Optimierung, Sensitivitäts- und Variationsanalyse von Armaturen

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optiSLang

- is an general purpose tool for variation analysis

using CAE-based design sets (and/or data sets) for the purpose of

- sensitivity analysis
- design/data exploration
- calibration of virtual models to tests
- optimization of product performance
- quantification of product robustness and product reliability
- Robust Design Optimization (RDO)
  and Design for Six Sigma (DFSS)

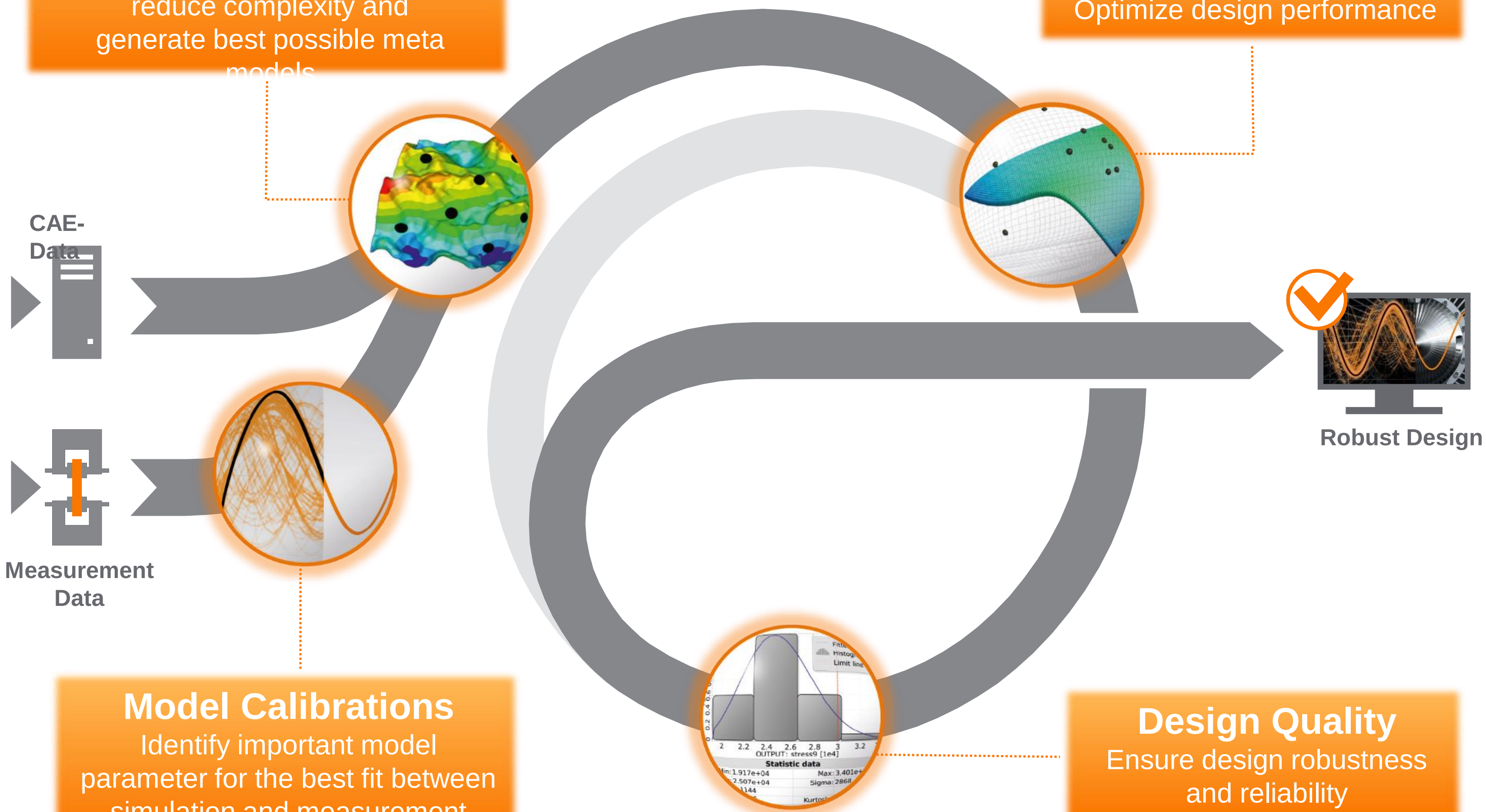
serves arbitrary CAX tools with support of process integration, process automation and workflow generation

Design Understanding

Investigate parameter sensitivities, reduce complexity and generate best possible meta models

Design Improvement

Optimize design performance

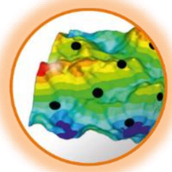


Model Calibrations

Identify important model parameter for the best fit between simulation and measurement

Design Quality

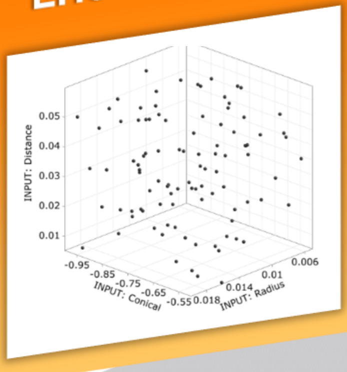
Ensure design robustness and reliability



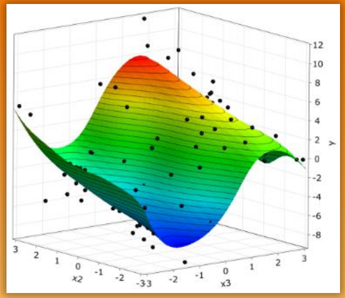
Sensitivity Analysis

Understand the most important input variables!

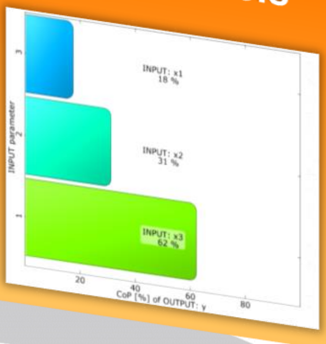
LHS-Sampling



MOP- Metamodel of Optimal Prognosis



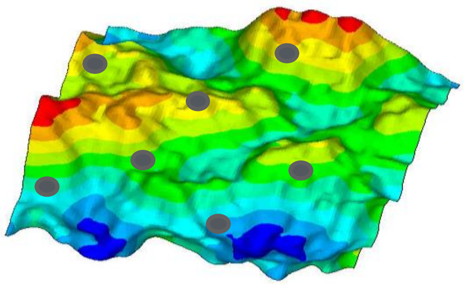
CoP - Coefficent of Prognosis



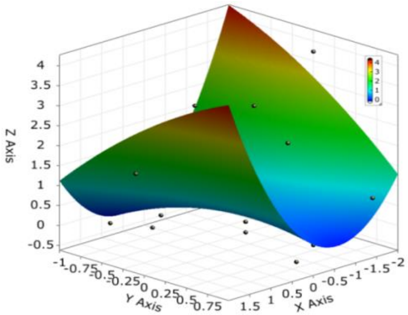
<u>Automatic workflow</u>
<u>with a minimum of solver runs to:</u>

- **identify the important parameters for each response**
- **Generate best possible metamodel (MOP) for each response**
- **understand and reduce the optimization task**
- **check solver and extraction noise**

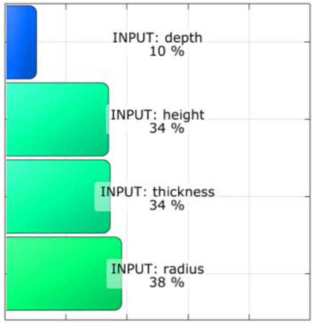
Sensitivity Analysis Flowchart



Design of Experiments
- Deterministic
- (Quasi-)Random

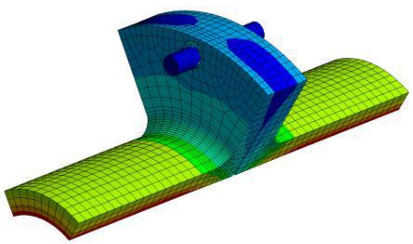


Regression Methods
- 1D regression
- nD polynomials
- Sophisticated metamodels



Sensitivity Evaluation
- Correlations
- Variance-based quantification

Solver

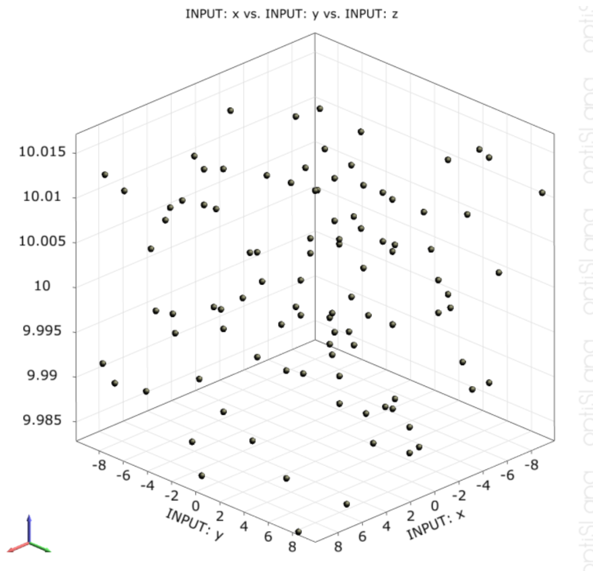


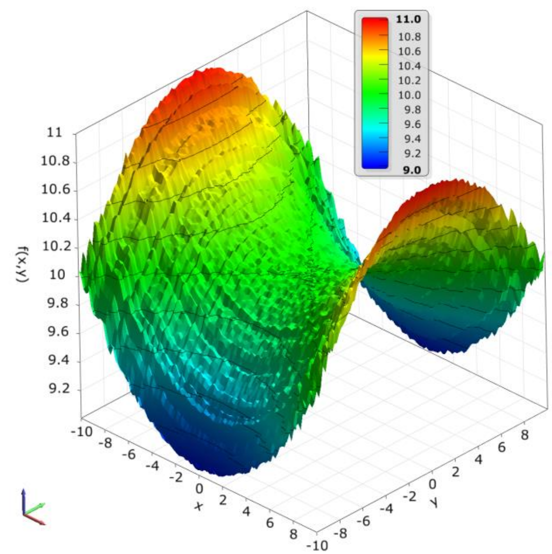
1. Design of Experiments generates a specific number of designs which are all evaluated by the solver
2. Regression methods approximate the solver responses to understand and to assess its behavior
3. The variable influence is quantified using the approximation functions

Scanning the Design Space

Inputs | Design of Experiments | Model evaluation | Outputs

$$X_1, X_2, \vdots, X_k$$

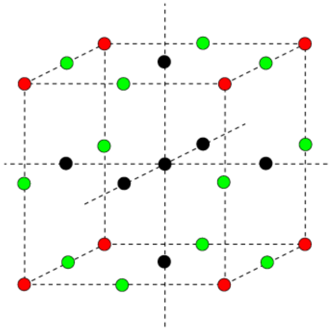




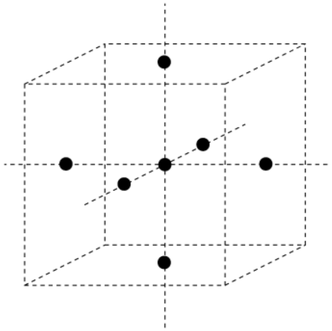
$$Y_1, Y_2, \vdots, Y_m$$

- Minimum number of designs should cover the input space optimally and avoid clustering and unwanted correlations
- For each design the outputs are calculated or measured

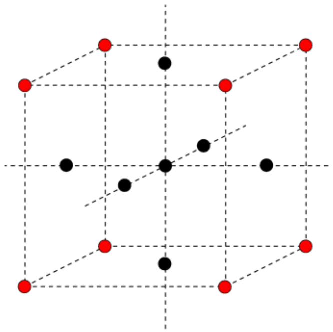
Some Deterministic and random DOE schemes



