Ansys WOST WORKSHOP 2022

Recent Developments in Metamodeling, Optimization, and Uncertainty Quantification in optiSLang

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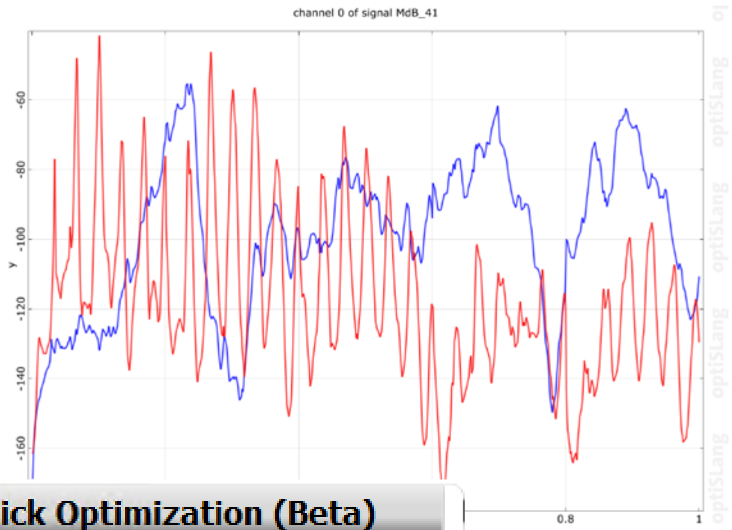
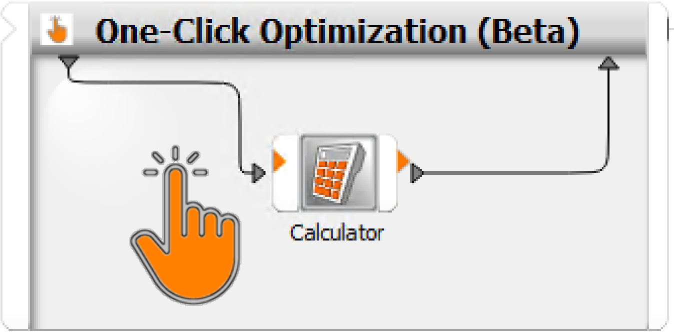
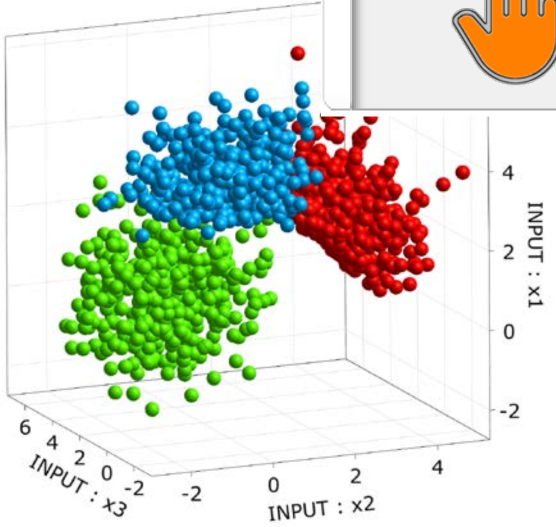
Outline







Machine Learning & AI

- Overview & Guideline
- DIM-GP models in scalar MOP
- DIM-GP for signal approximation

Single & Multi-Objective Optimization

- One Click Optimization
- Derivative-based optimizer for HFSS

Robustness & Reliability Analysis

- Discrete distributions
- Reliability Importance Measures

Machine Learning & AI

MOP – Automatized Metamodeling & Machine Learning

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Premium

- Polynomials
- MLS: Moving Least Squares
- Kriging (Isotropic / Anisotropic)
- GARS: Genetic Aggregation of Response Surface
  (NEW 2022R1: linux support)
- Support Vector Regression
  (NEW 2022R1: linux support)

Enterprise

- DFFN: Deep Feed Forward Network
  (2021R2 - Integral part)
- DIM-GP: Deep Infinite Mixture of Gaussian Process
  (NEW 2022R1)
- Signal MOP
- DIM-GP signal (Beta)
  (NEW 2022R2)

Models	
Polynomials	
Use	☑ True
Order	2
Coefficient factor	2.00
Moving least squares	
Use	☑ True
Order	2
Coefficient factor	8.00
Kriging	
Use	☑ True
Anisotropic	☐ False
Coefficient factor	8.00
Genetic Aggregation Response Surface	
Use	☐ False
Support Vector Regression	
Use	☐ False
Deep Feed Forward Network	
Use	☐ False
Deep Infinite Mixture Gaussian Process (DIM-GP)	
Use	☐ False
Signal MOP	
Use	☑ True
External	
ASCMO	☐ False
DIM-GP Signal (Beta)	☑ True

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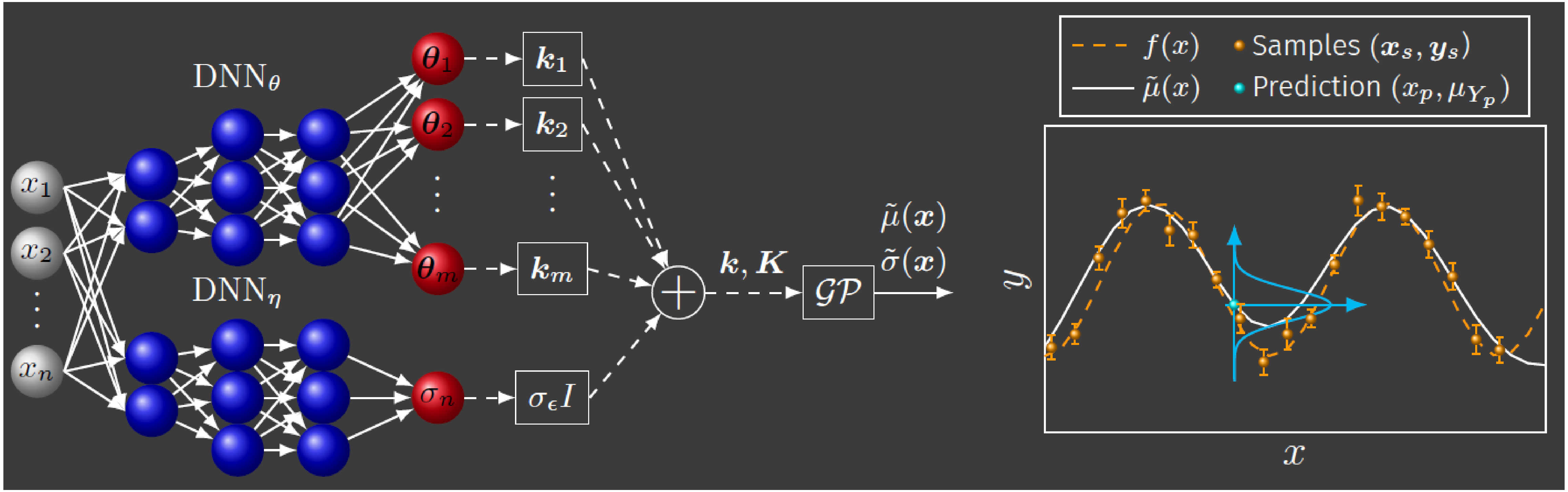
Deep Infinite Mixture Gaussian Process (DIM-GP)

- Stochos is an external library developed by Probaligence GmbH
- Since 2022 R1 delivered with oSL enterprise
- Stochos offers meta-models for scalar/signal/field inputs and outputs



Recommendation for Scalar Metamodel Usage

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Use case	Number of training samples	Polynomial	MLS	Isotropic Kriging	Anisotropic Kriging	SVR	GARS	DFFN	DIM-GP
Good compromise between training time and model quality	N ≤ 200	x	x	x	x	x	x		
	200 < N ≤ 1000	x	x	x		x		x	x
	N > 1000	x				x		x	
Best quality model for FMU export/digital twin	N ≤ 500	x	x	x	x				
	500 < N ≤ 2000	x	x	x					
	N > 2000	x							
Best quality model	≤ 500	x	x	x	x	x	x	x	x
	500 < N ≤ 2000	x	x	x		x		x	x
	N > 2000	x				x		x	

