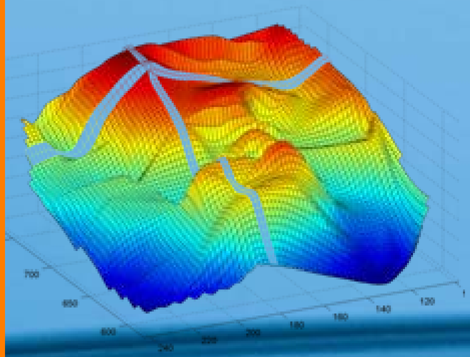
Corporate Research and Advance Engineering

Use of Metamodels for the Interdisciplinary Multi-Objective-Optimization (MOO)



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We shape technology for the future of Bosch

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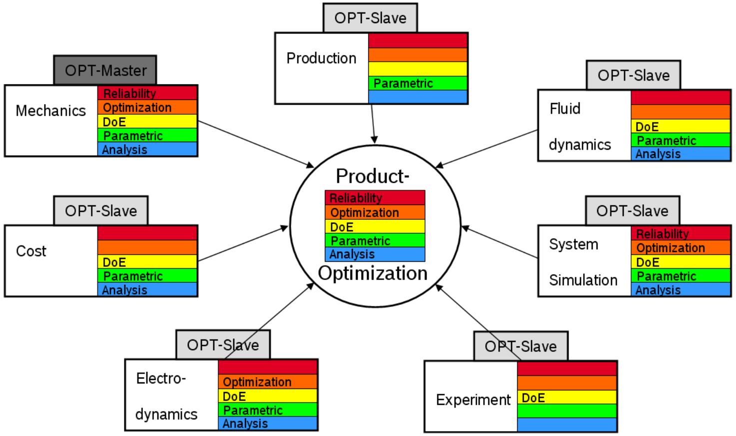
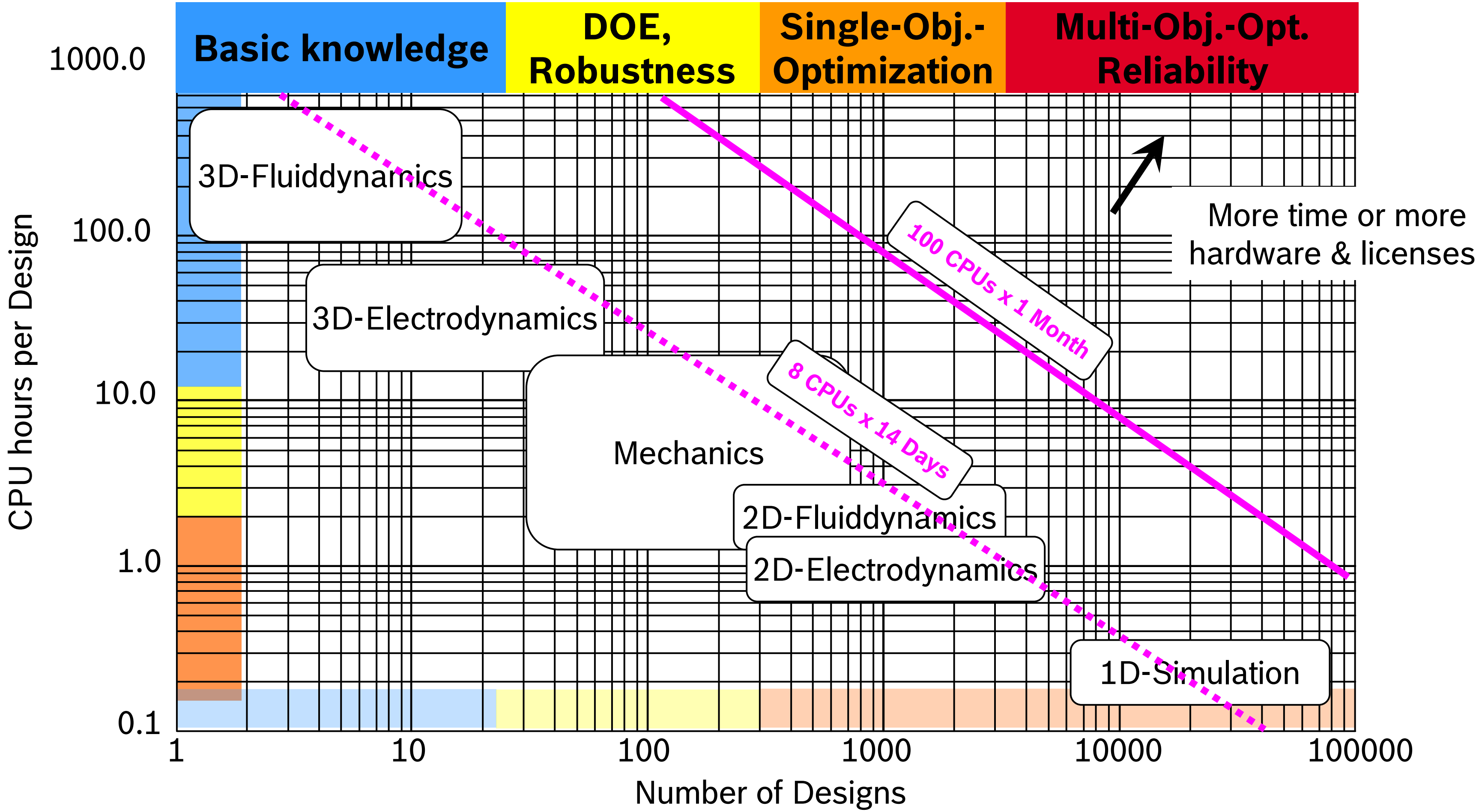
Requirements for MOO