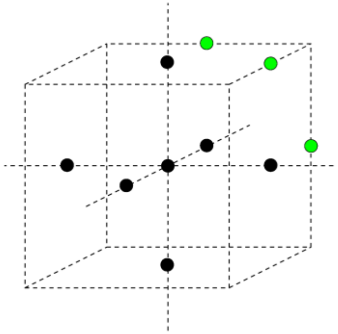
Full-factorial



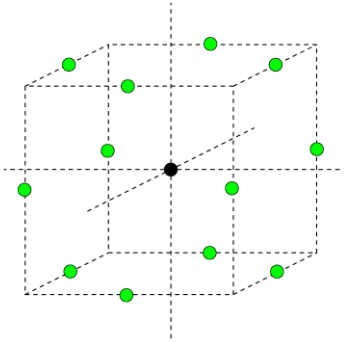
Star points



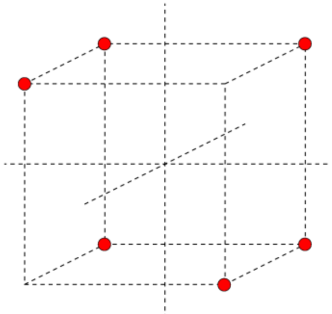
Central composite



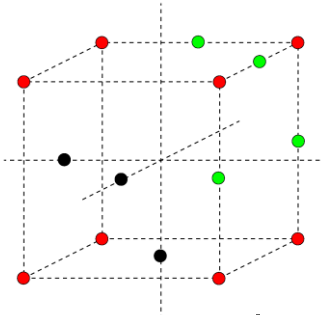
Koshal quadratic



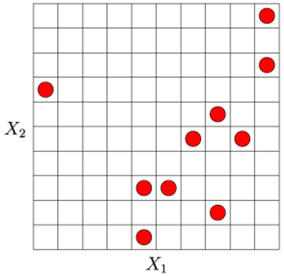
Box-Behnken



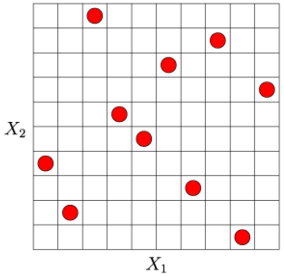
D-optimal linear



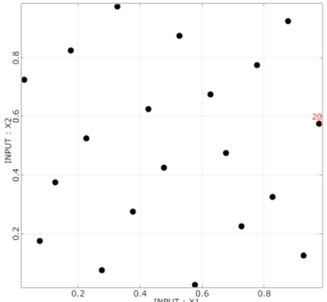
D-optimal quadratic



Monte Carlo



Latin Hypercube

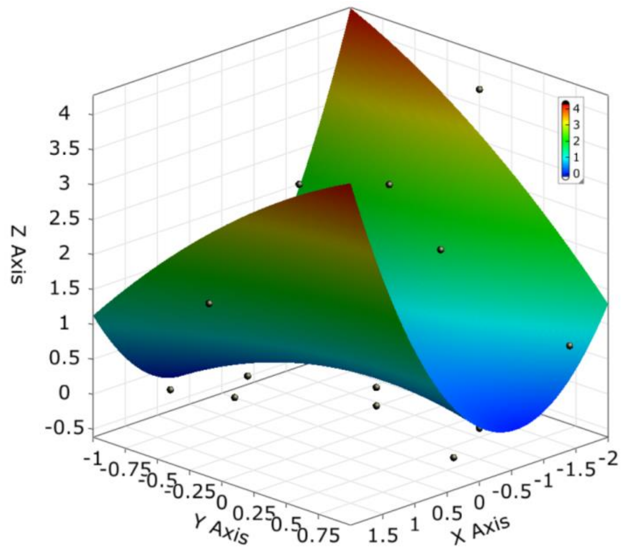


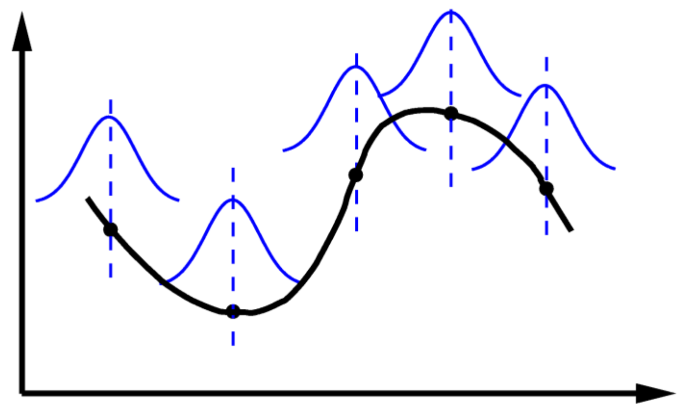
Space-filling LHS

- Choice depends on number of parameters, type of parameters (continuous/discrete), max. number of solver runs

Response Surface Method

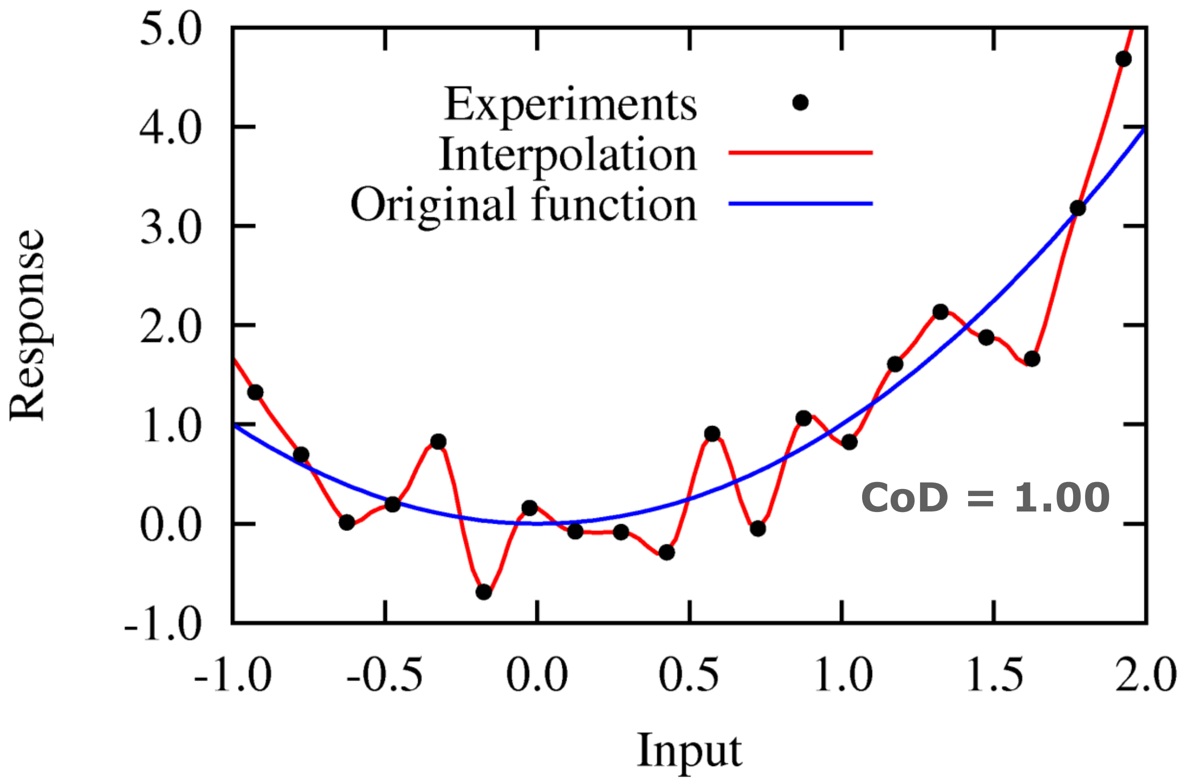
- Approximation of response variables as explicit function of all input variables
- Approximation function can be used for sensitivity analysis and/or optimization
- Global methods (**Polynomial regression**, Neural Networks, …)
- Local methods (Spline interpolation, **Moving Least Squares**, Radial Basis Functions, **Kriging**, …)
- Approximation quality decreases with increasing input dimension
- Successful application requires objective measures of the prognosis quality





Measure Goodness of Fit = Coefficient of Determination (CoD)

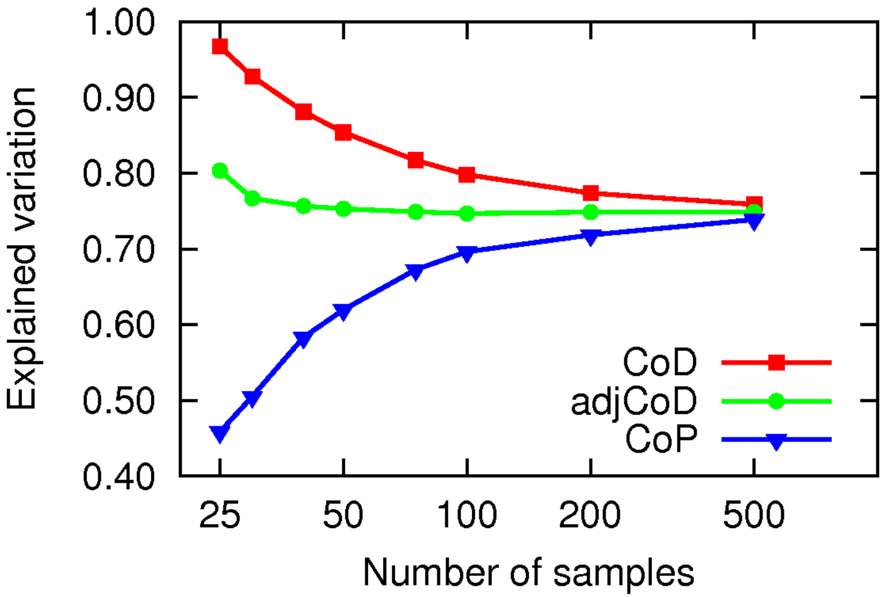
- Coefficient of Determination quantifies merely the Goodness of Fit.
- Interpolation models (e.g. MLS, Kriging) can reach CoD of 1.00
- **But perfect fit does not mean perfect forecast quality!**



Coefficient of Prognosis (CoP)

- The CoP measures how good the regression generalizes for unknown data points
- Fraction of explained variation of the prediction of a response

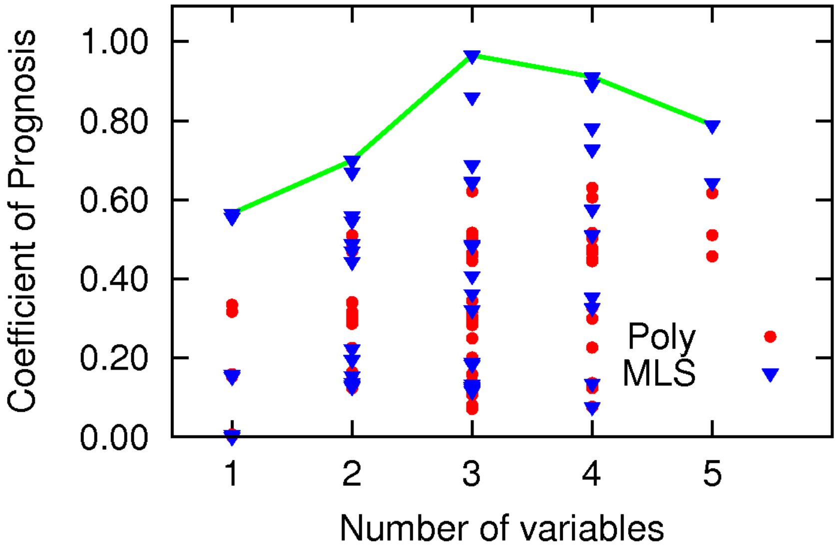
$$CoP = 1 - \frac{SS_E^{Prediction}}{SS_T}$$

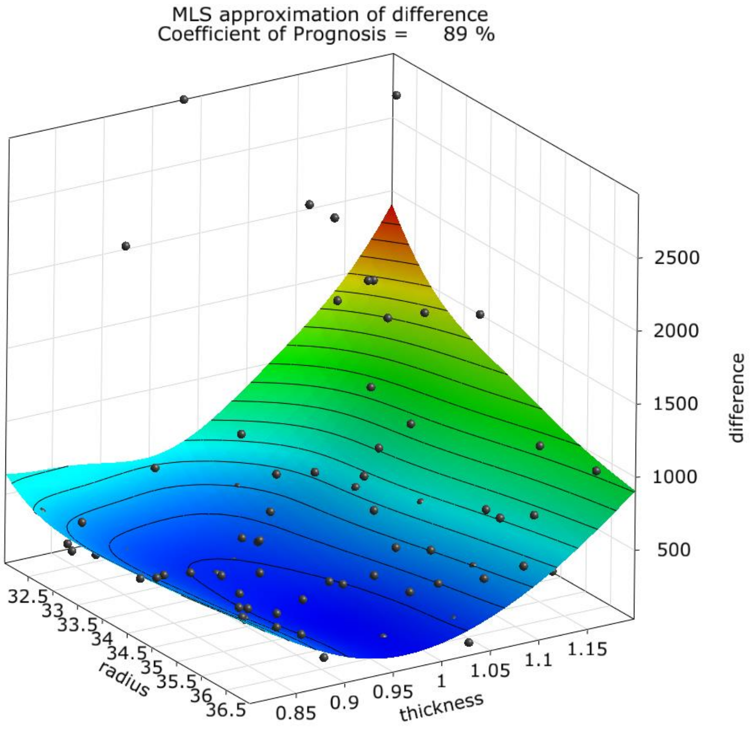


- CoP increases with increasing number of samples
- ➢ It assesses the approximation quality much more reliable than the CoD
- CoP is model-independent and suitable for other meta-models
- Estimation of CoP by additional (new) data set causes additional effort
- ➢ Cross validation using a partitioning of the available samples is applied

Metamodel of Optimal Prognosis (MOP)

