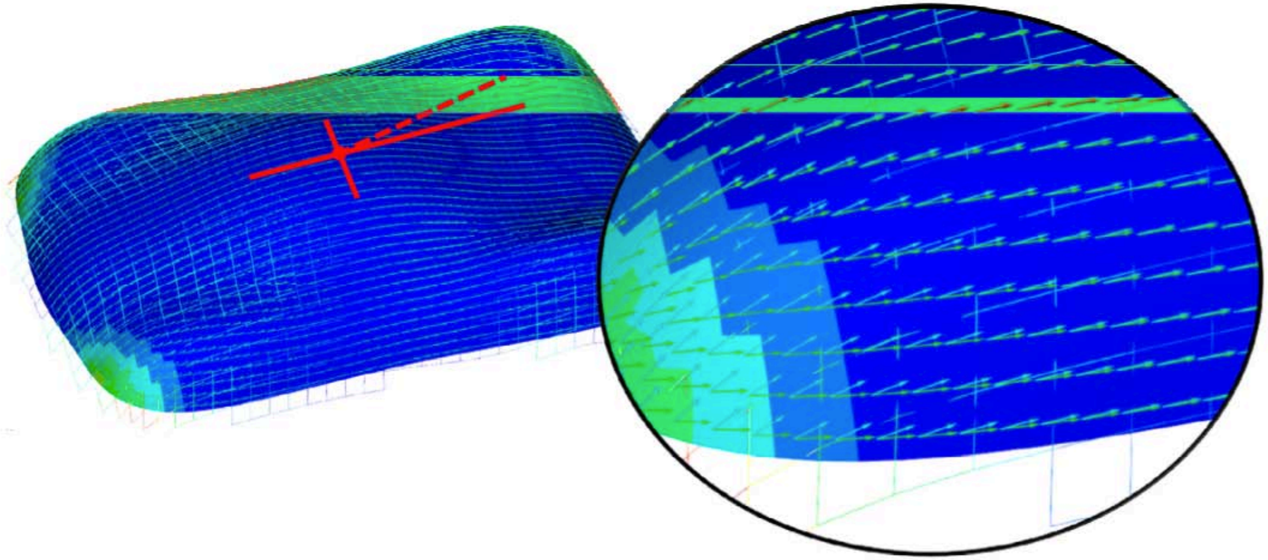
- Given: Measurement of spatial distribution of fibre angles after draping process
- Task: Model calibration of numerical ANSYS model to match fibre angles



With courtesy of CADFEM and KTM Technologies (Sources: Kellermeyer, WOST 2015; Wolff, RDO-Journal I/2016)

Field meta model of fibre angles (composites)
Calibrate draping process parameters

- Average difference in fibre direction between measurement and numerical models:
  - With pre-defined parameters: 7.3°
  - With optimized parameters: 5.2°



With courtesy of CADFEM and KTM Technologies (Sources: Kellermeyer, WOST 2015; Wolff, RDO-Journal I/2016)

Field meta models for signals

Random fields for signal data
One-dimensional variation patterns

- Signals:
  - dynamic processes (time, frequency),
  - load-displacement curves, FLD diagrams, Wöhler curves,
  - dynamic loading conditions (e.g. temperature in time)

- Karhunen-Loeve expansion: Modal analysis of the covariance matrix
- Spectral representation