Guideline is introduced in 2022 R2 in documentation and training

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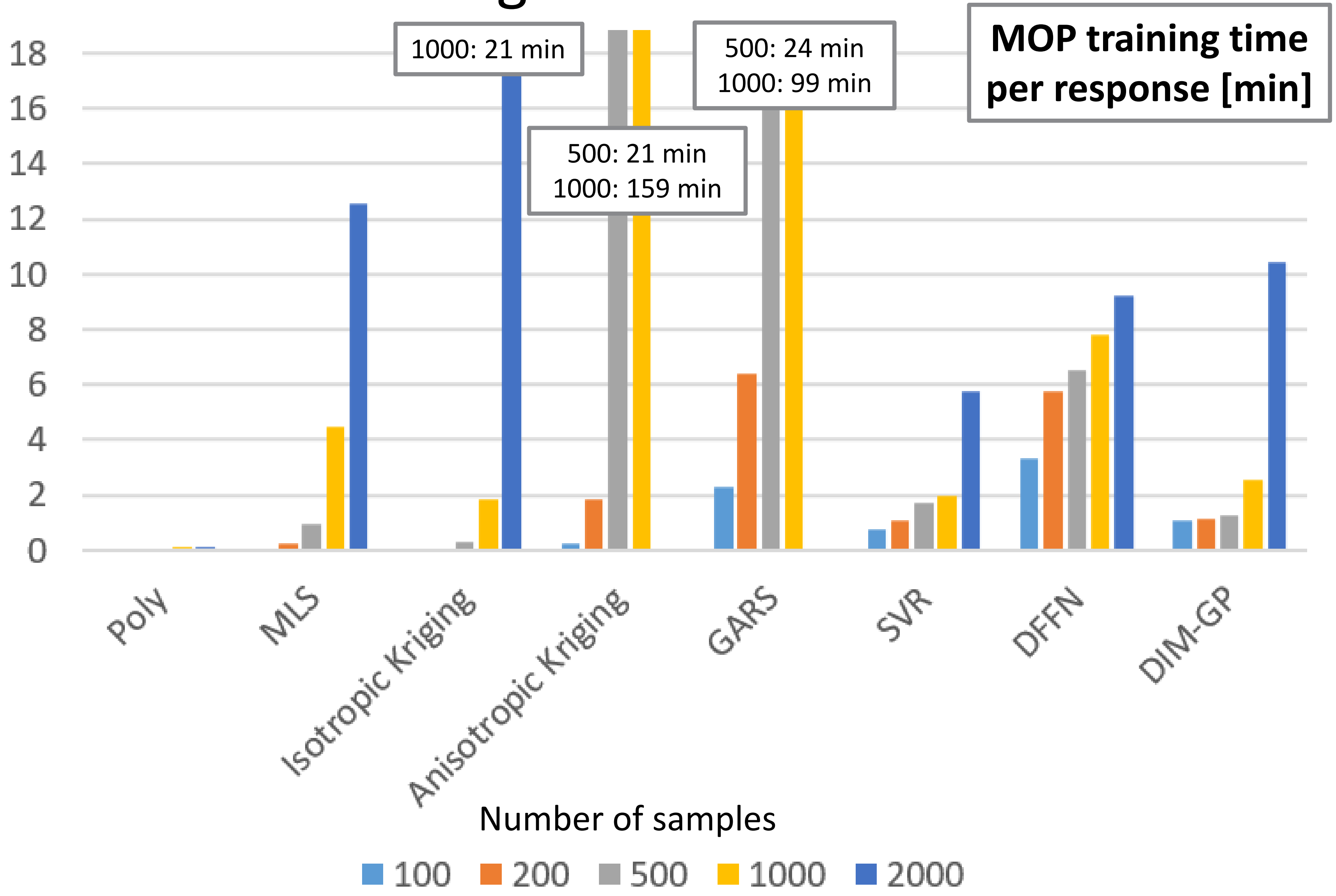
Example: Ten Bar Truss – MOP Training Performance

- For MLS, Kriging and GARS, the training time increases significantly with the number of sample
- SVR, and DIM-GP can be applied efficiently up to 2000 samples
- Polynomials and DFFN can be used for even larger data sets



DIM-GP for Signal Data Approximation (beta in 2022 R2)

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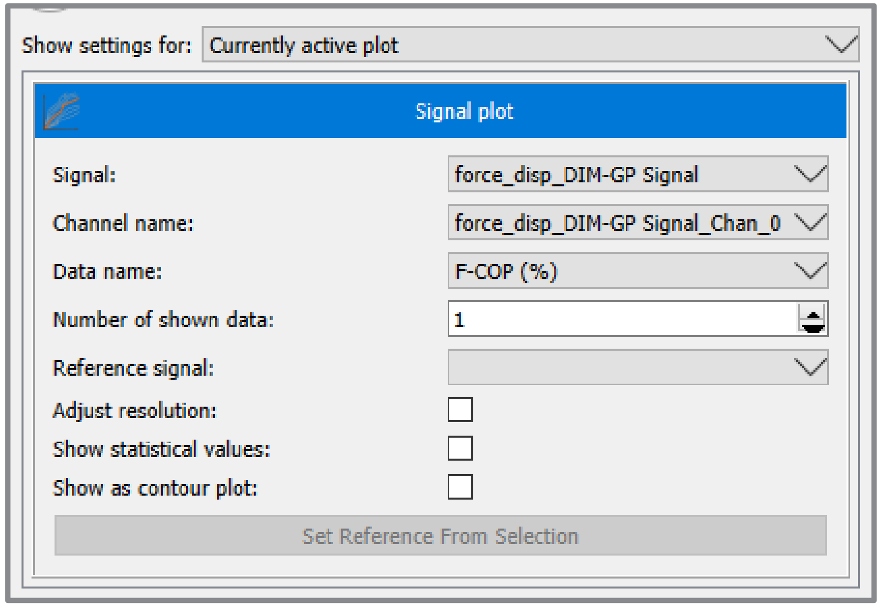
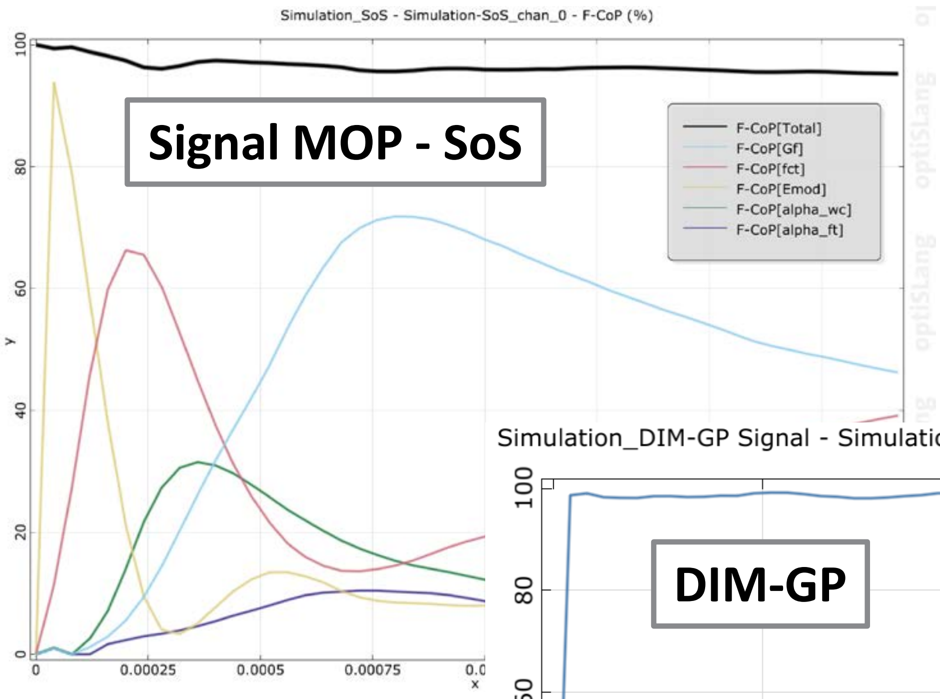
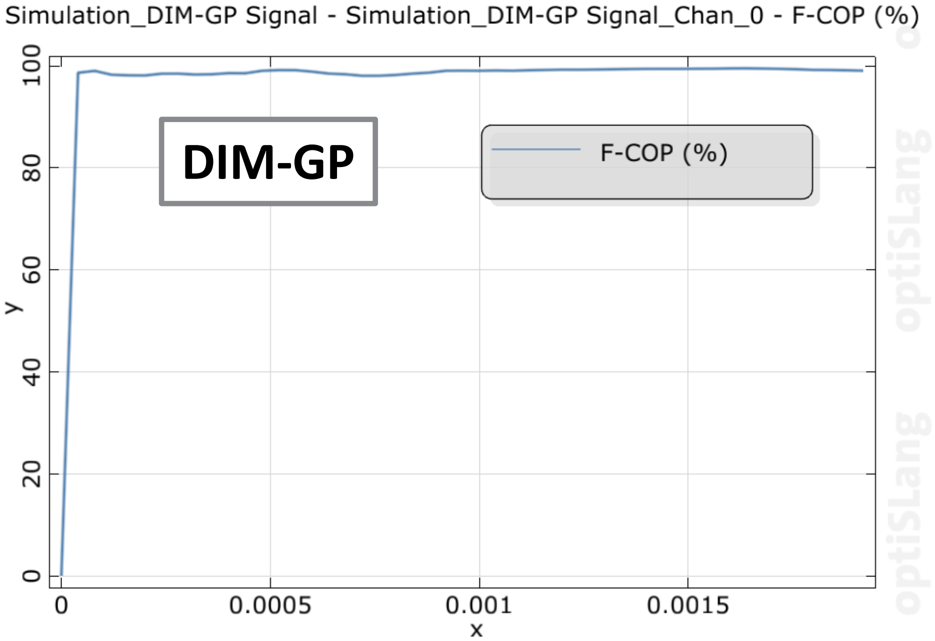
Post-processing:

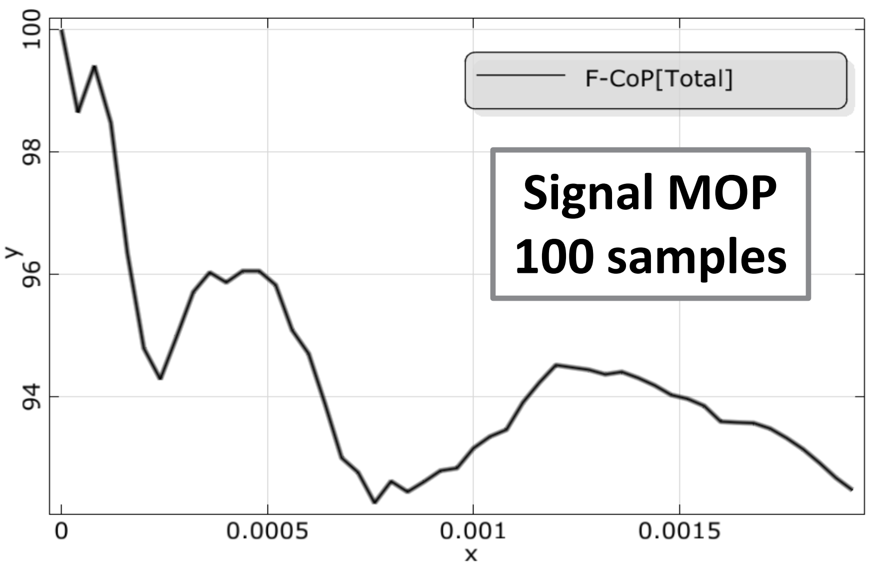
- Visualization of the F-CoP in % in the Signal Plot
- Limitation: no parameter sensitivities or correlations available yet