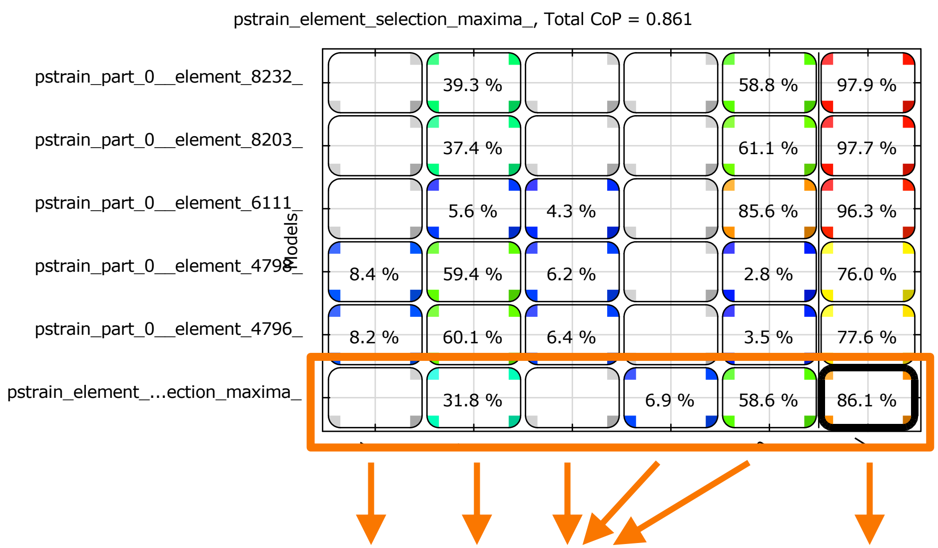
- Objective measure of **prognosis quality**
- Determination of **relevant parameter subspace**
- Determination of **optimal approximation model**
- Approximation of solver output by fast surrogate model **without over-fitting**
- Evaluation of **variable sensitivities**

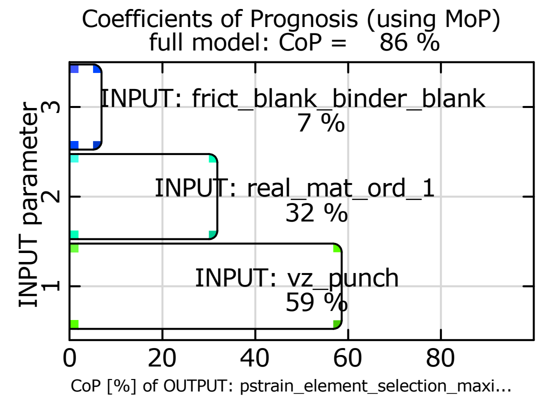


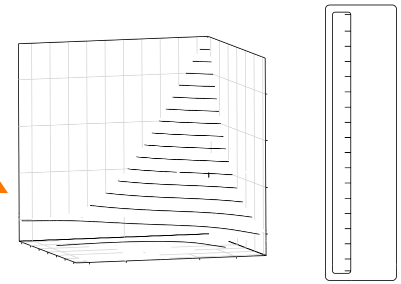


MOP: Sensitivity analysis
CoP matrix

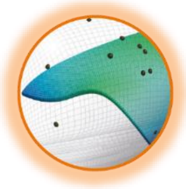
- MOP provides information on which input parameter X provides largest influence on the scatter of a measured response Y
- Design changes (e.g. the mean) to the input variables with largest CoP may have the largest effect onto the robustness/performance of Y





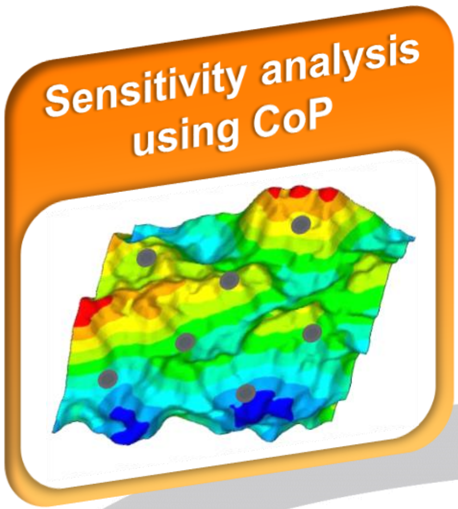


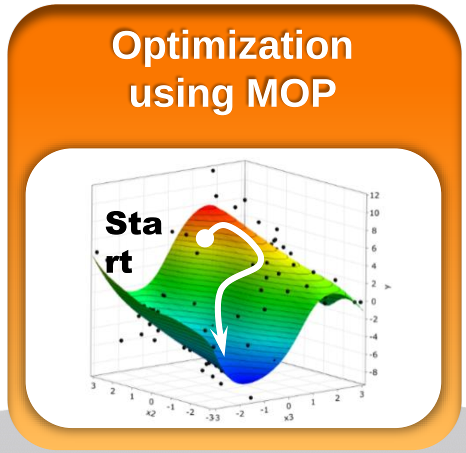
Influence of input parameters Accuracy of model



Optimization

Optimize your product design!

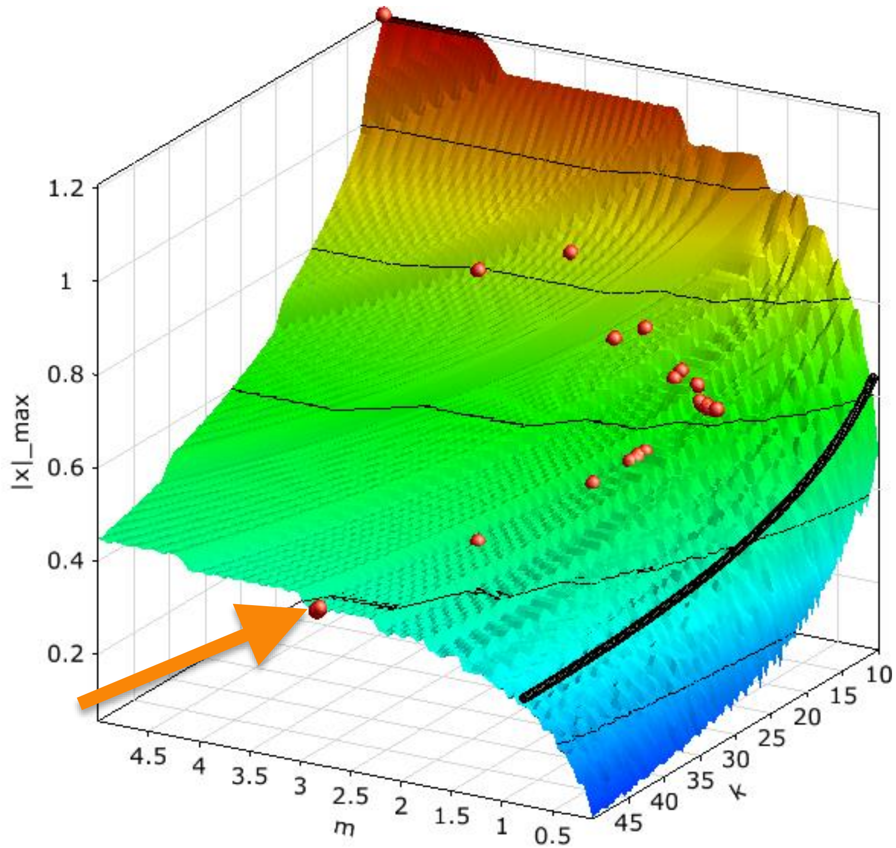


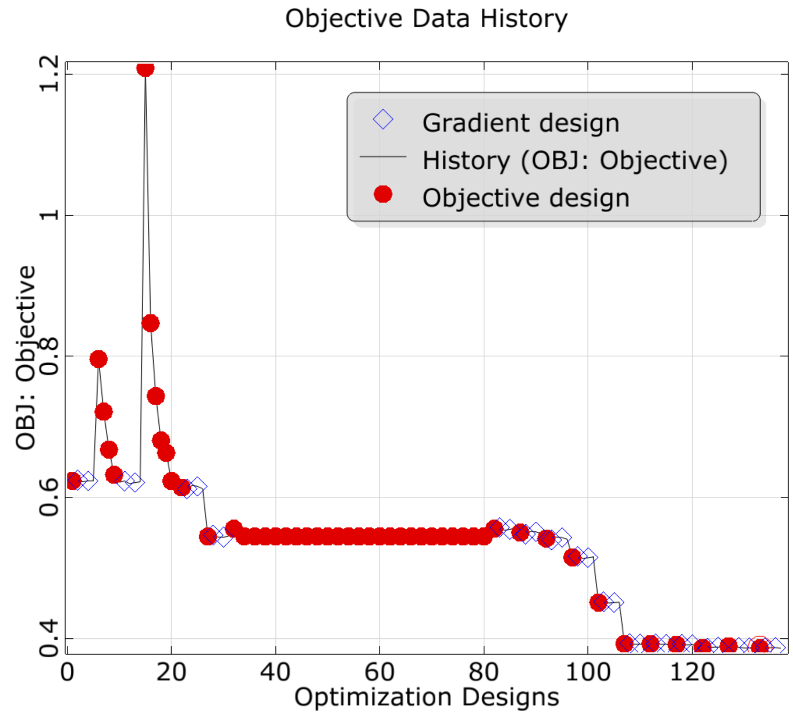


- **work with the reduced subset of only important parameters**
- **pre-optimization on meta model (one additional solver run)**
- **optimization with leading edge optimization algorithms**
- **decision tree for optimization algorithms**