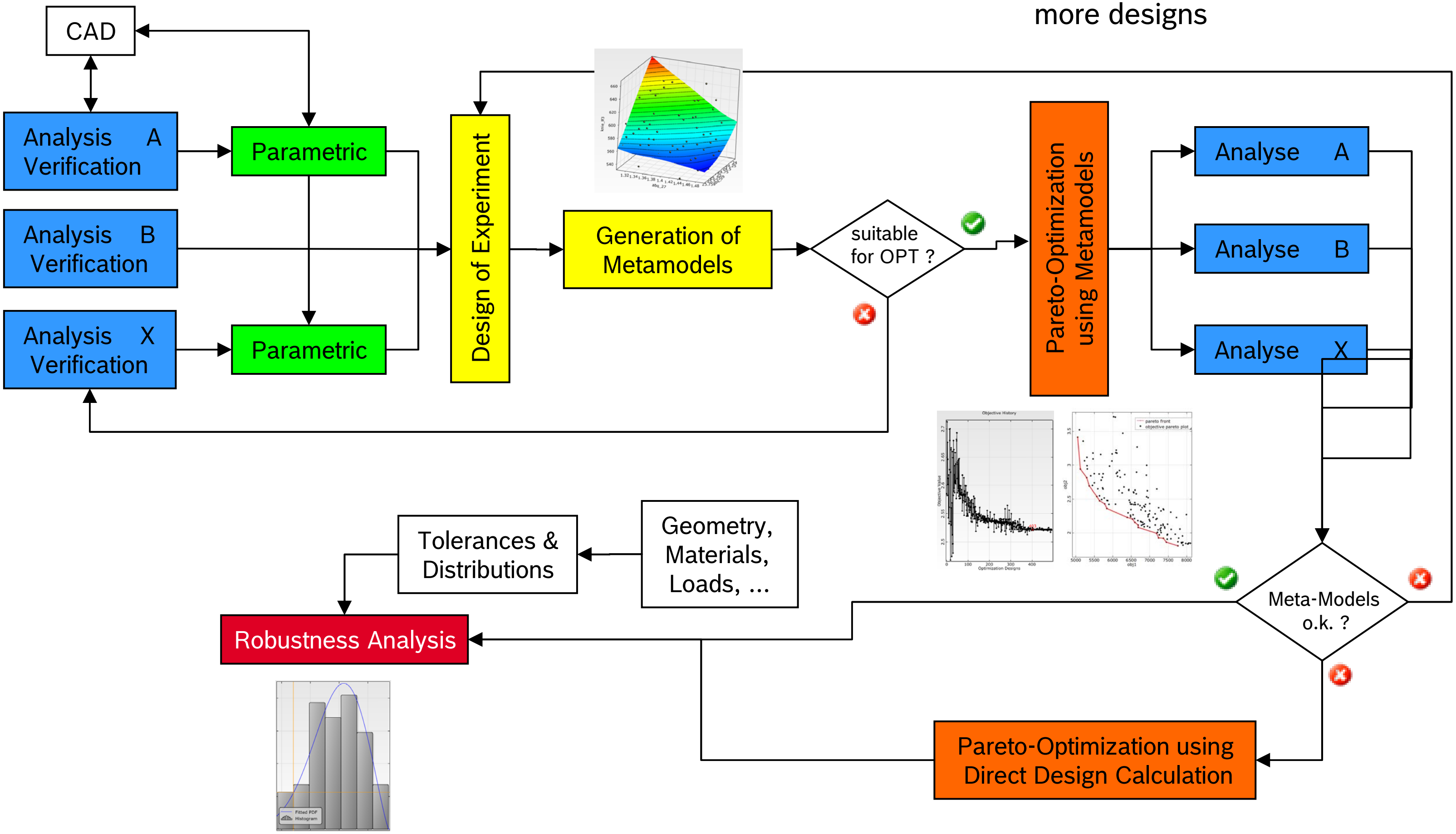


- ➔ General tasks
  - Project management
  - Assignment of parts
  - Simulation data management
  - Requirements engineering
  - Technical tasks
- ➔ Technical tasks
  - Automatic built-up of parametric models (CAD, Morphing, CAE-Scripting)
  - Automatic results evaluation (ETK, Python, Matlab, CAE-Scripting)
  - Performing optimization using an appropriate approach/algorithm
  - Selection of the optimal design
- ➔ Discrepancy
  - Minimum number of design evaluations more than 5000
  - Limited availability of time, hardware and software licences

Costs-Benefit of parametric studies of CAE-Models



Possible usage of Metamodels



CAD

Analysis A Verification

Analysis B Verification

Analysis X Verification

Parametric

Parametric

Design of Experiment

Generation of Metamodels

suitable for OPT ?

more designs

Pareto-Optimization using Metamodels

Analyse A

Analyse B

Analyse X

Meta-Models o.k. ?

Pareto-Optimization using Direct Design Calculation

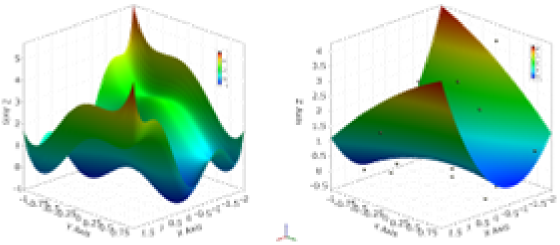
Geometry, Materials, Loads, ...