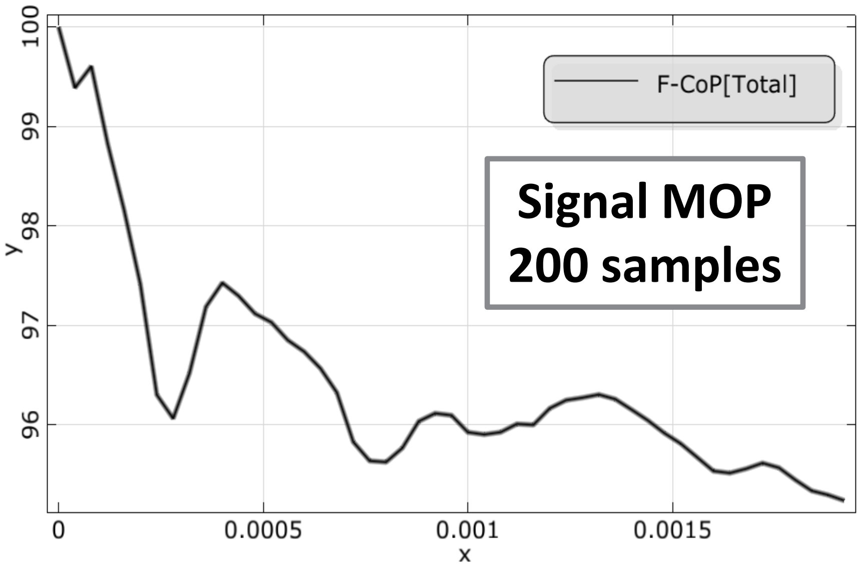


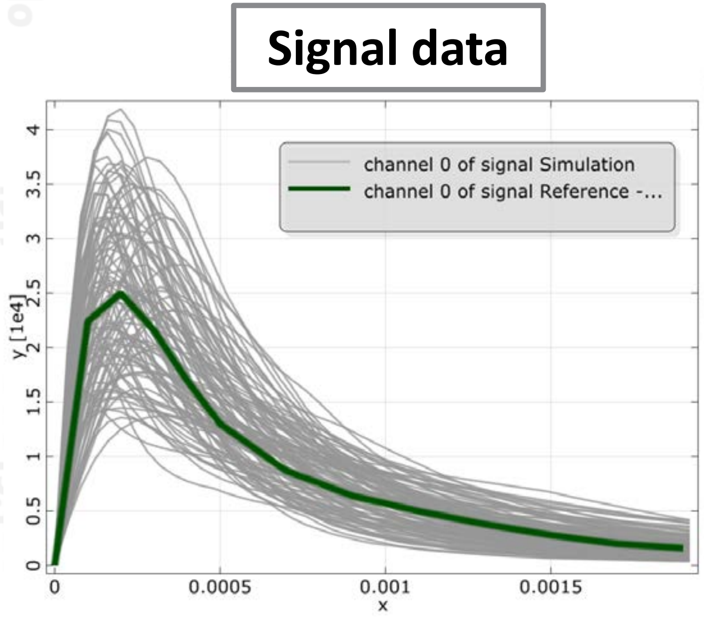


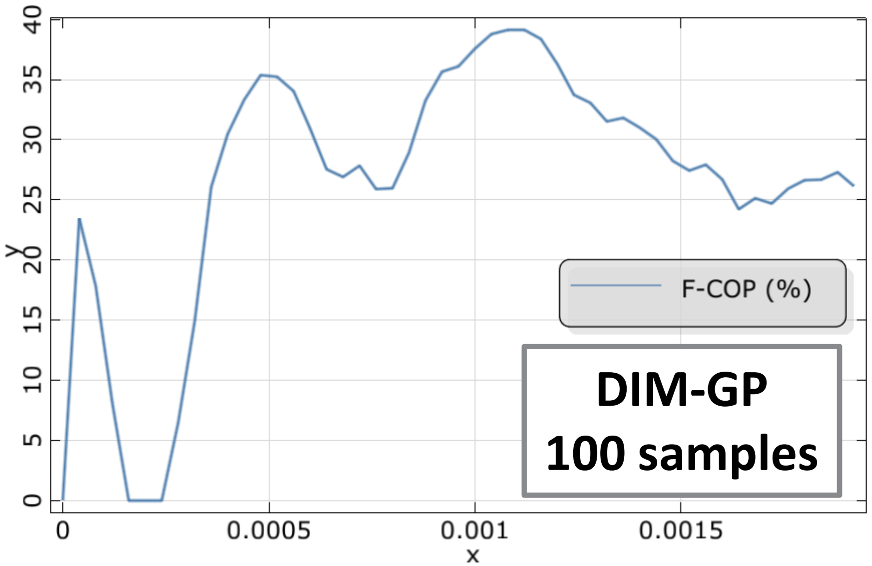


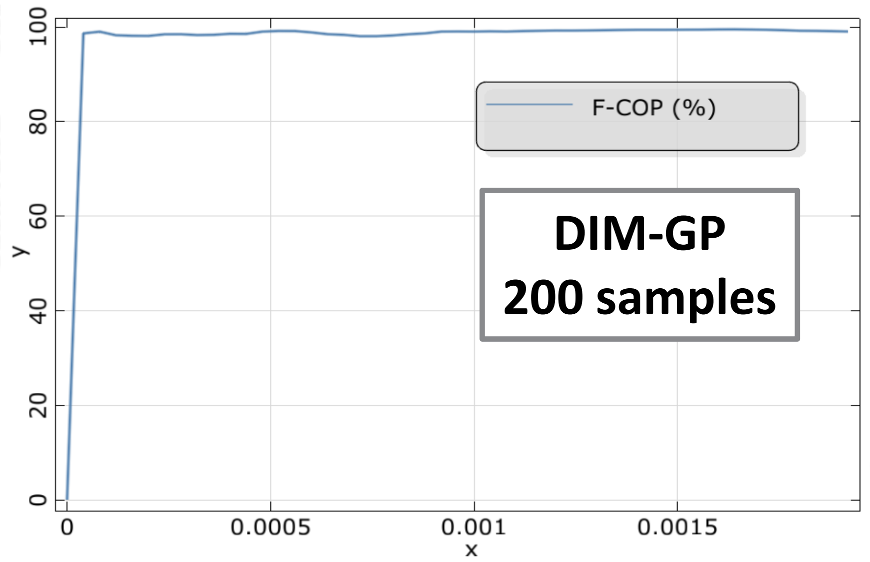
Example: Wedge Splitting Test – Signal MOP vs. DIM-GP