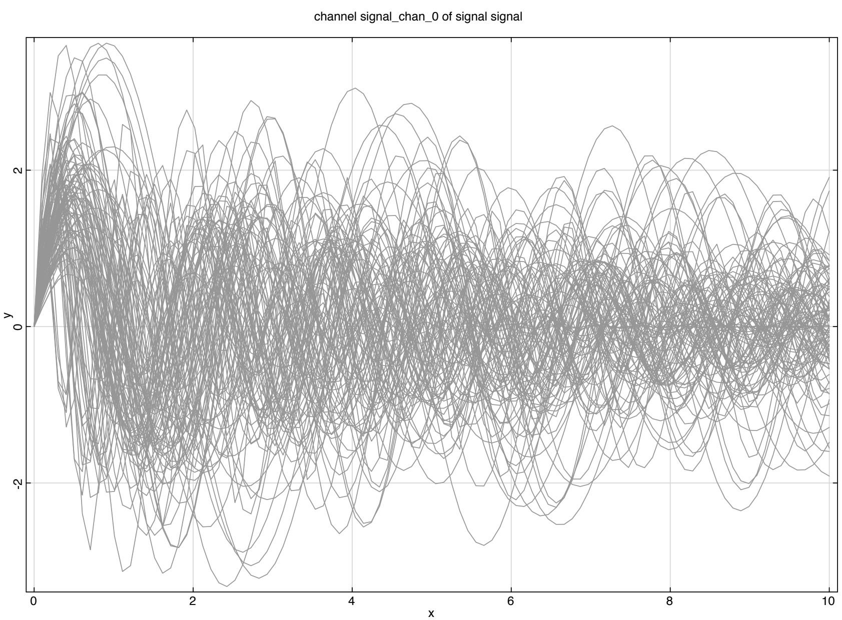
$$\mathbf{H} = \mathbf{\Phi}\mathbf{z} + \mu_{\mathbf{H}}$$

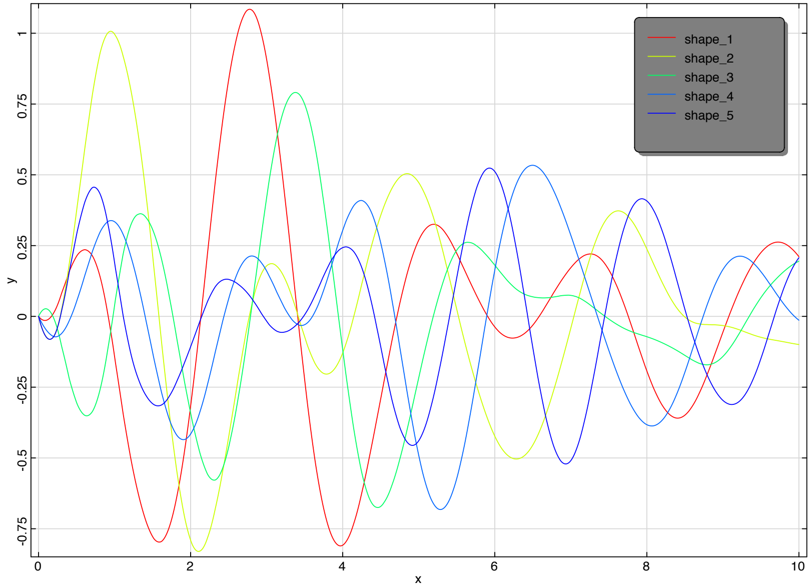
- Phi: Eigen vectors of covariance matrix (“mode shapes”, “scatter shapes”)
- z: vector of reduced set of uncorrelated random numbers (“amplitudes”)

$$\approx \quad + \quad \cdot z_1 + \quad \cdot z_2 + \quad \cdot z_3 + \quad \cdot z_4 + \dots$$

Parameterization of a dynamic process
Analysis of a DoE of a time series

- Generate random signals as solver inputs
- Perform sensitivity analysis and pre-optimization
- Left: Signal responses of Design of Experiments; Right: Scatter shapes (5 parameters)