Tolerances & Distributions

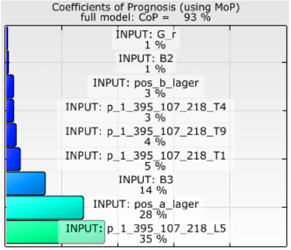
Robustness Analysis

Contents

MOP (Dynardo)

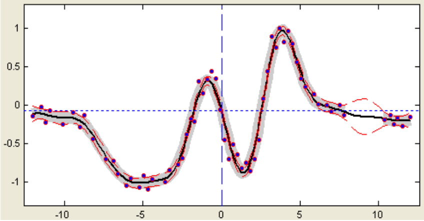


- ➔ Metamodels
  - Polynomial least square approximtaion (lin/quad)
  - Advanced moving least square approximation
- ➔ Expenditure
  - Design of Experiment/Simulation using CAE-Models
  - Calculation of the Metamodels
- ➔ Results
  - Best mathematical approximation for each responsevariable
  - List of important designvariables for each responsevariable
  - Error estimation by
    - Coefficient of Optimal Prognosis (COP)
    - R^2, R_{adj}^2, RMSE, …, r_{max}, r_{mean}, ..
  - Usage for optimization directly in OptiSLang, mopsolver.exe, mopsolver.dll

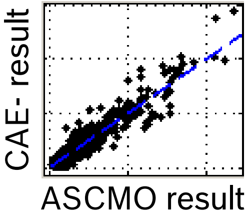


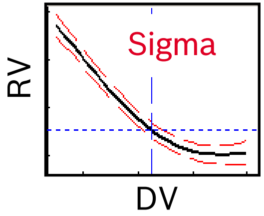
ASCMO (Bosch/ETAS)

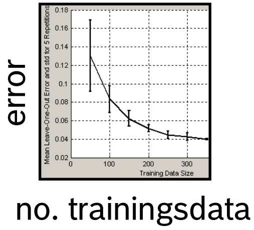
$$y(\vec{x}) = \sum_{i=1}^{N} C_i \cdot e^{-\frac{1}{2}\sum_{l=1}^{D}\frac{(X_{il}-x_l)^2}{r_l^2}}$$



- Metamodels
  - Statistical machine learning method
- Expenditure
  - Design of Experiment/Simulation using CAE-Models
  - Calculation of the Metamodels
- Result
  - Mathematical description between each designvariable and each responsevariable
  - Error estimation
    - True prediction plot
    - Sigma-Plot
    - R^2, RMSE
    - Error over training data size
  - Usage for optimization by export as Python-Code







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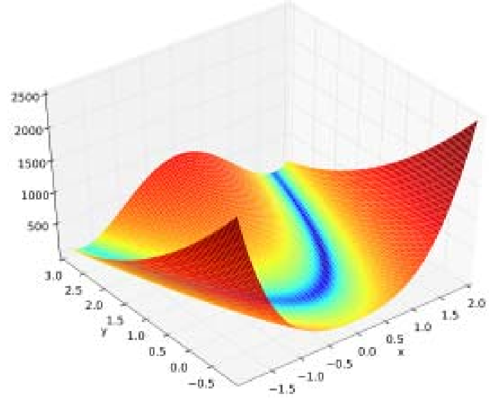
Applications

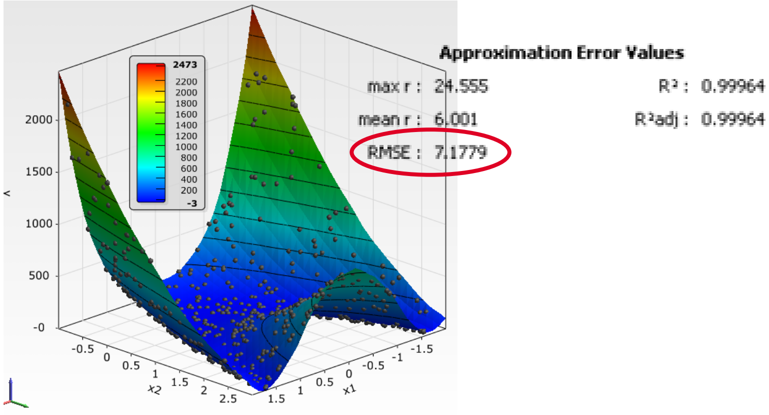
Rosenbrock-Function

Function	$f(x,y)=(1-x^2)+100(y-x^2)^2$
Limits	$-2<x<2$; $-1<y<3$
Optimum	x=1, y=1, f(1,1)=0
Starting point	(0,0)
DoE	500 Designs using LHS