Example: Noisy objective function

Gradient based optimization

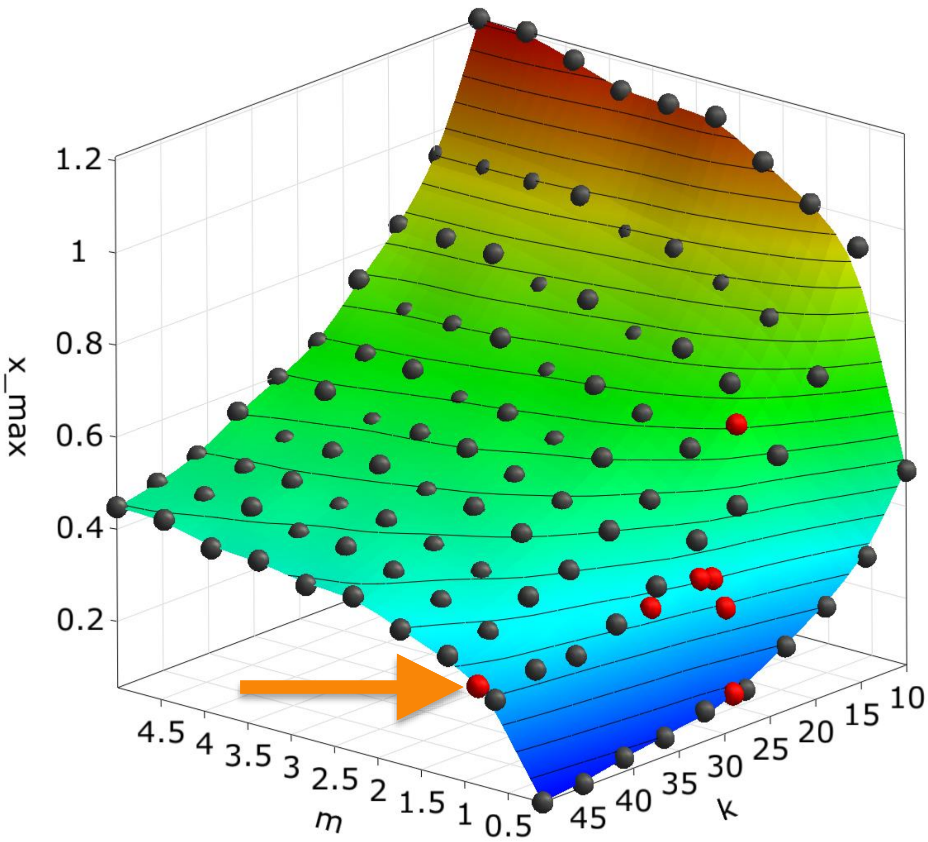


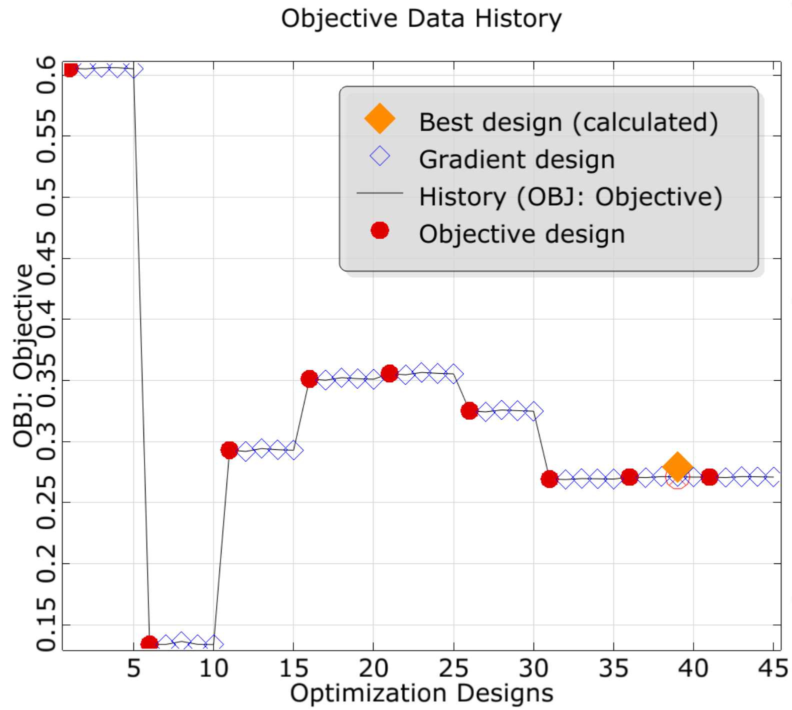


- Poor convergence
- Detected optimum is far away from reference solution

Example: Noisy objective function

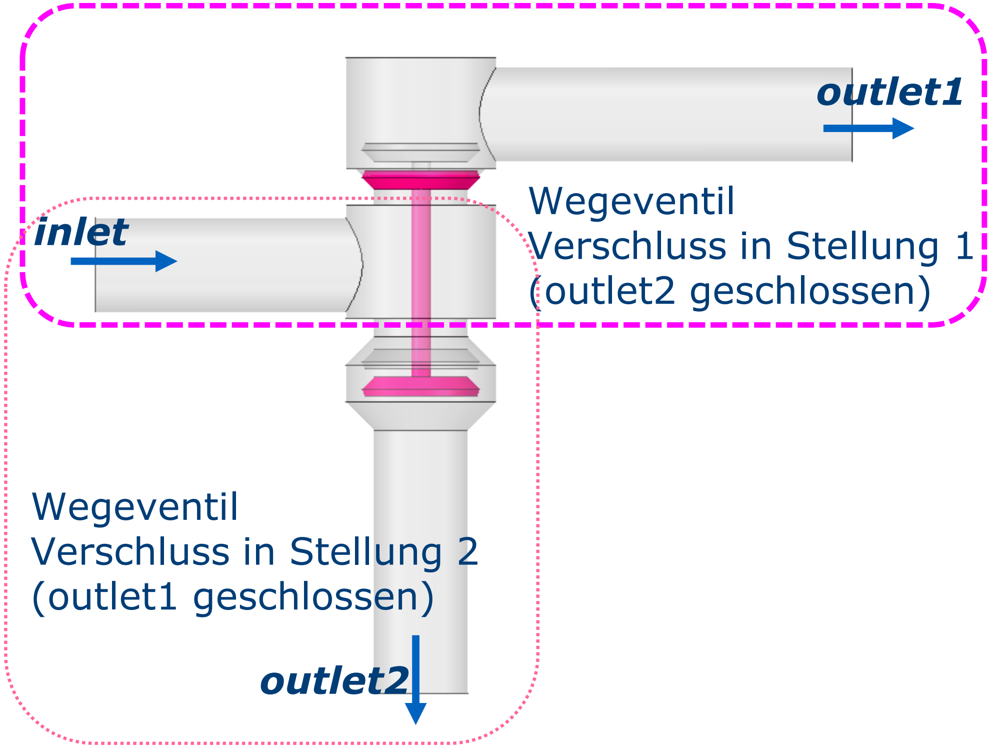
NLPQL on the MOP approximation





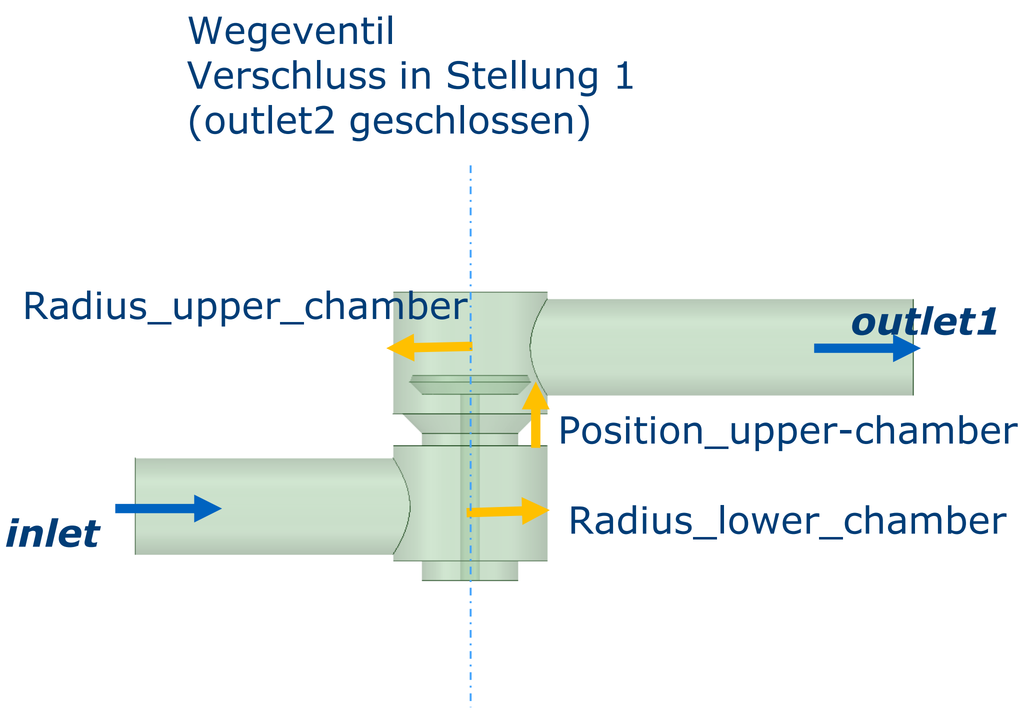
- Good convergence
- Best design fulfills the constraint

Beispiel: Wegeventil
Berechnung von Kennfeldern



- Schließvorgang 1:
  - Verschluss in maximaler oberer Stellung
  - System reduziert sich entsprechend (siehe nächste Seite)
- Schließvorgang 2:
  - Verschluss in maximal unterer Stellung:
  - ebenfalls möglich
  - hier nicht näher untersucht

Beispiel: Wegeventil
Parameter im System



Geometrische Parameter:

- Radius 1
- Radius 2
- Position oberer Ventilsitz

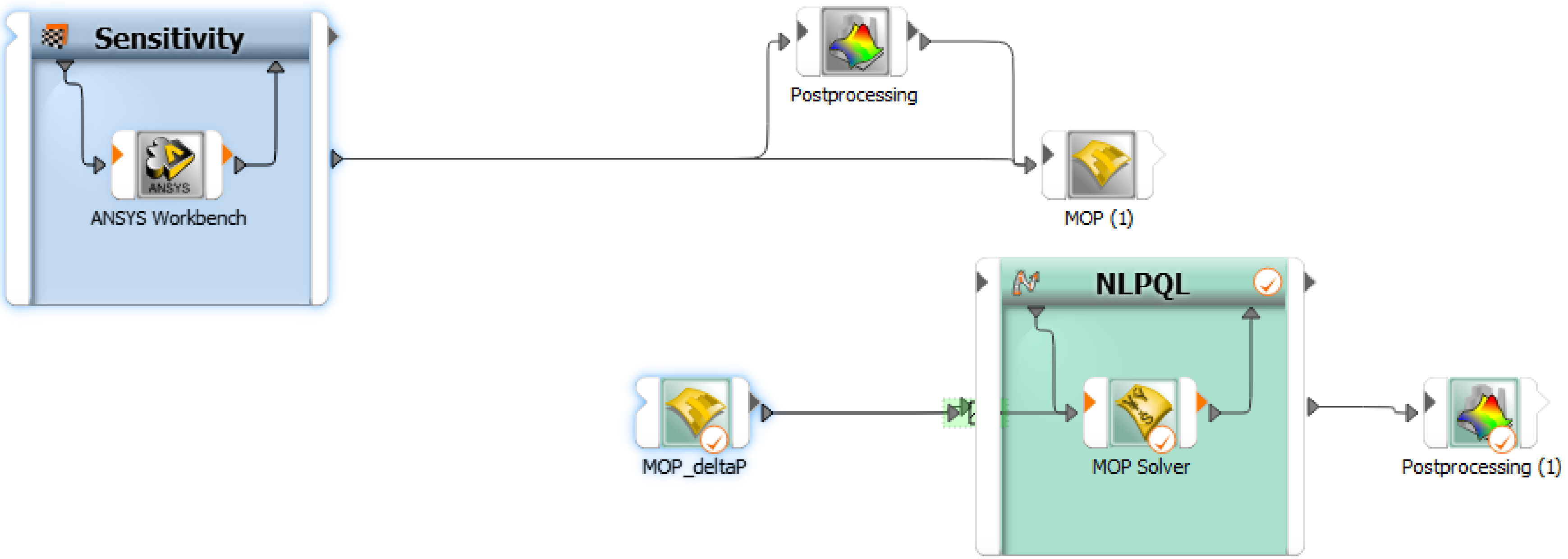
Kennfeld-Parameter:

- Massenstrom
- Viskosität (temperaturabhängig)

Zielgröße: Delta P (Druckverlust zwischen Inlet & Outlet)

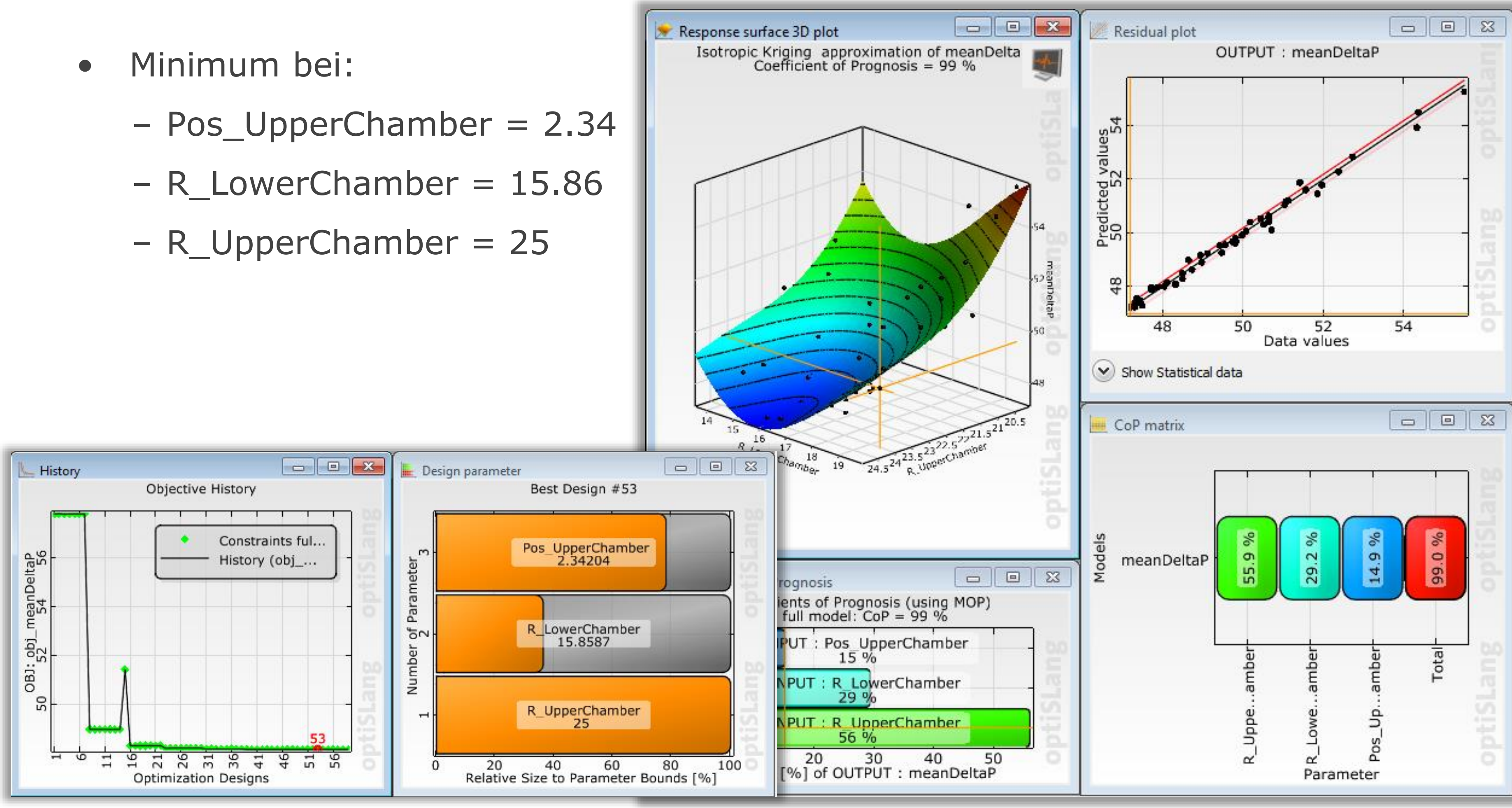
Beispiel: Wegeventil
Fall 1: Optimierung Geometrie