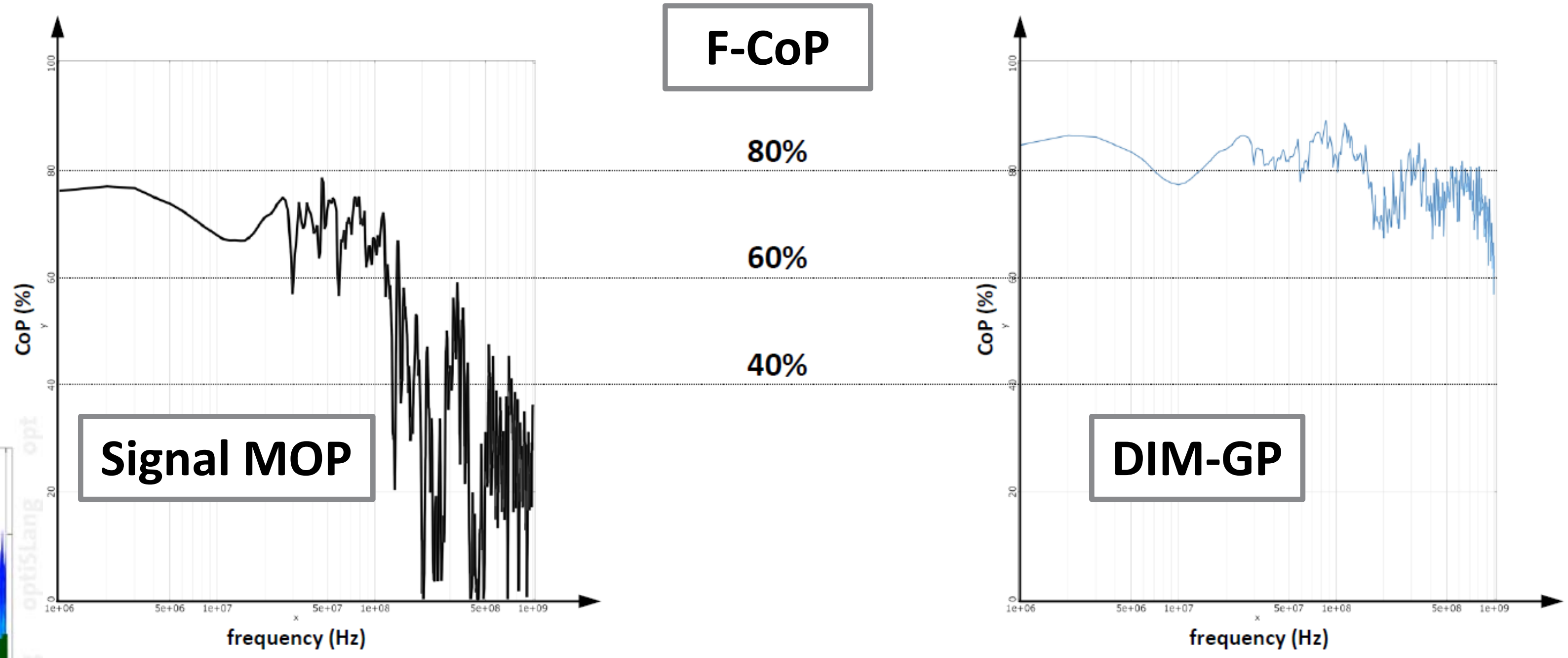




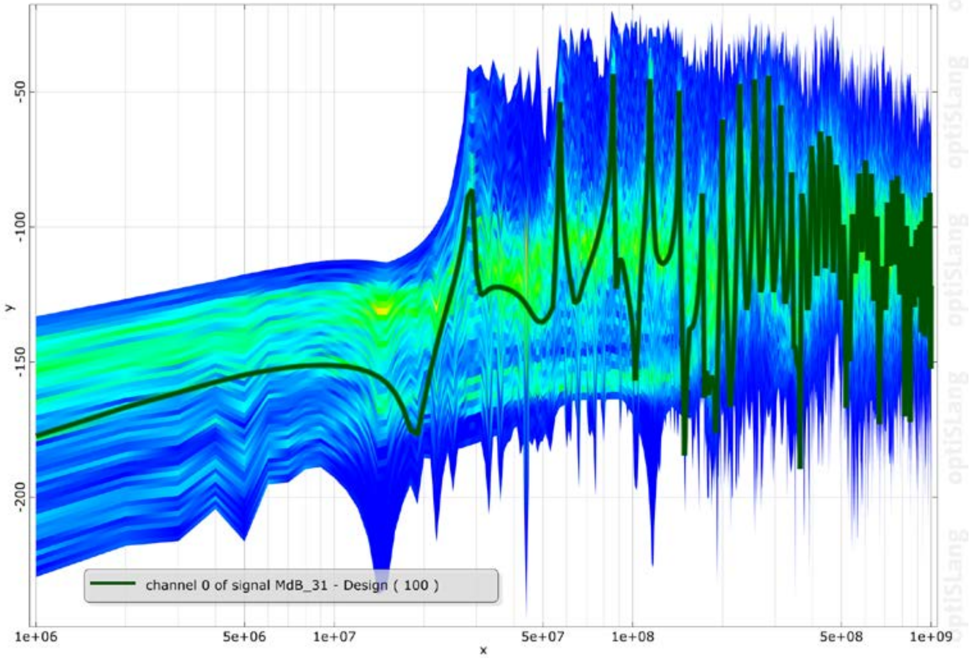




Customer Example: Signal MOP vs. DIM-GP



Original data

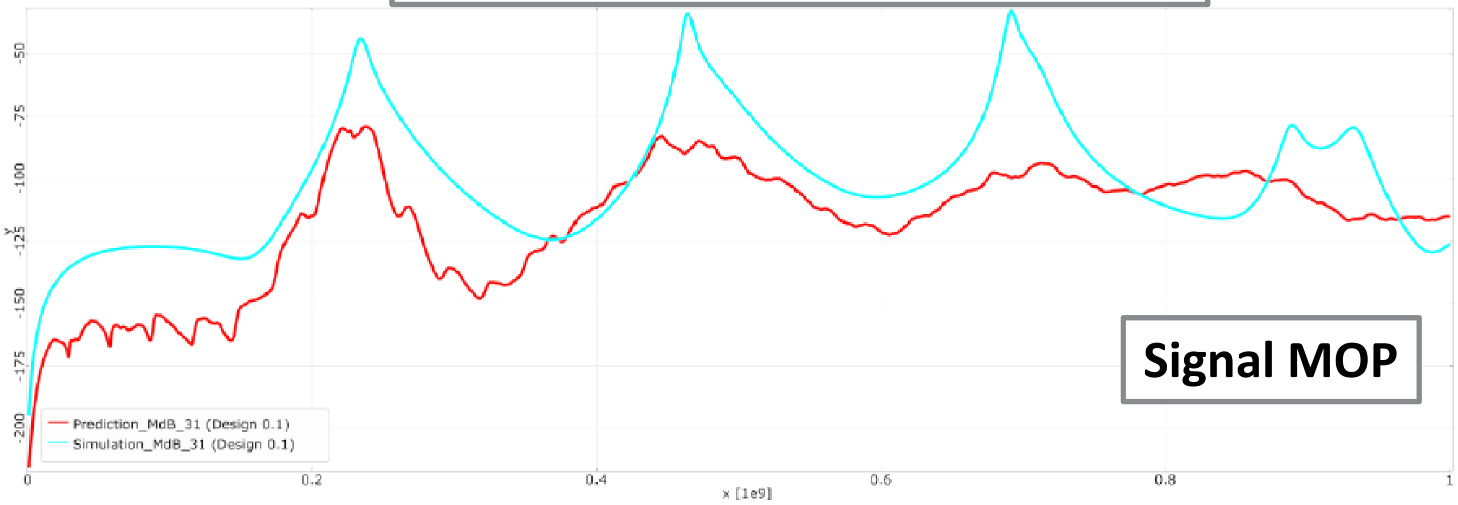


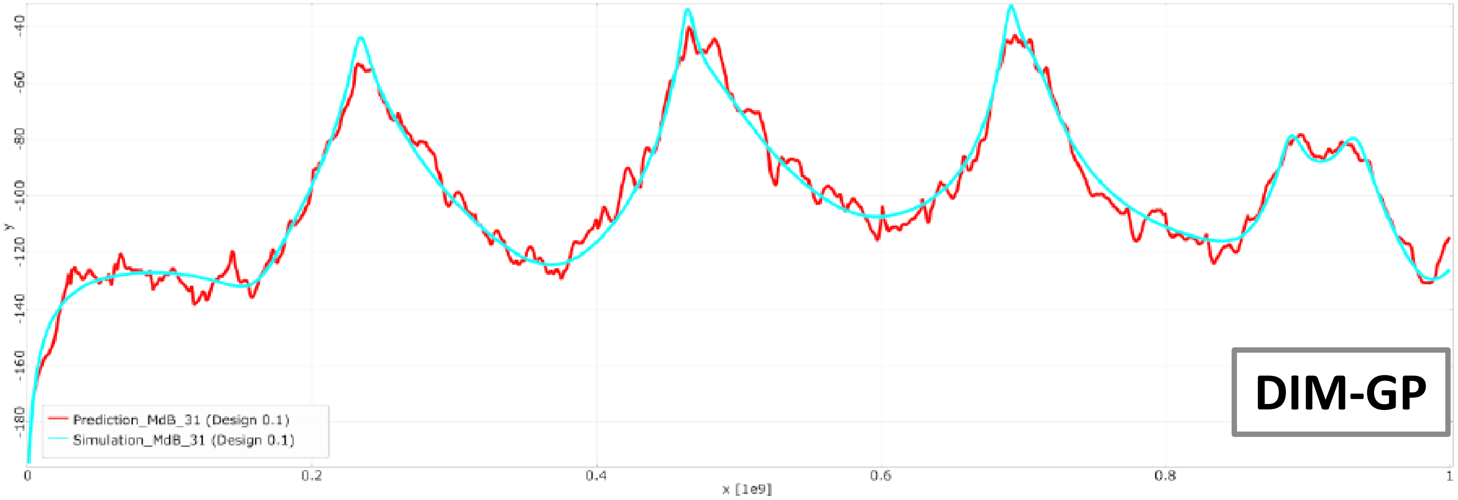
- 340 samples, 13 input parameters
- Data set contains low and high-frequency samples

Customer Example: Signal MOP vs. DIM-GP

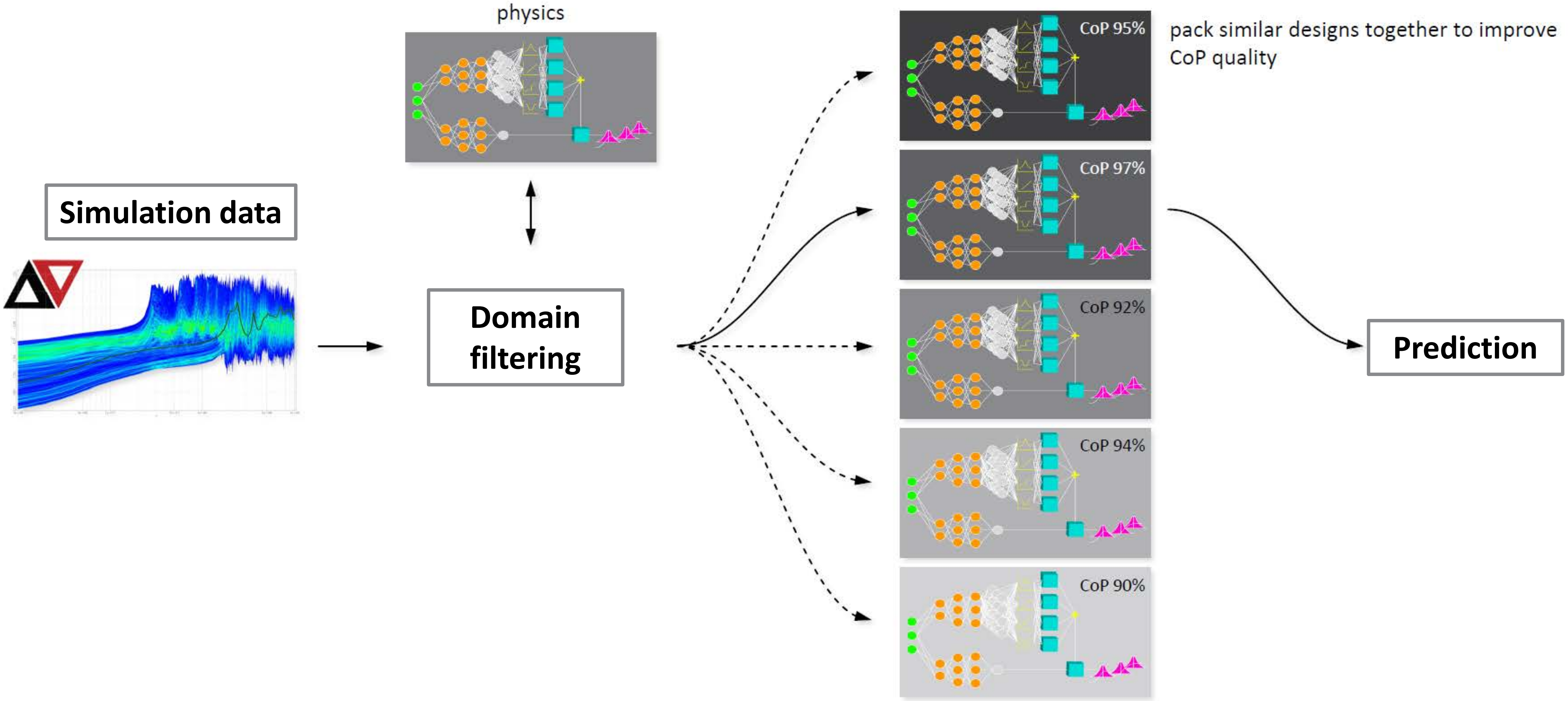
- Signal MOP can not distinguish between low and high frequency phenomena
- Main trends in data are represented by DIM-GP
- For low-frequency phenomena the DIM-GP approximation is distorted by artificial noise