MOP

ASCMO



Approximation Error Values

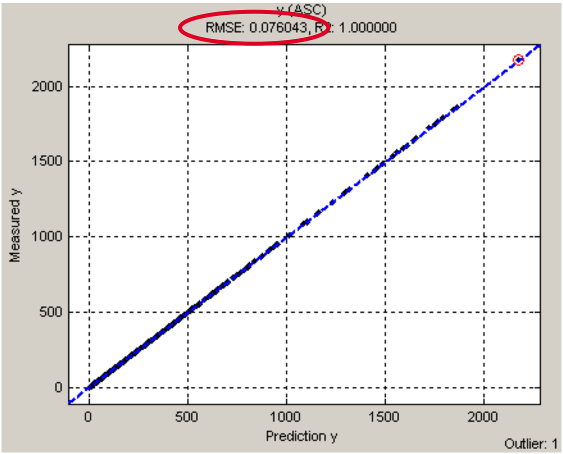
max r : 24.555

R² : 0.99964

mean r : 6.001

R²adj : 0.99964

RMSE : 7.1779



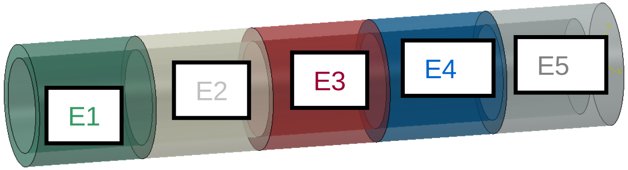
RMSE: 0.076043, R2: 1.000000

Comparison of error between MOP and ASCMO

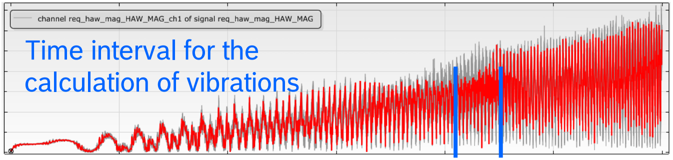
	OptiSLang using Pythoncode	OptiSLang using MOP	OptiSLang using ASCMO
NLPQL	x = 0.99680 y = 0.99362 f(x,y) = 1.018e-05 cpu = 106 sec	x = 0.24817 y = 0.11288 f(x,y) = 2.46806 cpu = 23 sec	x = 1.01843 y = 1.03698 f(x,y) = -0.03792 cpu = 240 sec
Evolutionary Algorithm	x = 0.98408 y = 0.99093 f(x,y) = 5.4e-05 cpu = 54000 sec	x = 1.71485 y = 3.00000 f(x,y) = -2.70721 cpu = 4800 sec	x = 1.11760 y = 1.05300 f(x,y) = -0.027984 cpu = 27000 sec
Problems	offending command at file open after 25155 designs	Bad approximation f(0.248,0.112) = 0.8283 f(1.71485,3.0) = 0.8625	offending command at file open after 12946 designs

Flexible bodies in MSC.Adams

- Task: Modification of 5 housing stiffnesses (elasticity modul E) in order to improve the vibrations



- Analysis
  - Substructure generation in ABAQUS
  - Generation of MNF-File
  - Multi-Body-Simulation in Adams



Time interval for the calculation of vibrations

- Results:
  - Stiffness and mass matrix of the substructure as a function of the 5 elasticity moduli

- Metamodels (Training/Test)
  - 26/14, 80/40

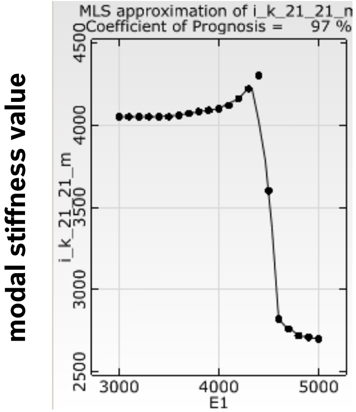
Result of Metamodels (MOP)

- Coefficient of Optimal Prognosis
  - High COP for static dofs
  - Mostly very low COP for modal dofs

$$K = \left(\begin{array}{c|c} K_{SS} & 0 \\ \hline 0 & \cancel{K_{MM}} \end{array}\right) \qquad M = \left(\begin{array}{c|c} M_{SS} & M_{SM} \\ \hline M_{MS} & \cancel{M_{MM}} \end{array}\right)$$

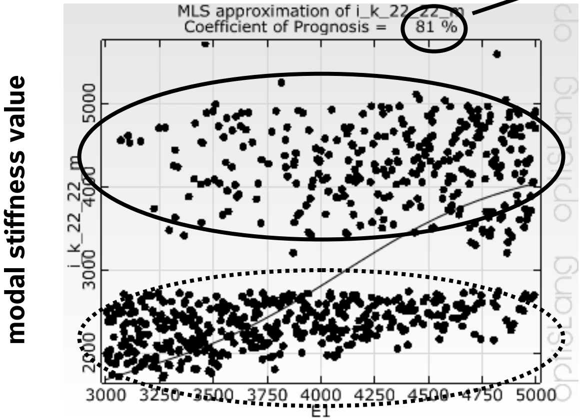
- Metamodel for different numbers of design variables

Variation of E1



Strong nonlinearity is a challenge for Metamodels, but no problem.

Variation of E1 and E4



81% pretends a good approximation

Clustering caused by mode switch is a huge problem for Metamodels.

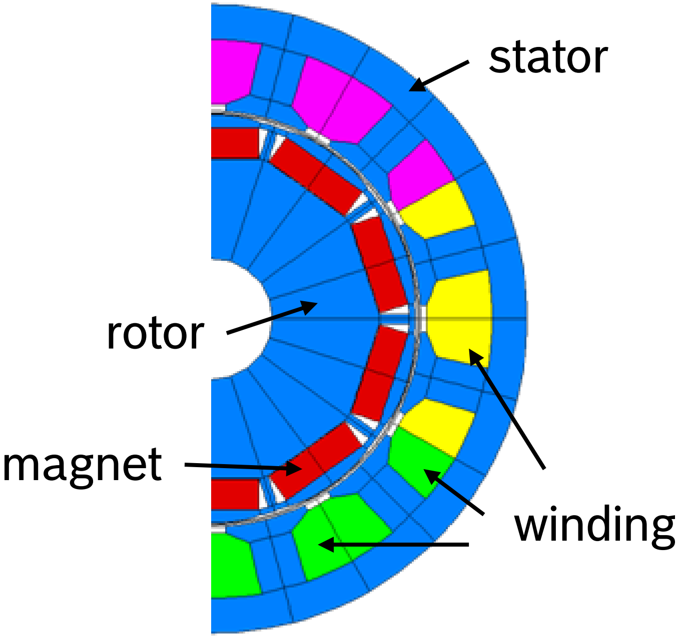
Electric drives in FEMAG

- Task: Modification of 14 geometric entities of the housing and the magnets in order to modify 27 electric properties of the electric drive