- 3 Geometrieparameter
- Zielfunktion: Minimiere Druckverlust
- DOE: LHS, Berechnung eines Metamodells für den Druckverlust
- Optimierung auf dem Metamodell



Beispiel: Wegeventil
Fall 1: Optimierung Geometrie

- Minimum bei:
  - Pos_UpperChamber = 2.34
  - R_LowerChamber = 15.86
  - R_UpperChamber = 25



Beispiel: Wegeventil
Fall 2: Kennlinie Druckverlust vs. Massenstrom

- Massenstrom: 1 Input-Parameter
- Druckverlust: Antwortgröße
- DOE: Full Factorial (z.B. 20 Designs)

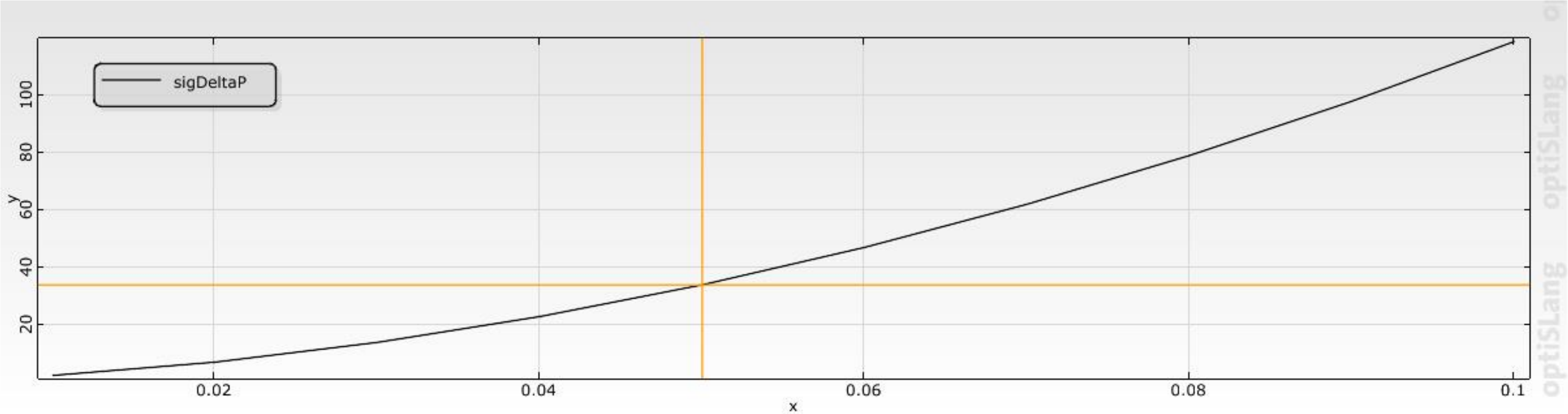
- Ziel: Berechnung der Kennlinie des Ventiles durch Abtastung

Beispiel: Wegeventil

Fall 2: Kennlinie Druckverlust vs. Massenstrom

- Massenstrom: 1 Input-Parameter – horizontale Achse
- Druckverlust: Antwortgröße – vertikale Achse

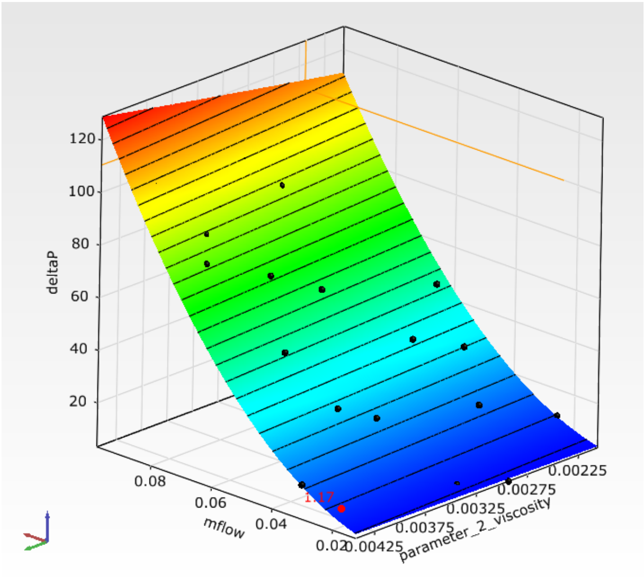
- Monotone Funktion, steigende Druckverlust mit steigendem Massenstrom

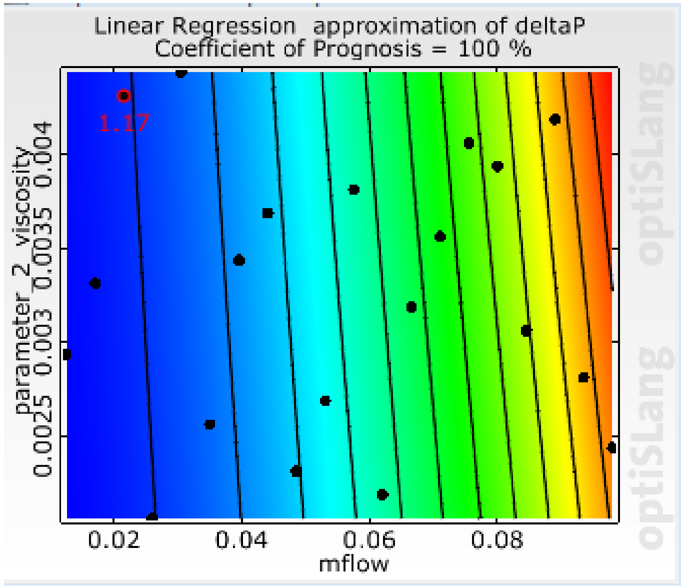


Beispiel: Wegeventil

Fall 3: Druckverlust vs Massenstrom + Viskosität

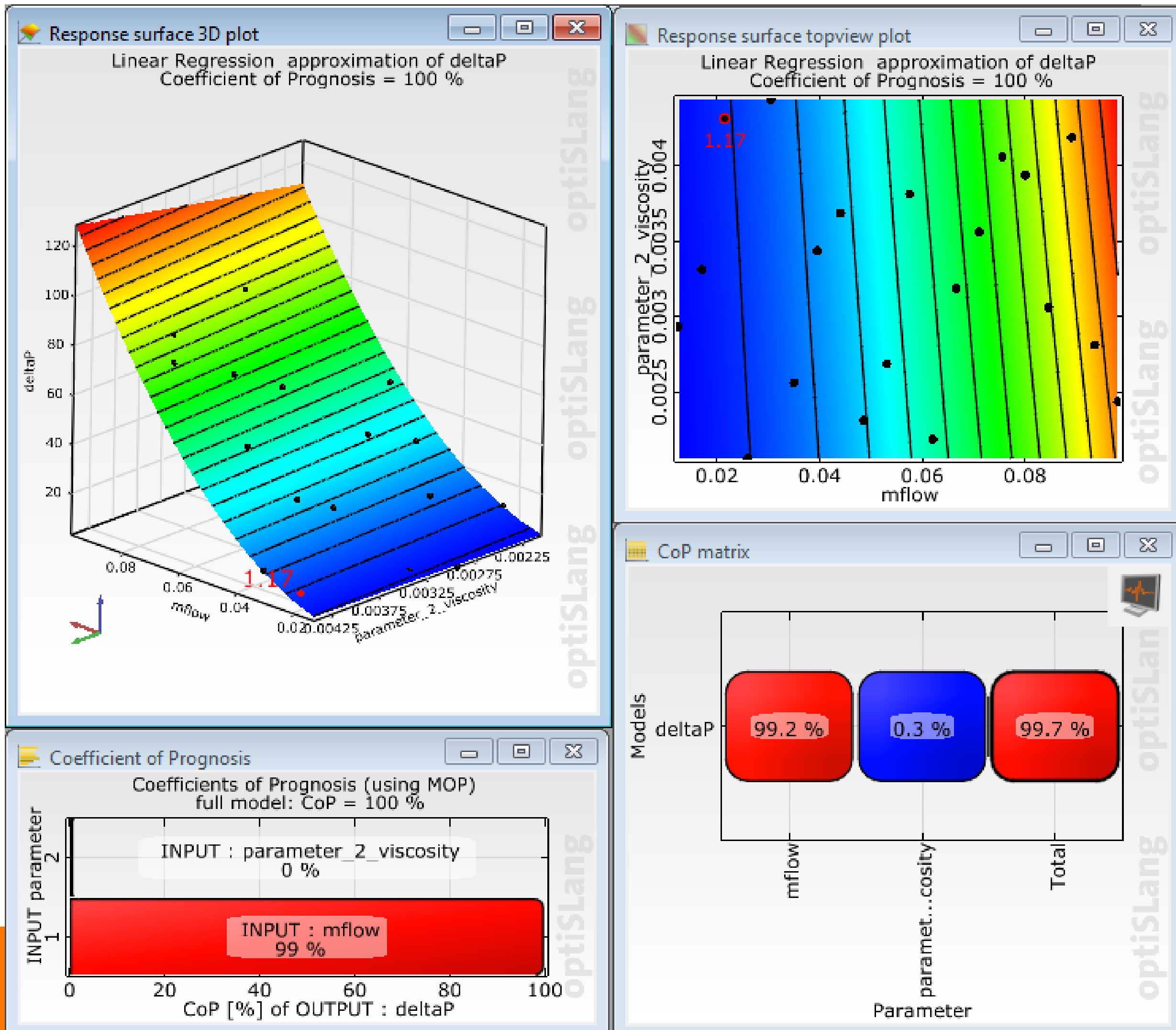
- Massenstrom + Viskosität: 2 Input-Parameter
- Druckverlust: Antwortgröße
  - Ergibt 2D-Kennfeld
- Effizientes Sampling über Latin Hypercubes und Interpolation mit MOP
  - Vergleich: Full Factorial: 10*10 Punkte ergeben 100 Designs!





Beispiel: Wegeventil

Fall 3: Druckverlust vs Massenstrom + Viskosität

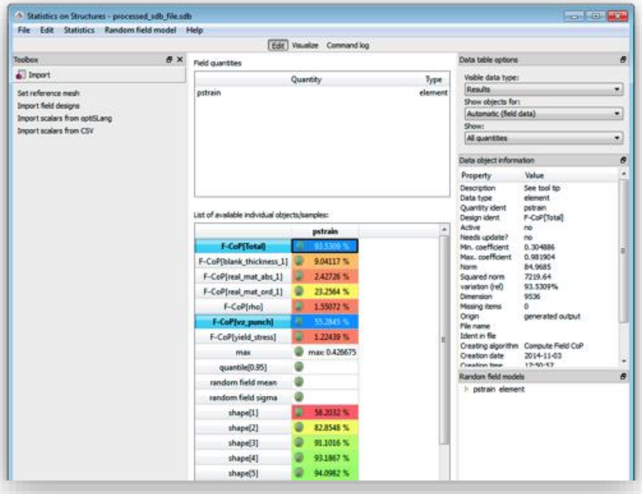


Analyse von Kennfeldern

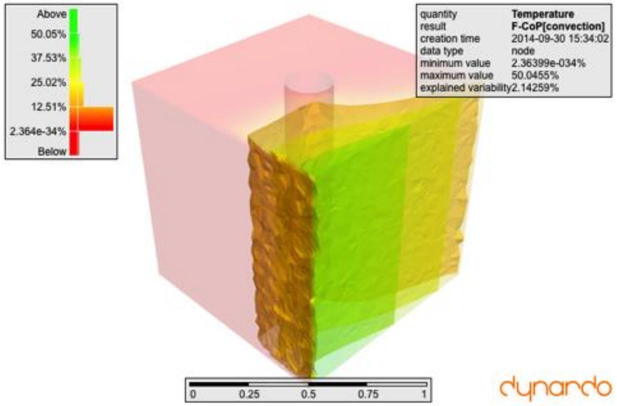
- Wie ändert sich ein Kennfeld
  - Wenn sich die Geometrie ändert (Designprozess)
  - Wenn man das Ventil in andere Pumpen einbaut (Steuerungsparameter)
- Analyse mittels Feld-Metamodelle:
  - Analyse von Variationen (Wo ändert sich das Kennfeld am stärksten?)
  - Analyse der Sensitivitäten (In welchem Arbeitspunkt des Kennfeldes hat welcher Geometrieparameter den größten Einfluss?)
  - Approximation per Echtzeitmodell
- Software: Statistics on Structures (SoS)