Approximation of selected sample



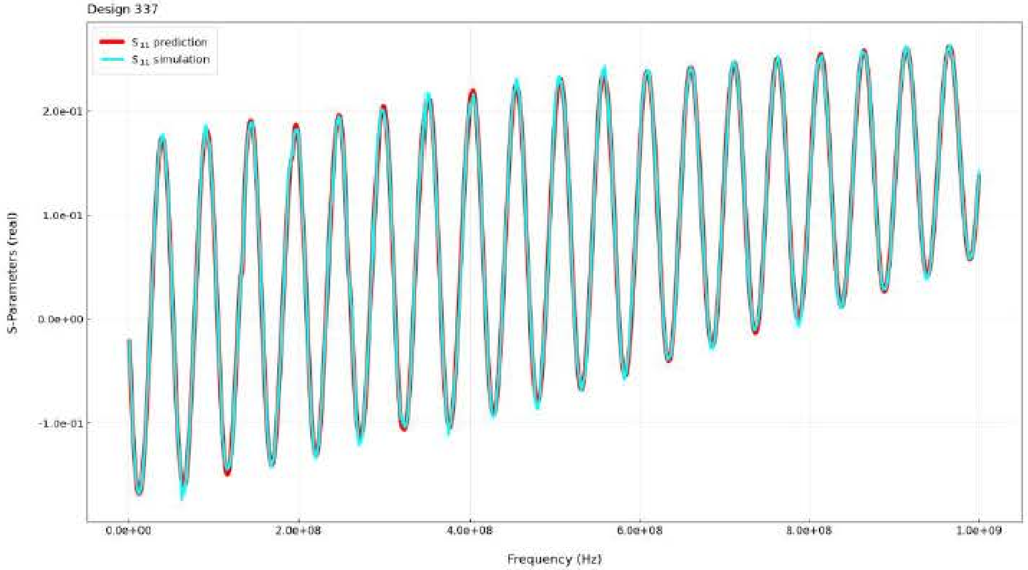


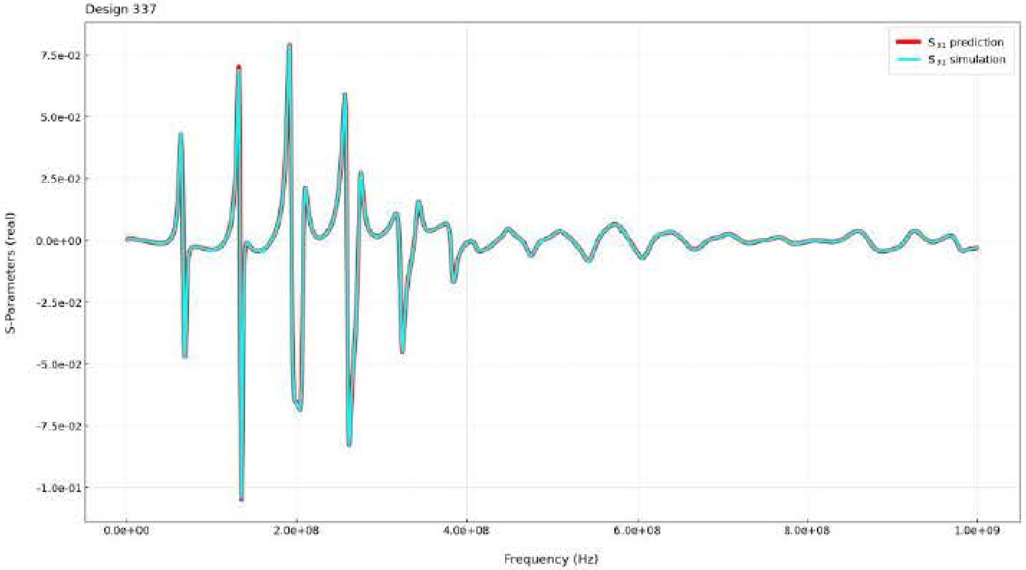
Customer Example: DIM-GP & Domain Filtering