- Analysis
  - Electrodynamic simulation in FEMAG

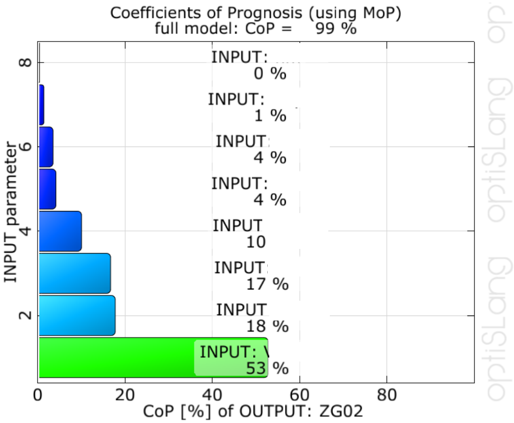
- Results
  - Electric properties (current, forces,...)
  - Geometric properties (inertia, mass)

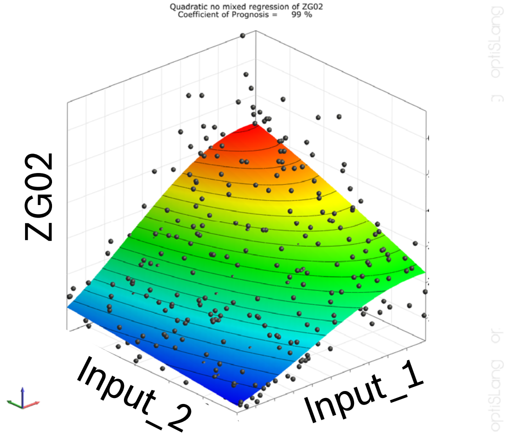
- Metamodels (Training/Test)
  - 200/100, 500/200
  - 67/33, 134/66, 335/165



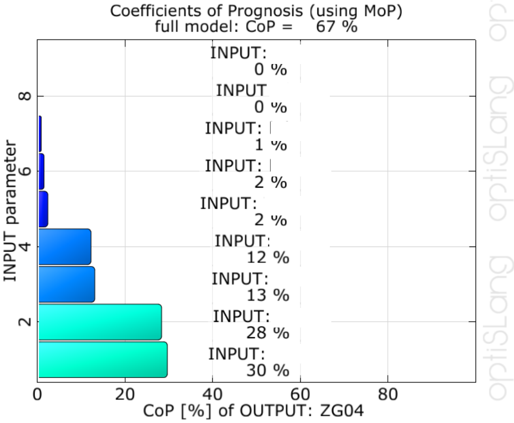
Approximation examples (MOP)

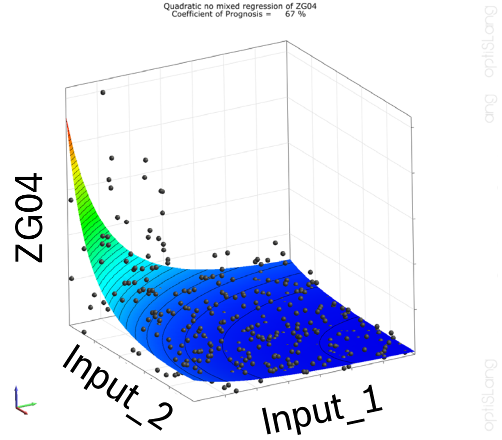
Good approximation for ZG02 (torque)
- smooth function
- COP 0.99





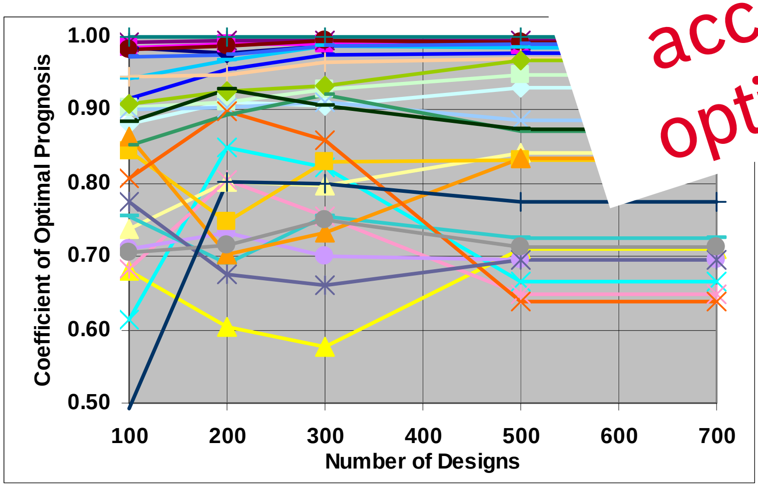
Bad approximation for ZG04 (peak-peak of torque dynamics)
- strongly nonlinear function
- COP 0.67



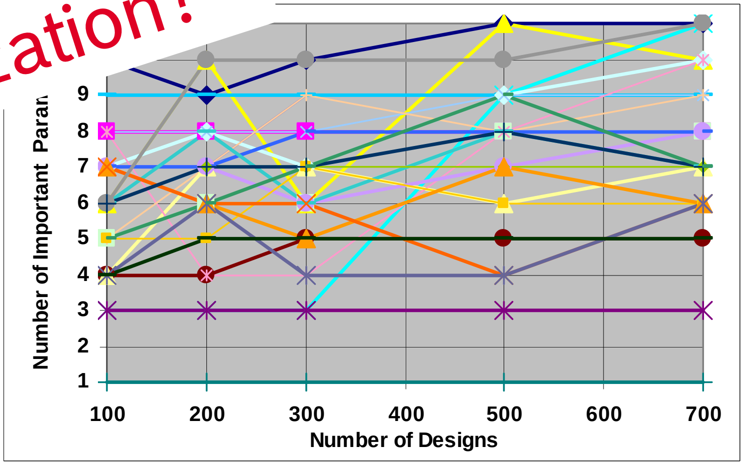


Convergence (MOP)