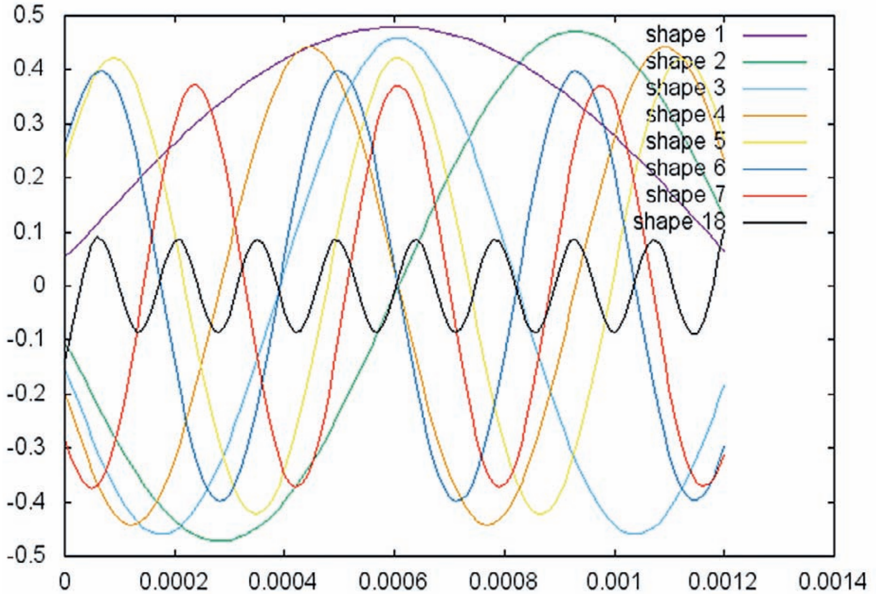




Source: Wolff, RDO-Journal I/2016

Synthetic random fields
Fourier series like approximation of signals

- Example: homogeneous mean (=0) and standard deviation (=1)

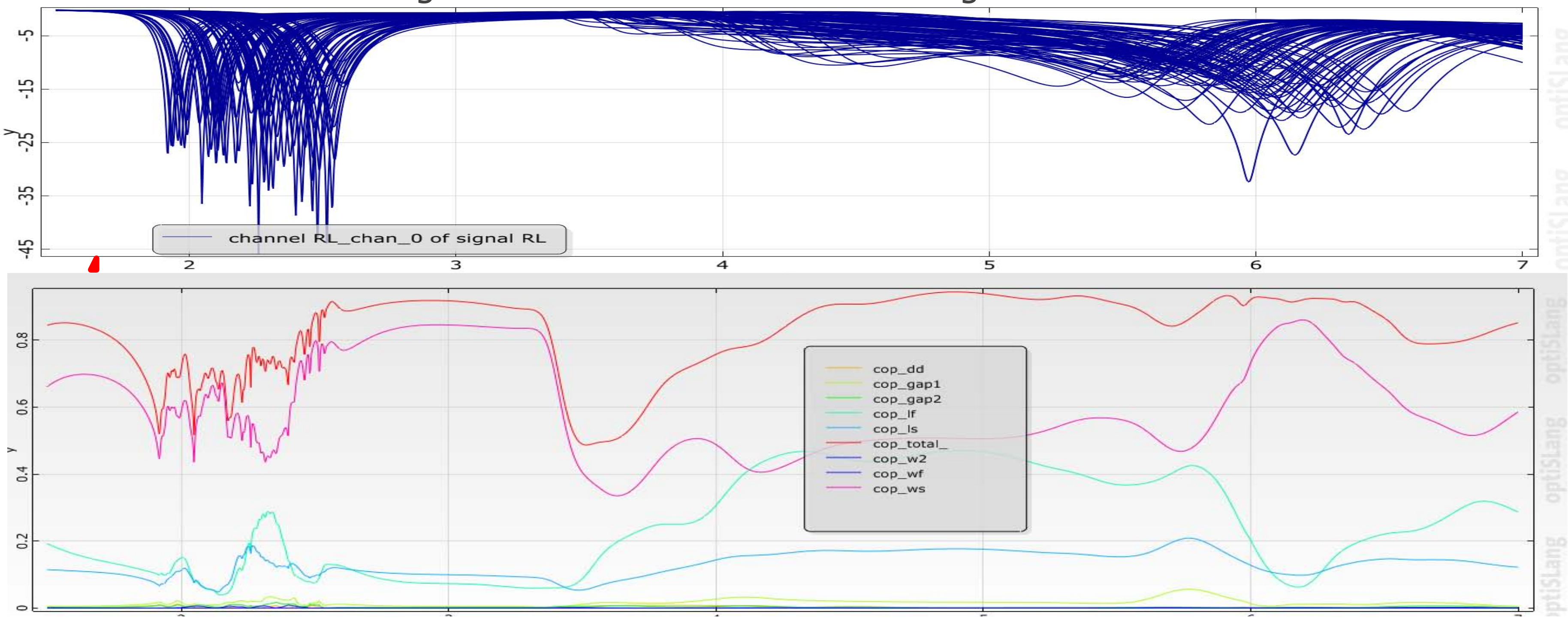


- Synthetic random field models:
  - Define correlation length parameters
  - Define (in)homogeneous distribution of mean and standard deviation