Customer Example: DIM-GP & Domain Filtering

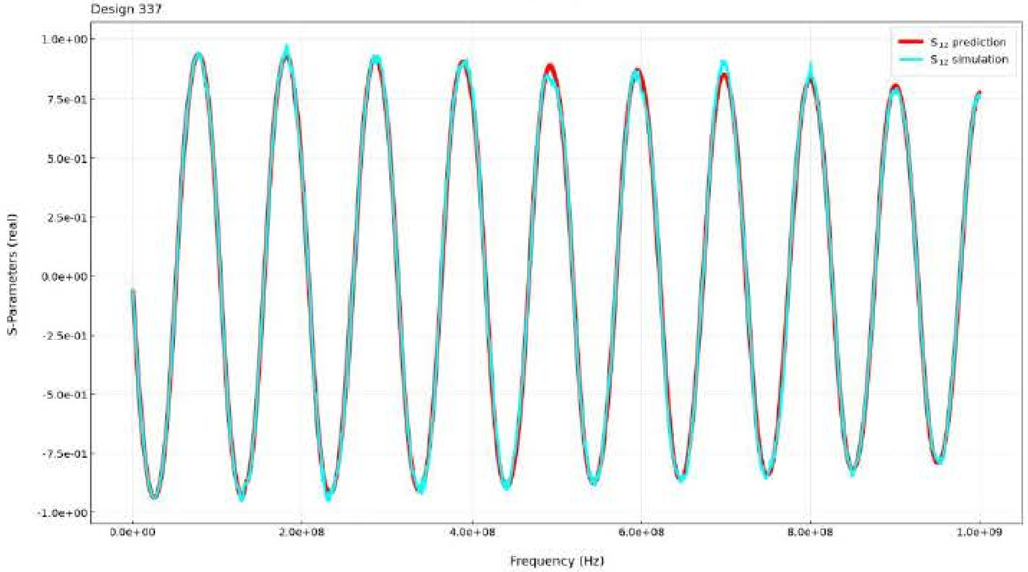
S11
real

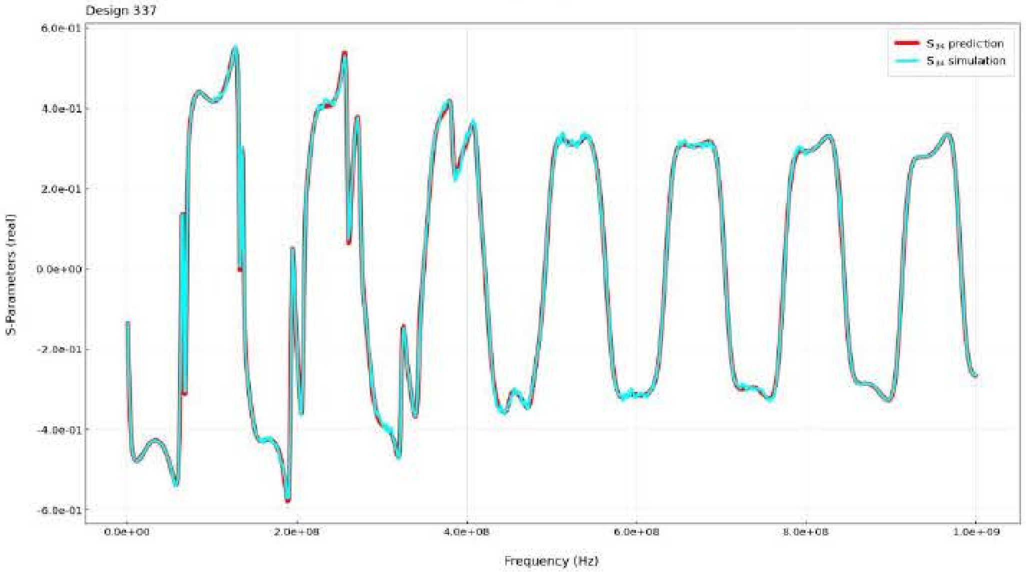




S31
real

S12
real





S34
real

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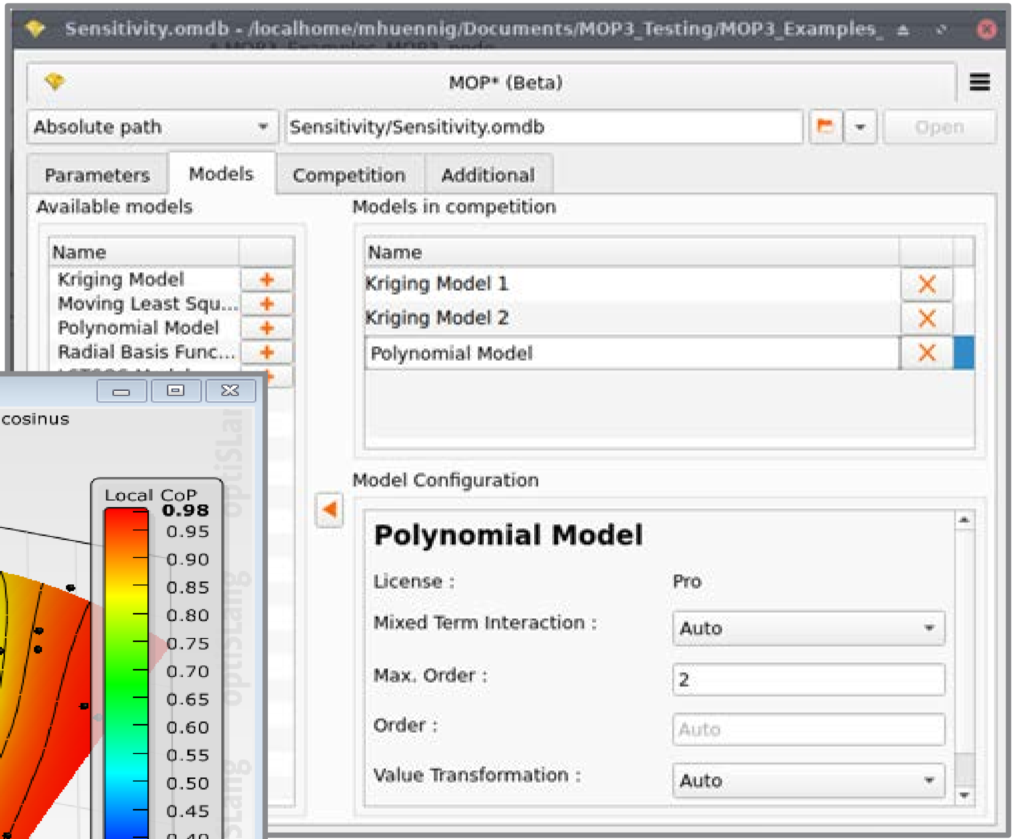
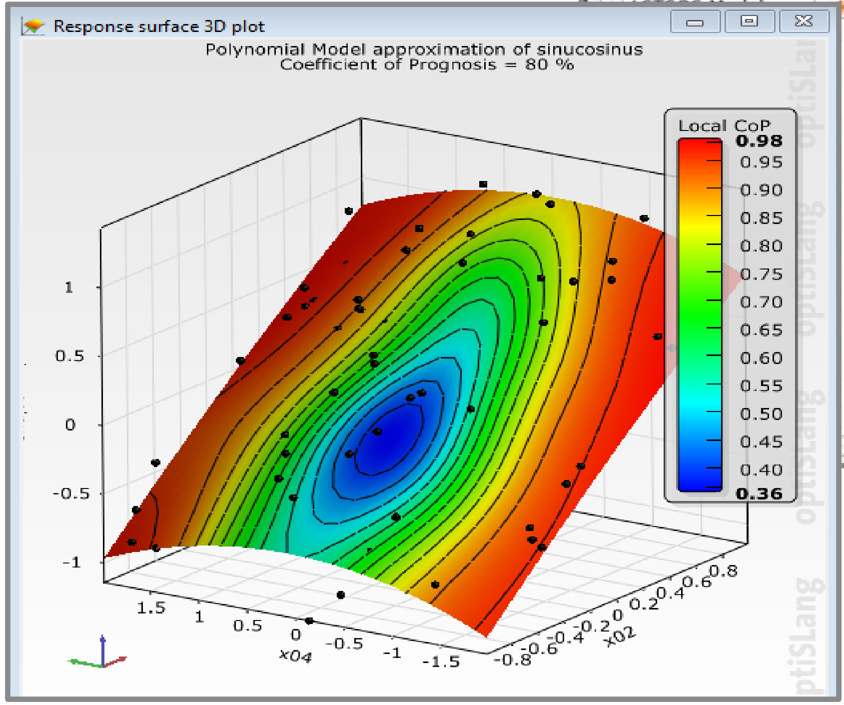
New MOP Framework – Scalar MOP in 22 R2 (beta)

- More control of MOP setup in UI
- Improved architecture
- New framework for more metamodels & better performance



- Available
  - MOP Build (“MOP3 node”)
  - Polynomial, MLS, Kriging, RBF
  - Postprocessing
  - MOPSolver



- Limitations in 22 R2:
  - No wizard
  - No AI/ML models yet

Single- and Multi-Objective Optimization

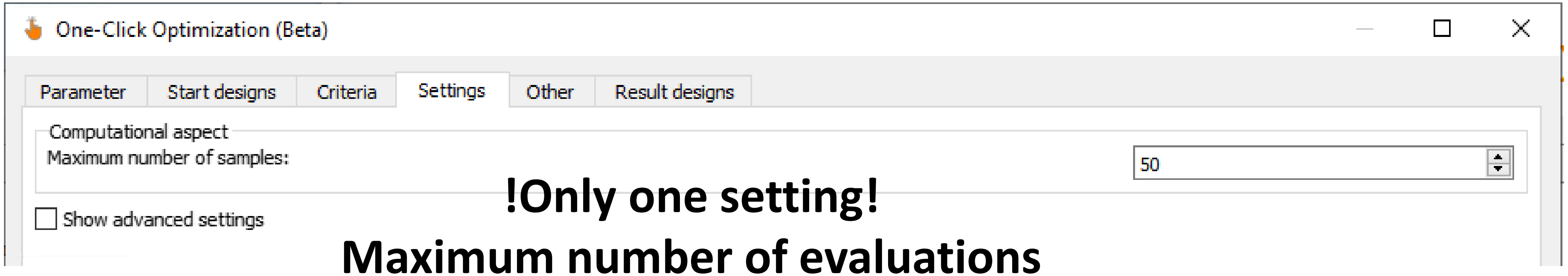
One-Click-Optimization (OCO) (Beta)

Objectives:

- "Settingsless" optimization algorithm that could automatically suit any optimization problem.
- The results should be as good as possible: optimal or close to the optimal algorithms.
- Improve our standing with competitors (SHERPA, pilOPT,...).

General philosophy:

- Algorithm competition where some "selected algorithms are running".
- Challenging algorithms are trying to take over the spots of the running algorithms.