- Coefficient of Optimal Prognosis
  - Minimum value is 0.64
  - Partly large changes
  - No change between 500 and 700 (500/200) designs
  - Partly no convergence to a maximum value
- Number of Important Parameters
  - Relativly constant values
  - Constant COP does not mean co nt NIP



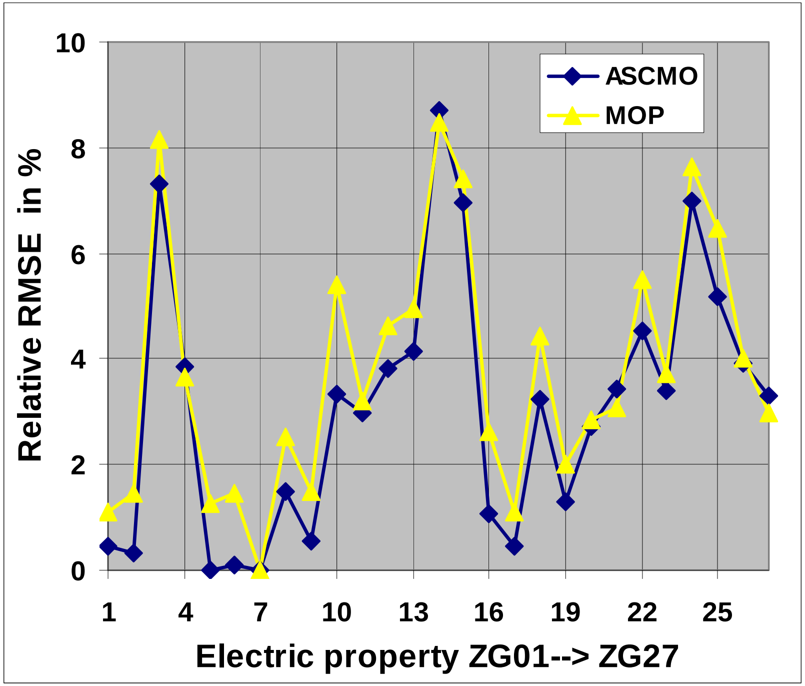
Sufficient accuracy for optimization?



Comparison of error between MOP and ASCMO

- The relative RMSE of ASCMO is mostly smaller than MOP.
- Global properties like inertia, torque,.. have a small error.
- Peak-Peak-Values of dynamic properties have a higher error.

$$RMSE\_rel = \frac{\sqrt{\frac{1}{N}(y_i - \tilde{y}_i)^2}}{\max(y_i) - \min(y_i)} * 100\%$$



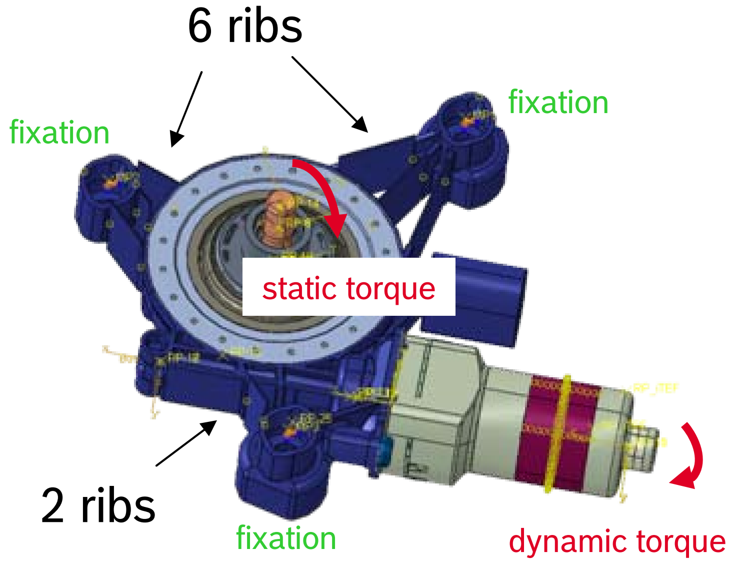
Electric window lift in ABAQUS

- Task: Modification of height and width of 8 ribs of the housing in order to modify static stress distribution and dynamic reaction forces.

- Analysis
  - Structural mechanics in ABAQUS

- Results
  - Max. stress at ribs and mountings
  - Frequency of first bending mode
  - Maximum and integral value of dynamic reaction forces

- Metamodels (Training/Test)
  - 300/150



Coefficient of Prognosis (300 training / 150 test)