Source: Wolff, RDO-Journal I/2016

Sensitivity analysis of a signal
Return loss of an antenna in frequency domain

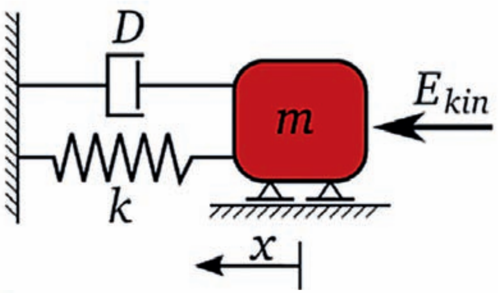
- MOP: Gives only single numbers for pre-defined hot spots or for extremal values
- F-MOP: More insight due to location of low or large sensitivities

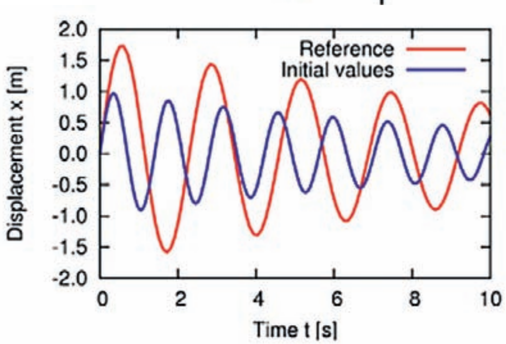


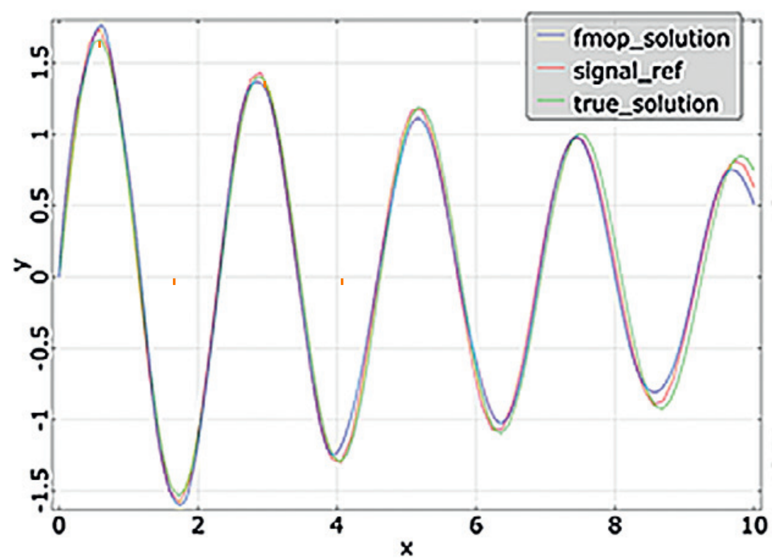
CADFEM With courtesy of CADFEM (Sources: Vidal/Römelsberger, WOST 2015; Wolff, RDO-Journal I/2016)

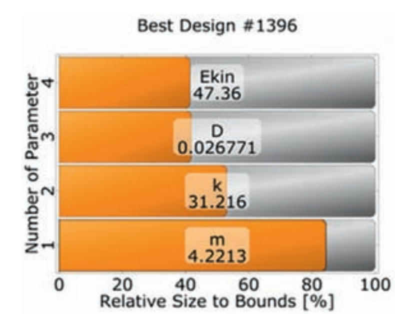
Pre-optimization on field meta model
Model calibration of dynamic process

- Without F-MOP: Find MOP for Euklidian norm or minimize error for values at pre-selected hot spots
- With F-MOP: Find F–MOP for signal and then minimize Euklidian error norm; Consider also shape of signal between discrete support points