Statistics on Structures

Random fields

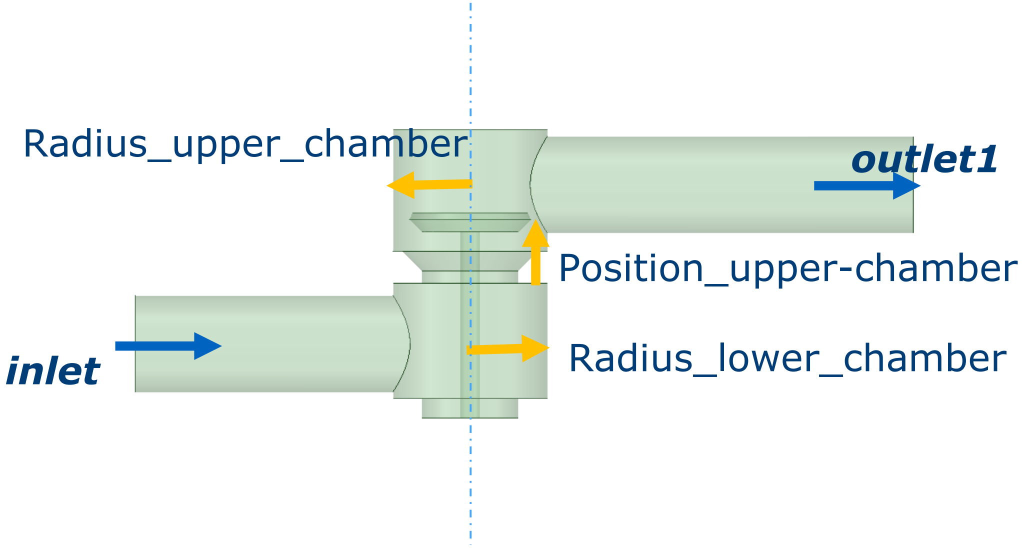


- **SoS is the software solution for the analysis and simulation of data variations being distributed in space or time**
- Features:
  - Real-time approximation of FEM solutions (3D) for digital twins
  - Free-form geometric variations
  - Generate geometric imperfections based on 3D laser scans
  - Automatic and optimal parameterization of spatial variations
  - Analysis of statistical quantities by visualization directly on 3D mesh
  - Detection of hot spots (failure regions…)



Beispiel: Wegeventil
Parameter im System

Wegeventil
Verschluss in Stellung 1
(outlet2 geschlossen)



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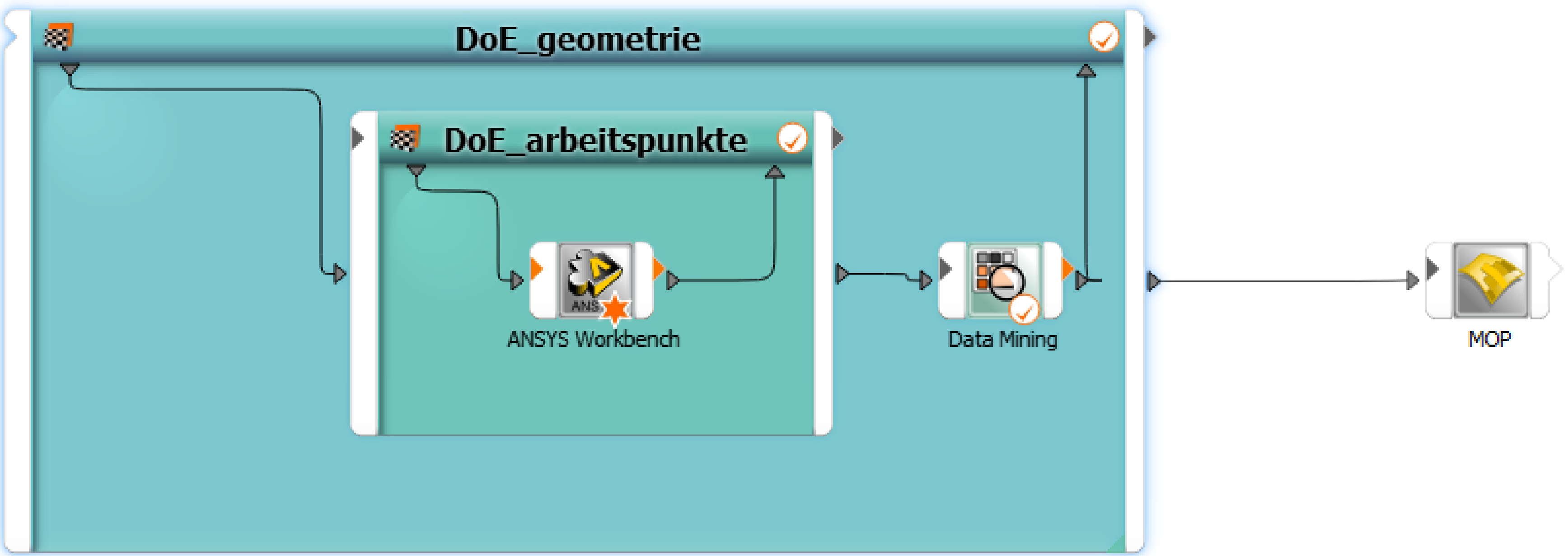
Zielgröße: Delta P
(Druckverlust zwischen Inlet & Outlet)

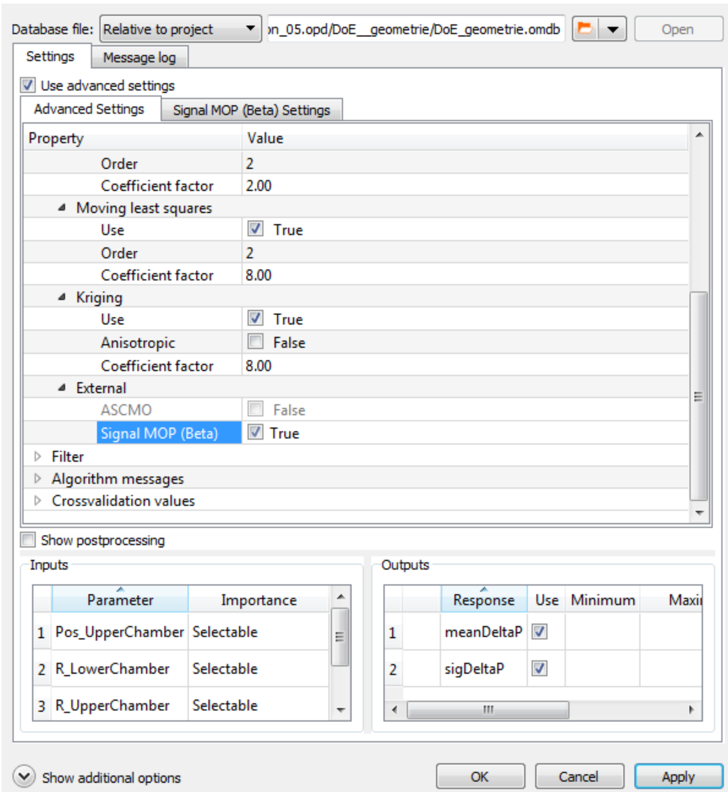
Fall 1: Einfluss der Geometrie auf 1D-Kennlinie

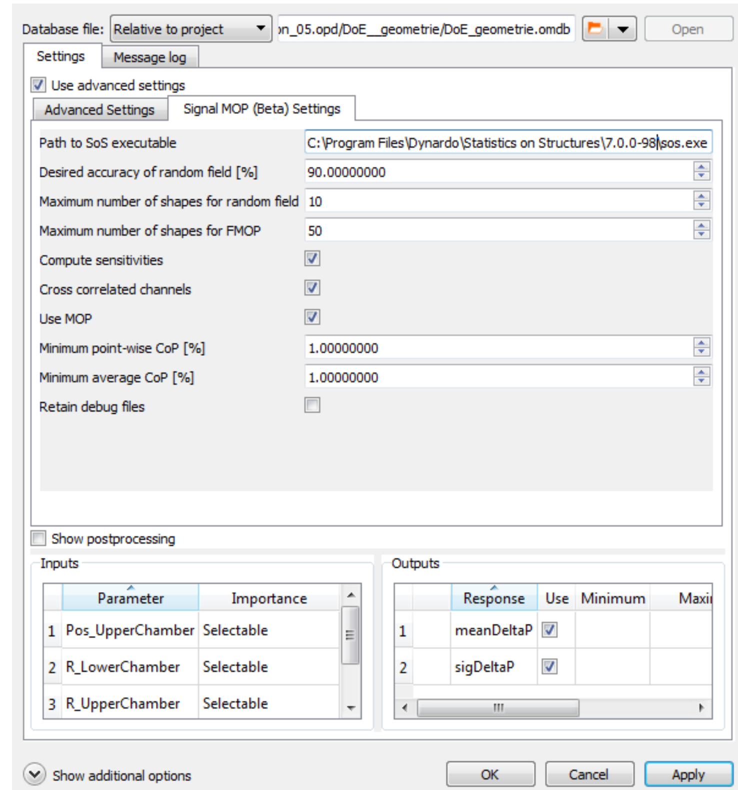
- optiSLang: Geschachteltes DOE
- Außen: Variation Geometrieparameter
- Innen: Variation der Arbeitspunkte (Massenstrom)



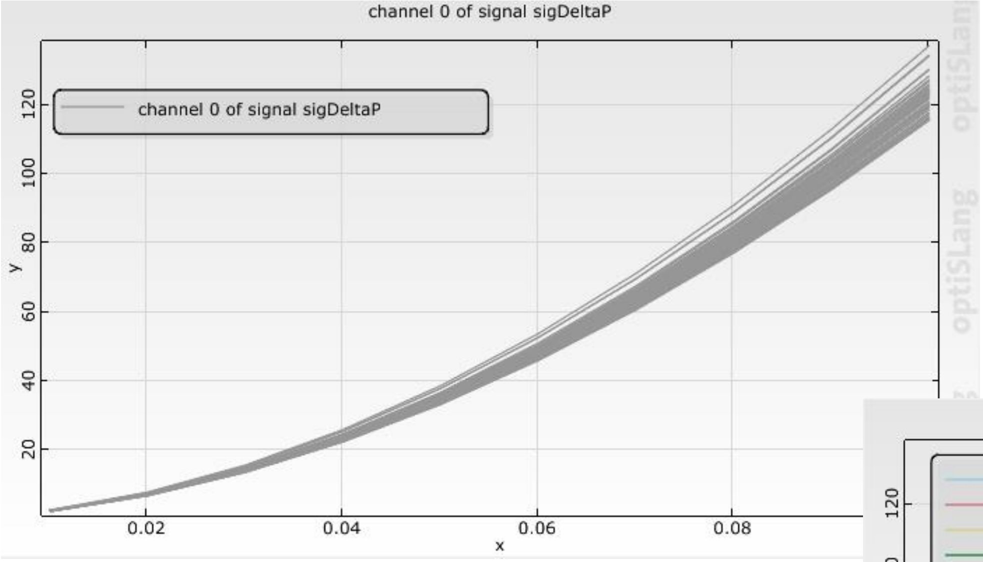
Fall 1: Einfluss der Geometrie auf 1D-Kennlinie

- SignalMOP: Wird für Kennlinien (“Signale”) automatisch von optiSLang berechnet, sofern SoS installiert ist