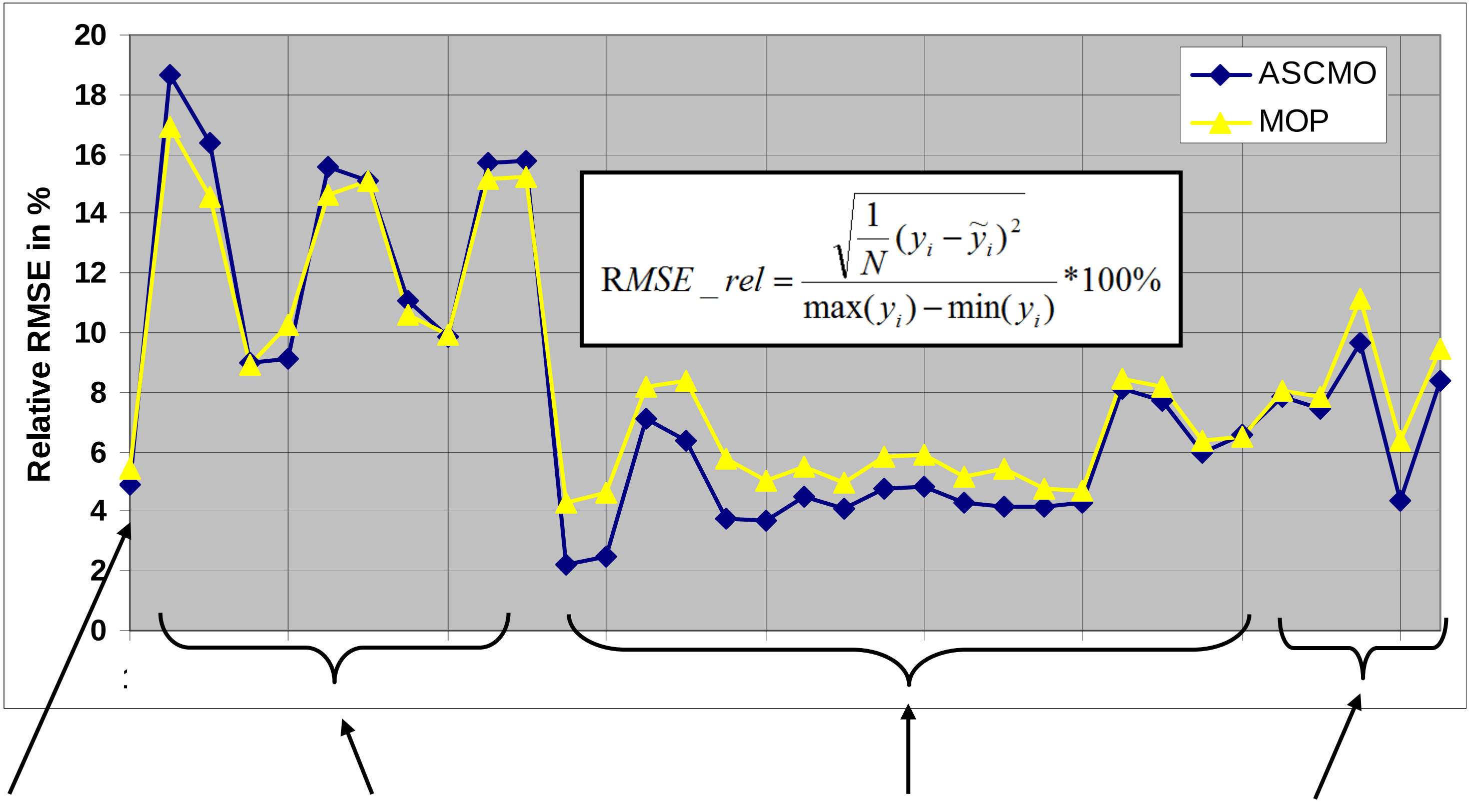
- Max. stress at the inner part and the mountings have a high approximation error.
- Max. stress at m the frequency of t mode can be appr well.
- Integral reaction fo better COP than ma mum reaction forces.

Which type of response variables and which mathematical transformations have high or low errors?

Responsevariable	COP
Max. stress at inner part	🟧 0.21
Max. stress at m nting 1	🟧 0.71
ting 2	🟧 0.38
ting 3	🟧 0.48
	🟩 0.97
	🟨 0.83
	🟩 0.93
	🟩 0.92
	🟩 0.92
	🟩 0.90
	🟩 0.95
	🟨 0.84
ode	🟩 0.94
equency range 1	🟨 0.80
frequency range 1	🟨 0.86
equency range 2	🟧 0.67
reaction force in frequency range 2	🟩 0.92

🟧 = too low COP
🟨 = acceptable COP
🟩 = good COP

Comparison of error between MOP and ASCMO



$$RMSE\_rel = \frac{\sqrt{\frac{1}{N}(y_i - \tilde{y}_i)^2}}{\max(y_i) - \min(y_i)} * 100\%$$

Frequency of 1. bending mode

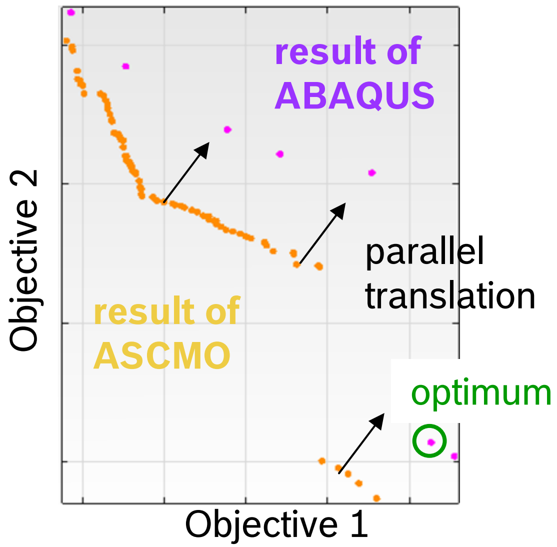
v.Mises stress at inner part /mounting points

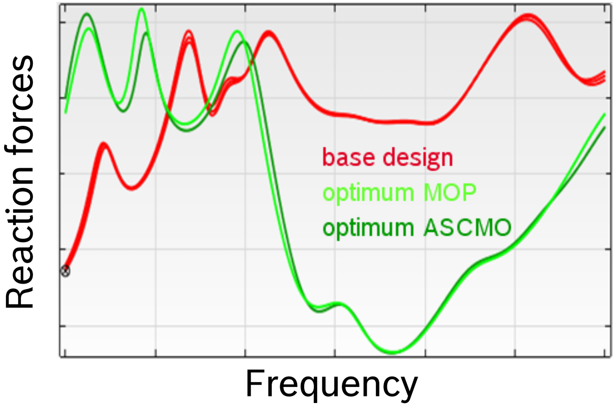
v.Mises stress at ribs

total reaction forces as maximum and integral value

Pareto-Optimization

- Objectives:
  - Integral of total reaction forces of two frequency ranges.
- Constraints:
  - Lower limit for frequency of first bending mode
  - Stress limits for ribs and mouting points
- Solver:
  - ASCMO for optimization
  - ABAQUS for re-calculation of optimal designs