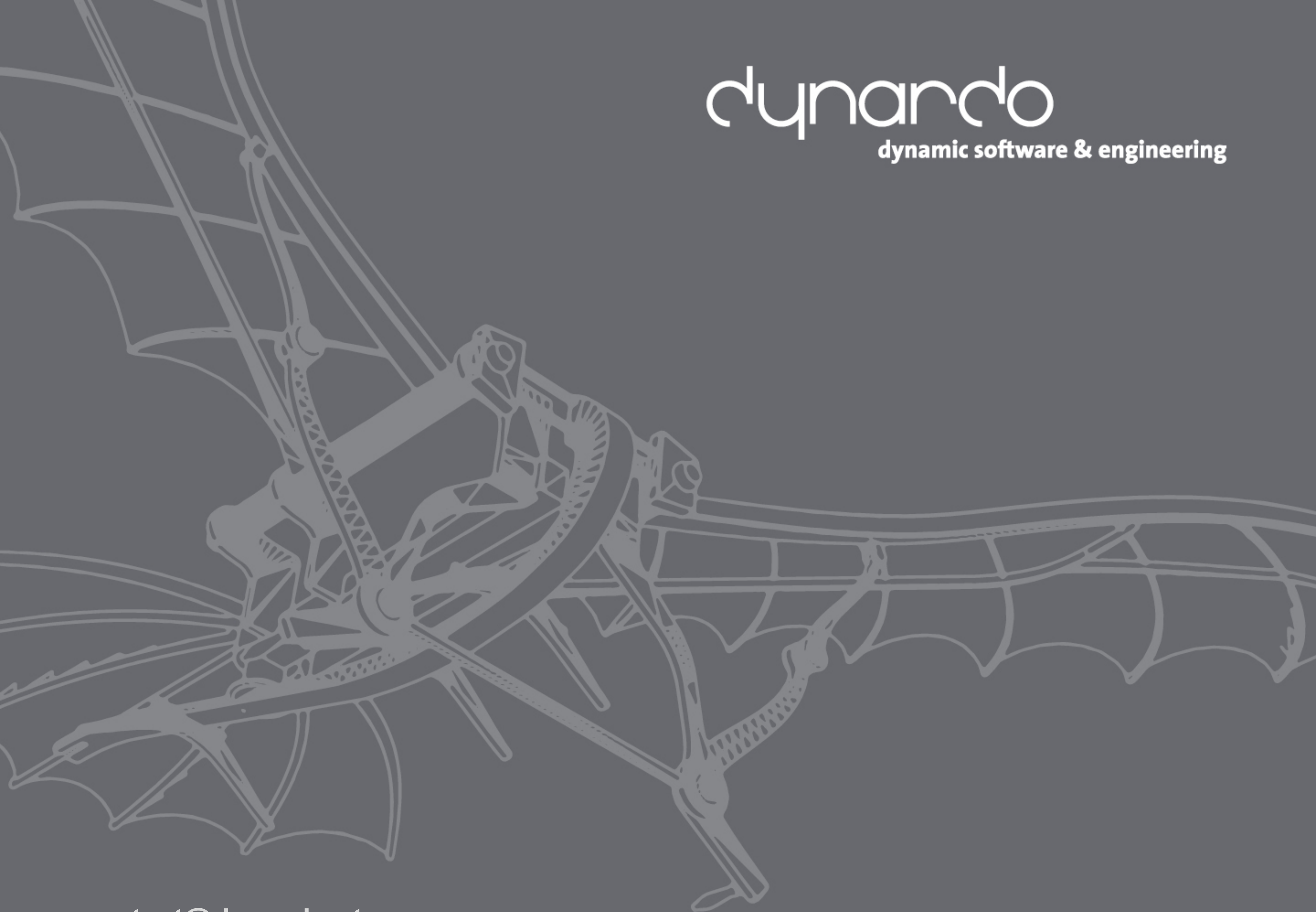




Source: Wolff, RDO-Journal I/2016

Summary
Field meta models and Random fields

- Recommended application if
  - Critical locations in space or time are varying and important
  - Distributed effects are considered (geometries, dynamics)
- Spatial variations (3D) or Signal variations (1D)
- Simple and straight forward methodology to parameterize arbitrarily complex field variations
- Allow better model understanding
- Transfer statistics from measurements into virtual product development
- Can be used to test if expensive measurements need to be obtained
- Can be used to improve
  - Robustness analysis (Generation of random designs)
  - Sensitivity analysis (Add the "location" to CoP values: F-CoP)
  - Pre-optimization (Predictive field meta models: F-MOP solver)



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