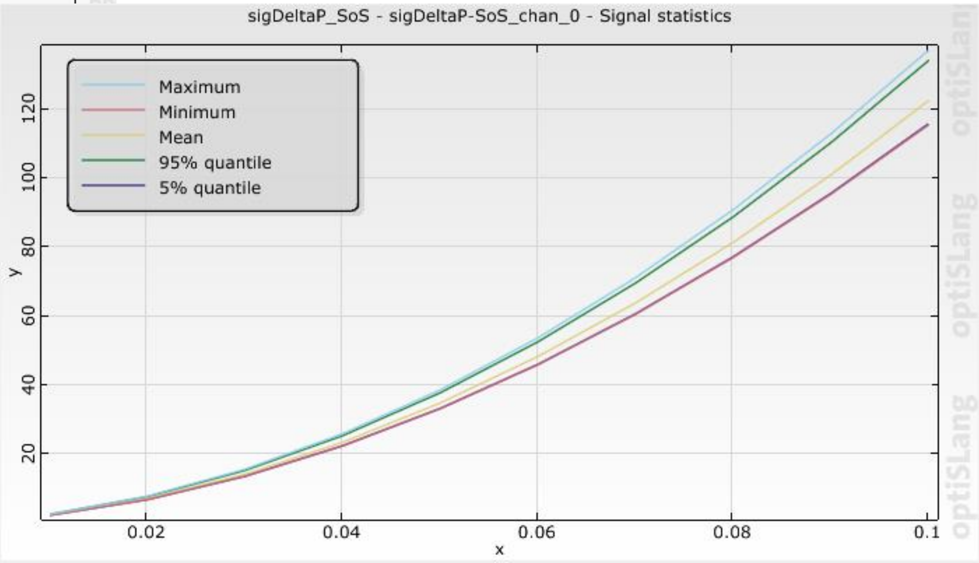


Fall 1: Einfluss der Geometrie auf 1D-Kennlinie

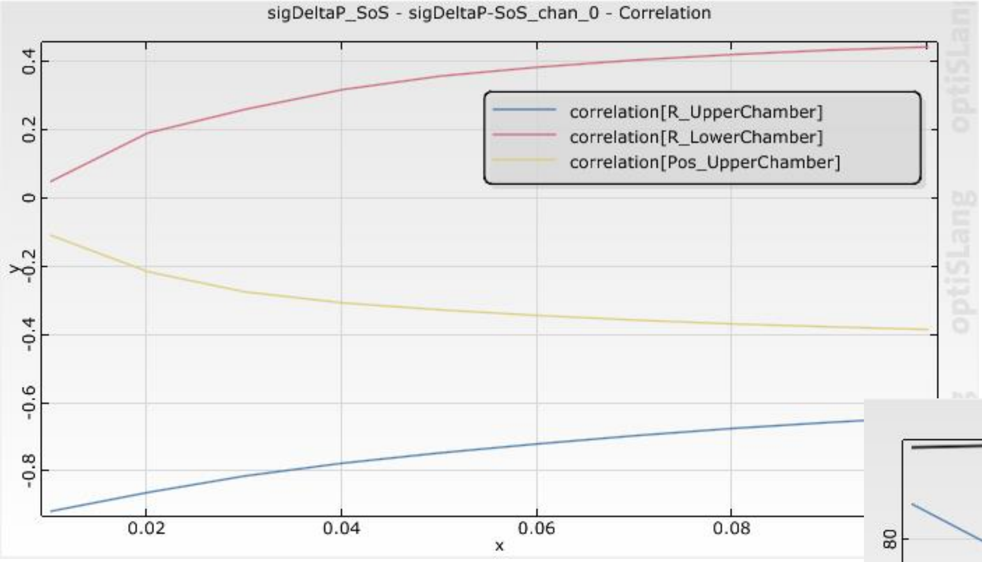


- Kurvenscharen aus DOE

- Signal-Statistik:
  - Untere/Obere Grenzen
  - Mittelwert, Quantilwerte

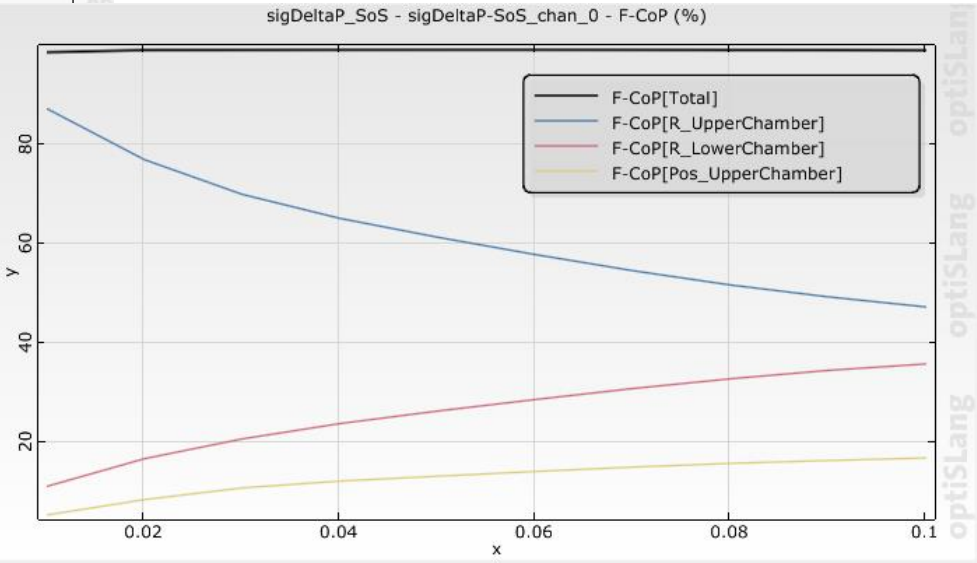


Fall 1: Einfluss der Geometrie auf 1D-Kennlinie



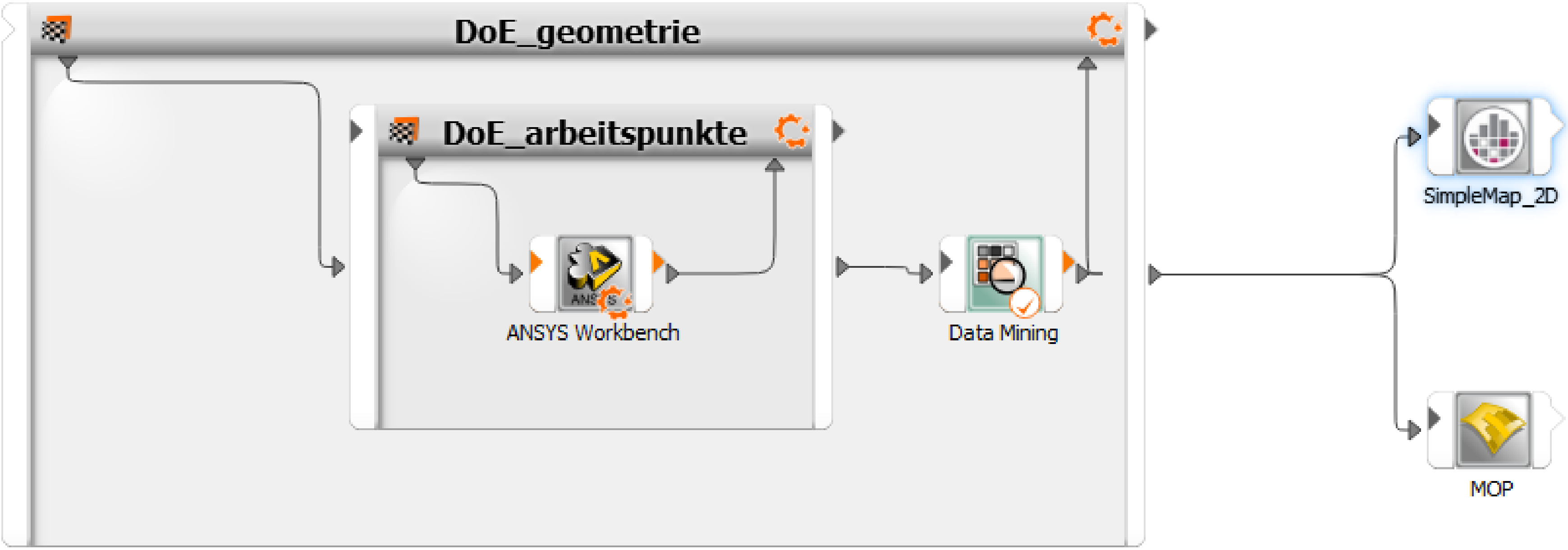
- Lineare Korrelation bzgl. der Geometrieparameter (z.B. positiv/negativ)

- F-CoP-Total: Genauigkeit des Feldmetamodells
- Sensitivitätsinidizes (F-CoP) geben an, an welchen Arbeitspunkten welcher Geometrieparameter wie wichtig ist



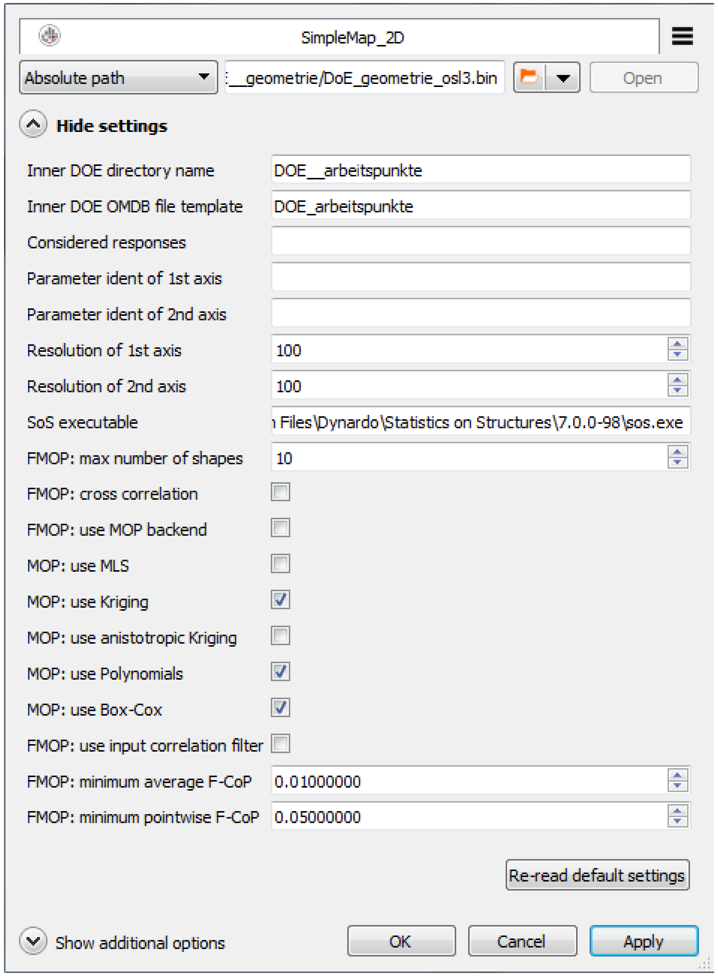
Fall 2: Einfluss der Geometrie auf 2D-Kennfeld

- optiSLang: Geschachteltes DOE
- Außen: Variation Geometrieparameter - LHS
- Innen: Variation der Arbeitspunkte (Massenstrom + Viskosität) - LHS



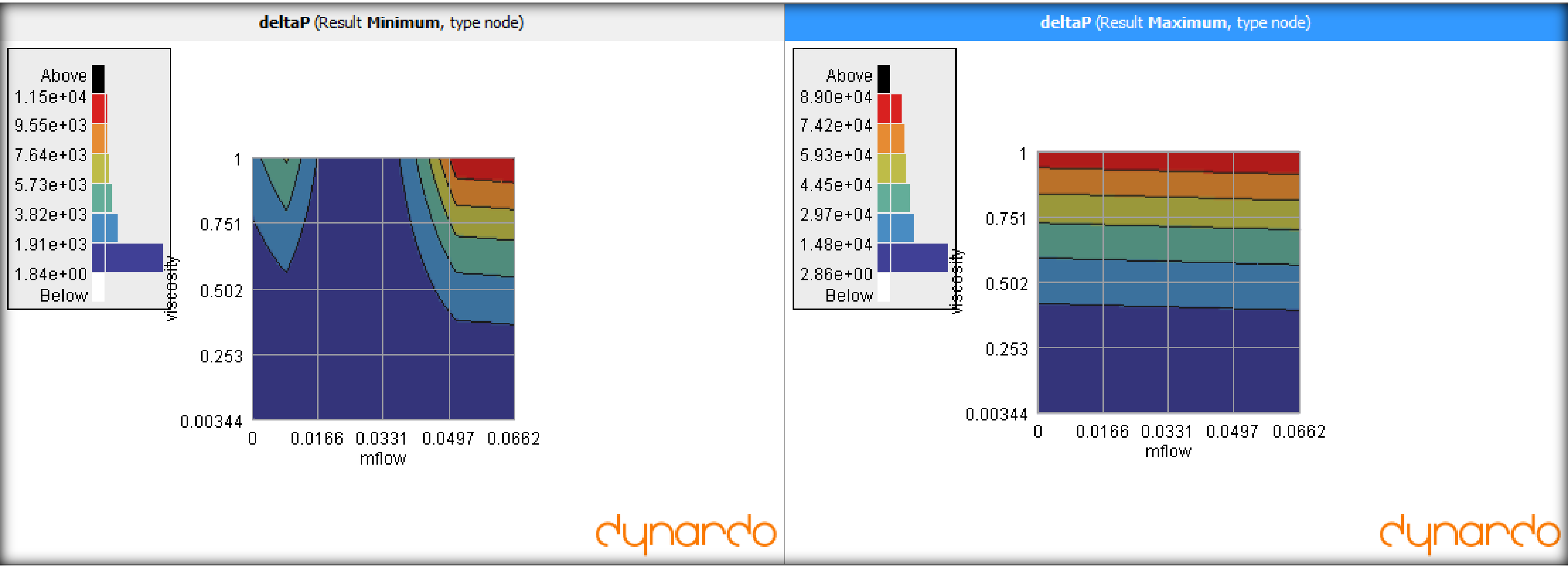
Fall 2: Einfluss der Geometrie auf 2D-Kennfeld

- Kennfeld-FMOP:
  - Integrationsknoten in OSL mit Optionen, z.B.:
  - Angabe der Abtastrate (z.B. 100x100)
  - Einstellungen für FMOP
- Ergebnis:
  - SoS Datenfiles für Postprocessing in SoS