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Requests For Enhancements

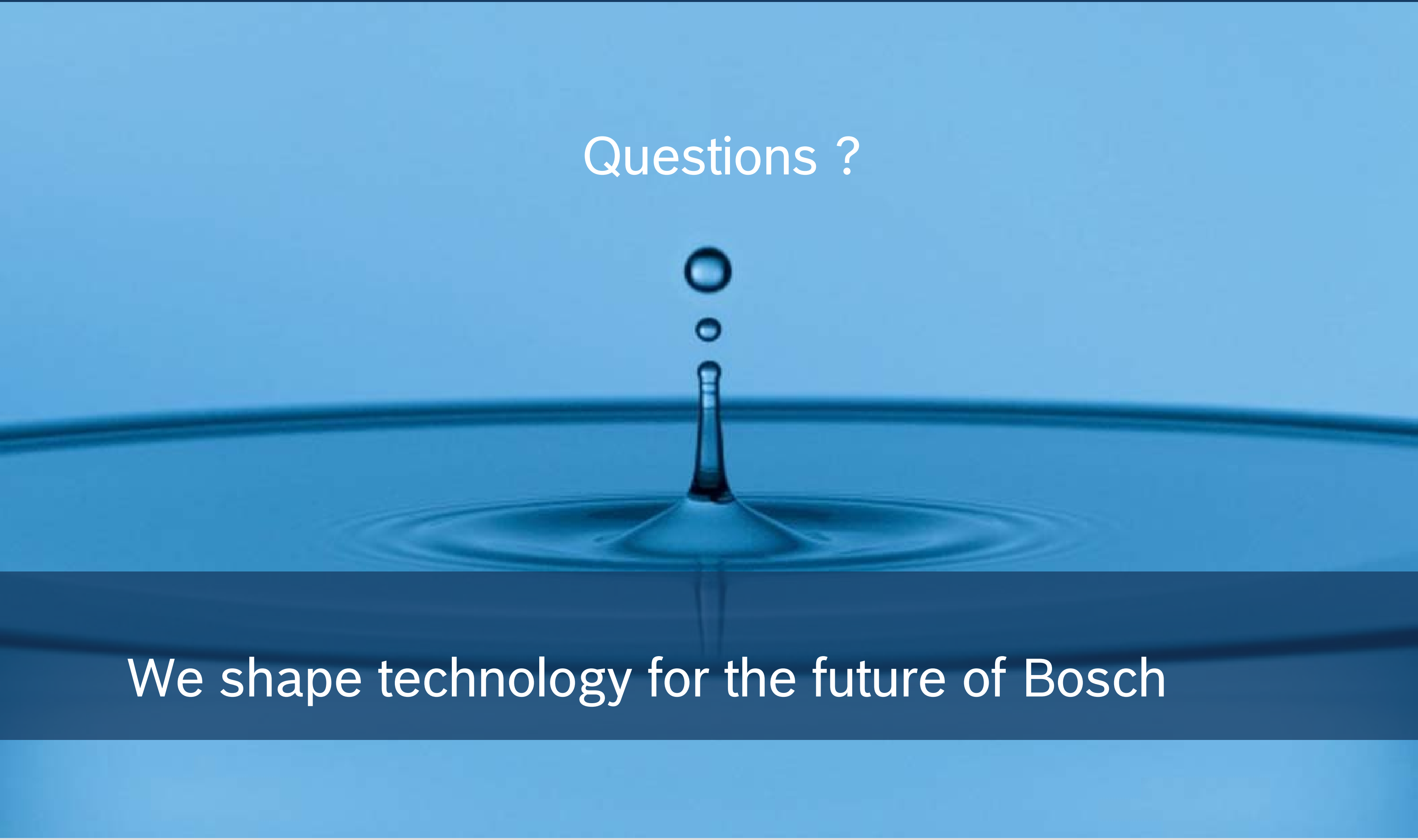
- → Direct usage of ASCMO-Metamodels in OptiSLang 4.0.
- → Development of new DoE-schemata in order to define designs in areas with large approximation errors.
- → Automatic recognition of input correlations during the calculation of the metamodels.
- → More error plots like used in ASCMO (true prediction plot, convergence plot,….,)
- → New result plots for the interactions of design variables
- → Automatic detection of outliers

Applications

- ➔ The metamodels of ASCMO and OptiSLang allow the use for the optimization on condition that
  - the variables do not face a change in the order (e.g. eigenmodes)
  - the design space has realistic limits of the design variable
  - the variables do not face a change in the location (e.g. stress)
- ➔ The minimum number of DoE-designs for an acceptable error of the metamodels is about 200-300.
- ➔ The metamodels of ASCMO and OptiSLang lead to similar optimization results.
- ➔ The error of the metamodels strongly increase at the limits of the design space and lead to wrong optimization results.

Software OptiSLang - ASCMO

- The ASCMO-Metamodels have mostly a smaller error than the OptiSLang-Metamodels.
- The calculation of the ASCMO-Metamodels is significantly faster than the calculation of OptiSLang-Metamodels (factor of 3-5).
- The CPU-time of ASCMO-Metamodels via Python is considerably larger than the OptiSLang-Metamodels (factor of 5).
- The error of ASCMO-Metamodels can be displayed graphically and more extensive than only the specification of single values like COP, r_{max}, RMSE,...



Questions ?

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