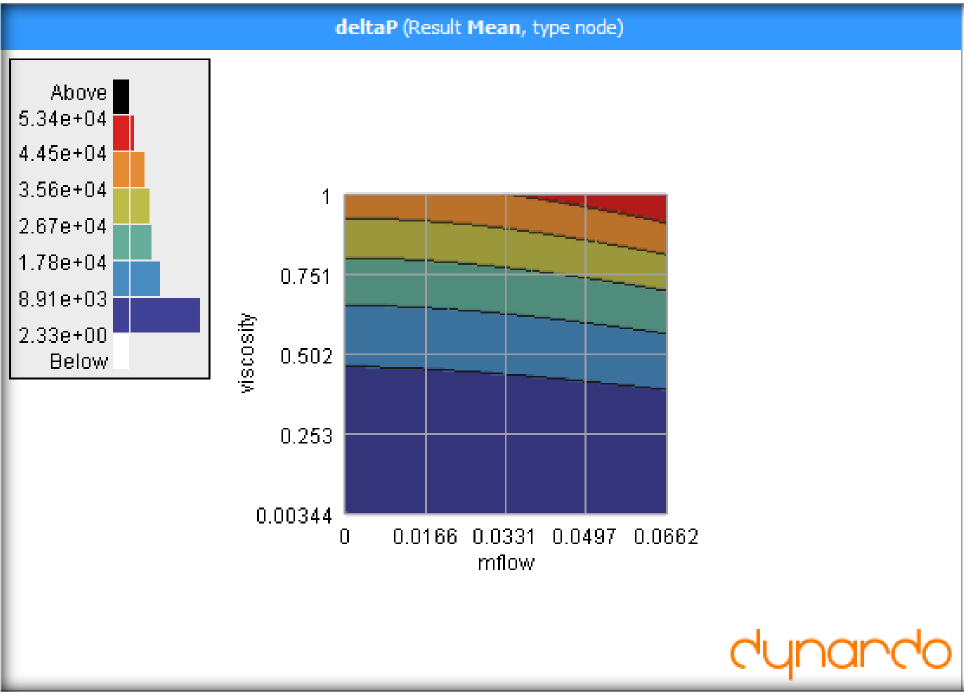
Fall 2: Einfluss der Geometrie auf 2D-Kennfeld

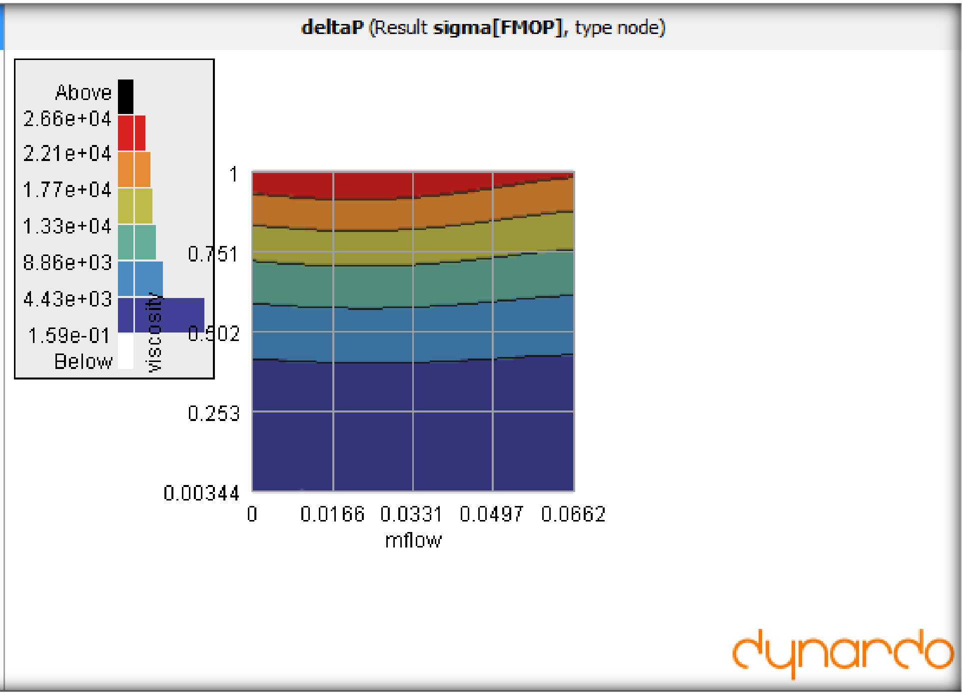
- Umhüllende: Bestimmung möglicher unterer und oberer Grenzen des Druckverlustes für alle Arbeitspunkte in Abhängigkeit der variierten Geometrie
- In welchem Wertebereich lässt sich das Kennfeld durch Geometrie ändern?



Fall 2: Einfluss der Geometrie auf 2D-Kennfeld

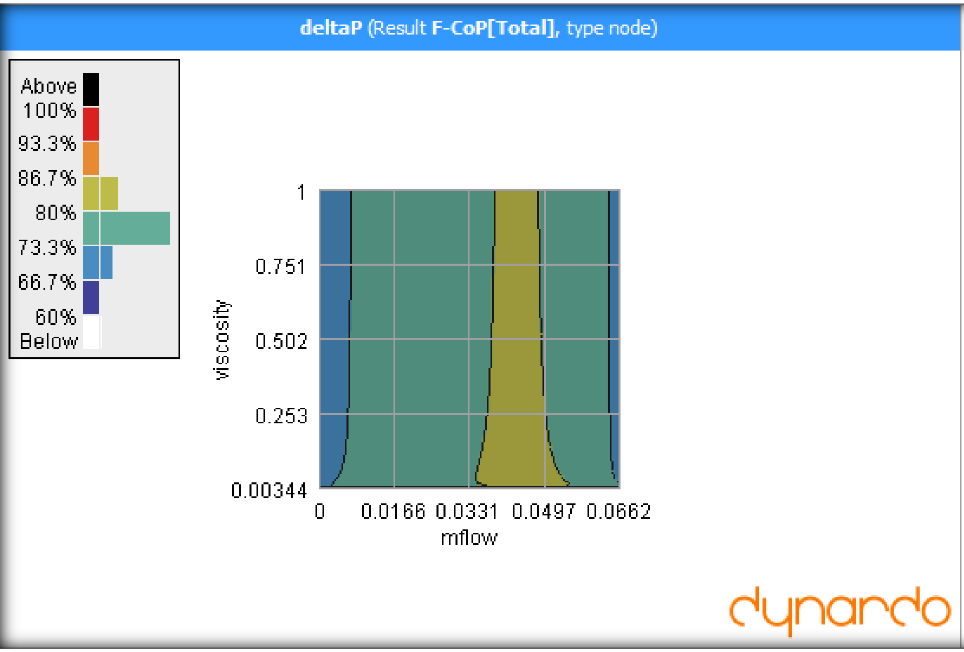
- Statistik: Bestimmung des mittleren Kennfeldes und der Standardabweichung (Maß für die mögliche Variation im Arbeitsraum)
- Wie stark kann man das Kennfeld durch die Geometrievariation verändern ?

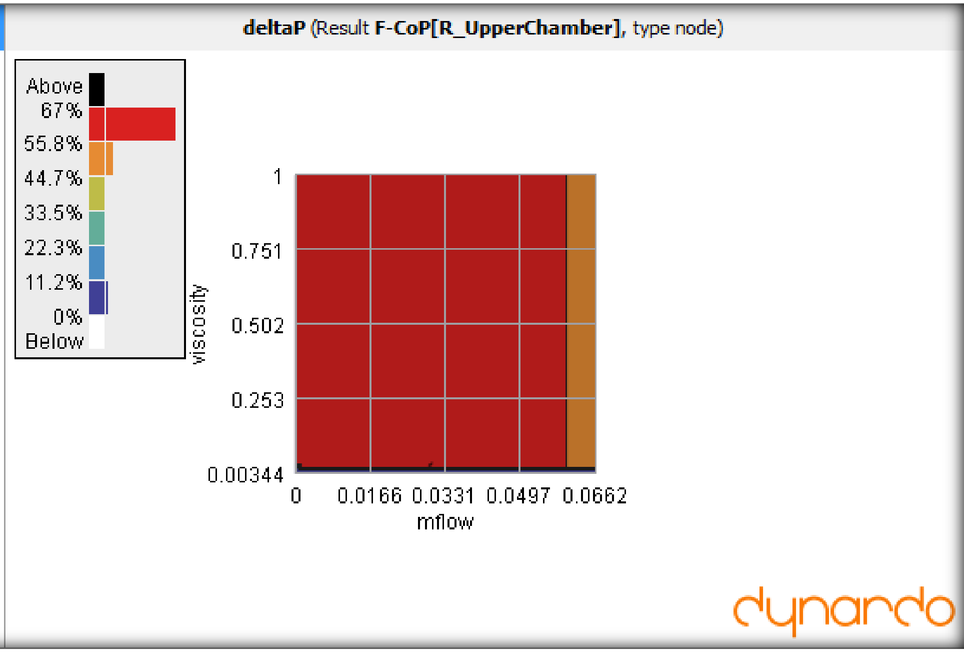




Fall 2: Einfluss der Geometrie auf 2D-Kennfeld

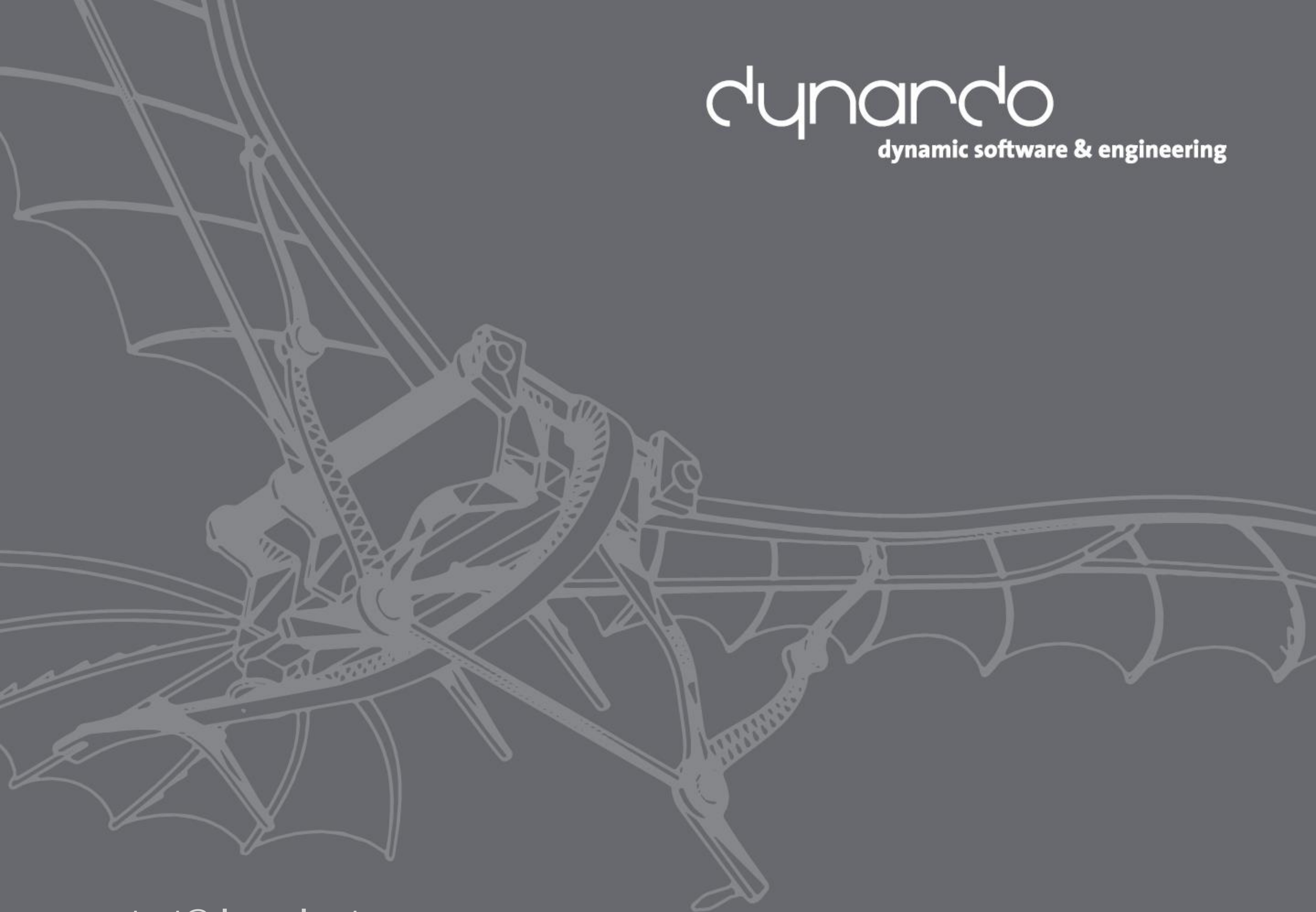
- F-MOP:
  - F-CoP(Total): Links: Prognosequalität des Metamodells
  - F-CoP(R_UpperChamber): Rechts: Sensitivät des wichtigsten Parameters





Zusammenfassung

- MOP (optiSLang):
  - Effiziente Erzeugung / Approximation eines Kennfeldes in 1d oder N-d
- Feld-MOP (SoS):
  - Analyse des Kennfeldes bzgl. äußerer Parameter
  - SignalMOP: Plugin in optiSLang für Analyse von Kennlinien
  - 2D- und 3D-Kennfelder: Analyse im SoS-GUI
- Feld-MOP liefert Aussagen zu:
  - Wie stark ändert sich das Kennfeld bei Ändrung äußerer Parameter ?
  - Welche Parameter beeinflussen das Kennfeld am meisten ?
  - Echtzeitapproximation für Optimierung und Vorhersage



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