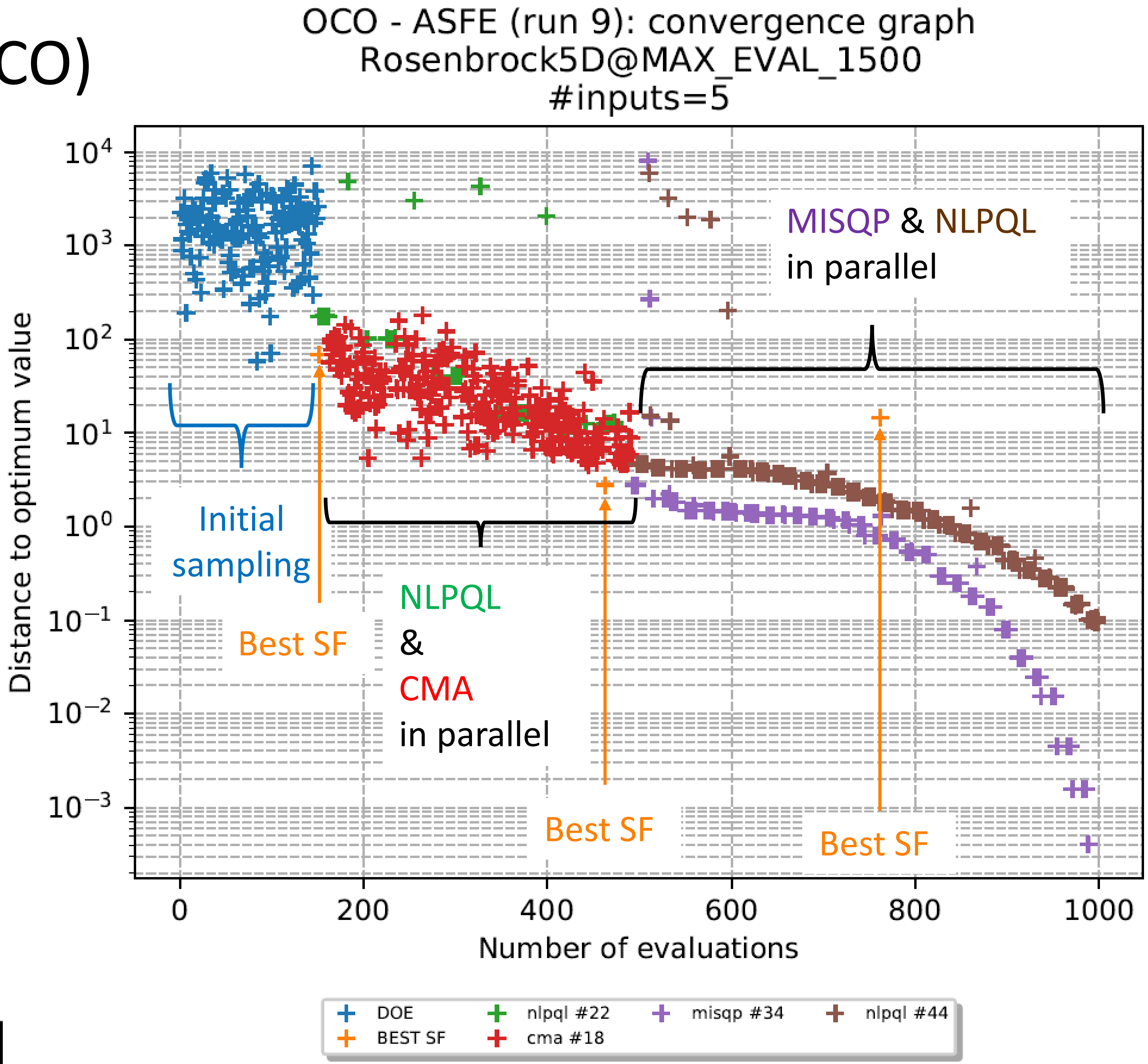


!Only one setting!

Maximum number of evaluations

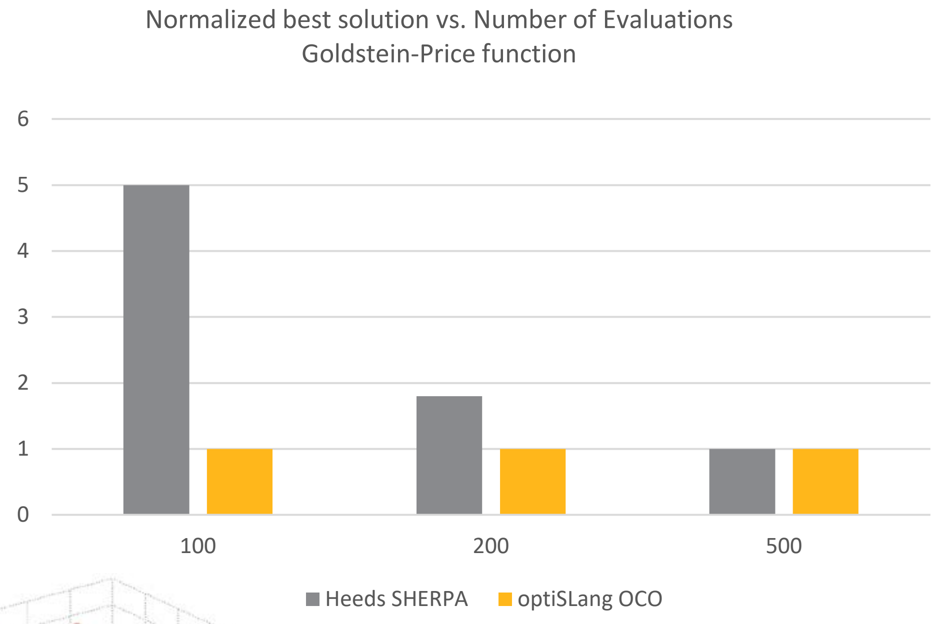
One-Click-Optimization (OCO)

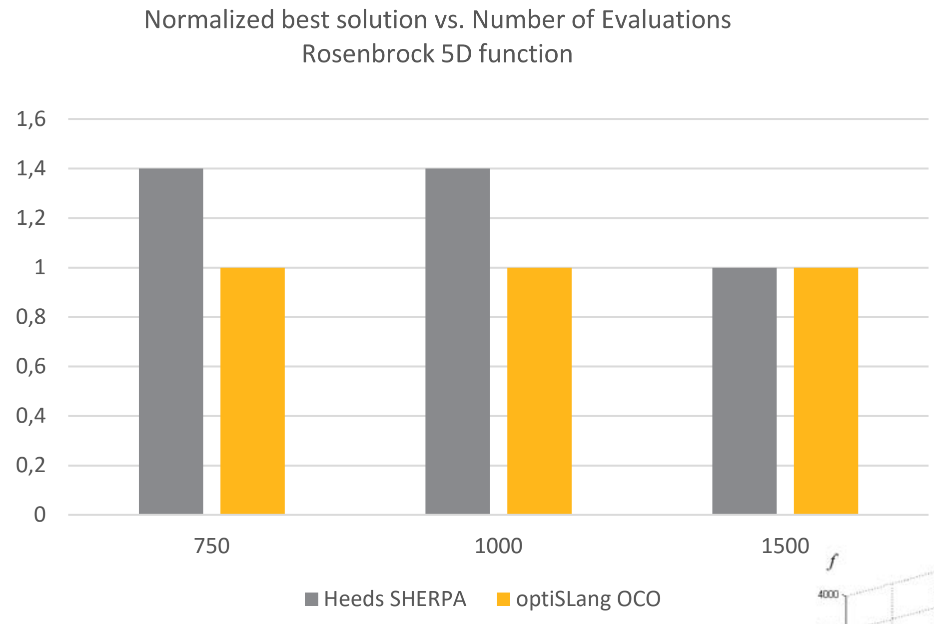
- Selects automatically & dynamically the most suitable optimization algorithms
- Runs simultaneously multiple optimization algorithms (global & local search)
- Supports continuous and integer parameters (discrete by value or ordered by index)
- Support of constrained single-objective optimization applications (New 2022R1)
- Multi-objective optimization support (New 2022R2)

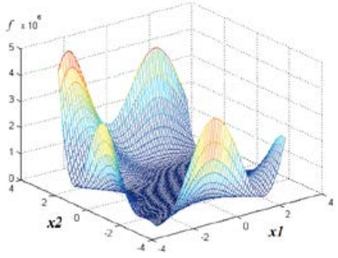


Validation of Performance

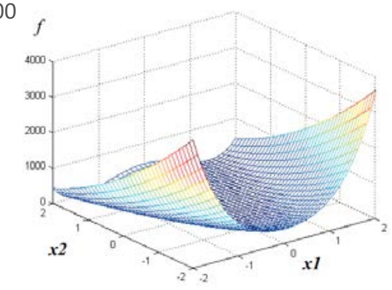
- Library of many single- and multi objective problems
- Very good results with practical examples with e.g. lighthouse customers (confidential data)
- Very good results compared to literature







e.g. SHERPA (Siemens-Heeds)
http://www.redcedartech.com/pdfs/SHERPA_Benchmark_0110.pdf



Example: One-Click-Optimization (OCO)

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Cantilevered beam example with mixed variables

objective function to be minimized is:

$$f(H,h_1,b_1,b_2) = V = [2*h_1*b_1 + (H - 2*h_1)*b_2]*L$$

The constraint functions are defined as:

$$g_1(H,h_1,b_1,b_2) = P*L*H/(2*I) = \sigma_{max} \leq \sigma_{all} = 5000$$

$$g_2(H,h_1,b_1,b_2) = P*L^3/(3*E*I) = \delta_{max} \leq \delta_{all} = 0.10$$

where:

$$I = 1/12*b_2*(H-2*h_1)^3 + 2*[1/12*b_1*h_1^3 + b_1*h_1*(H-h_1)^2/4]$$

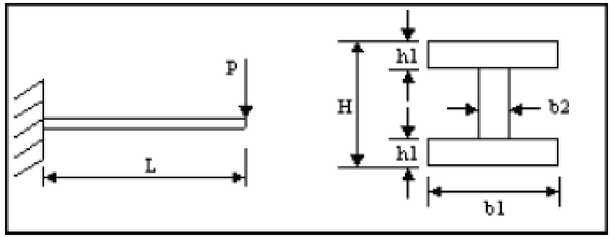
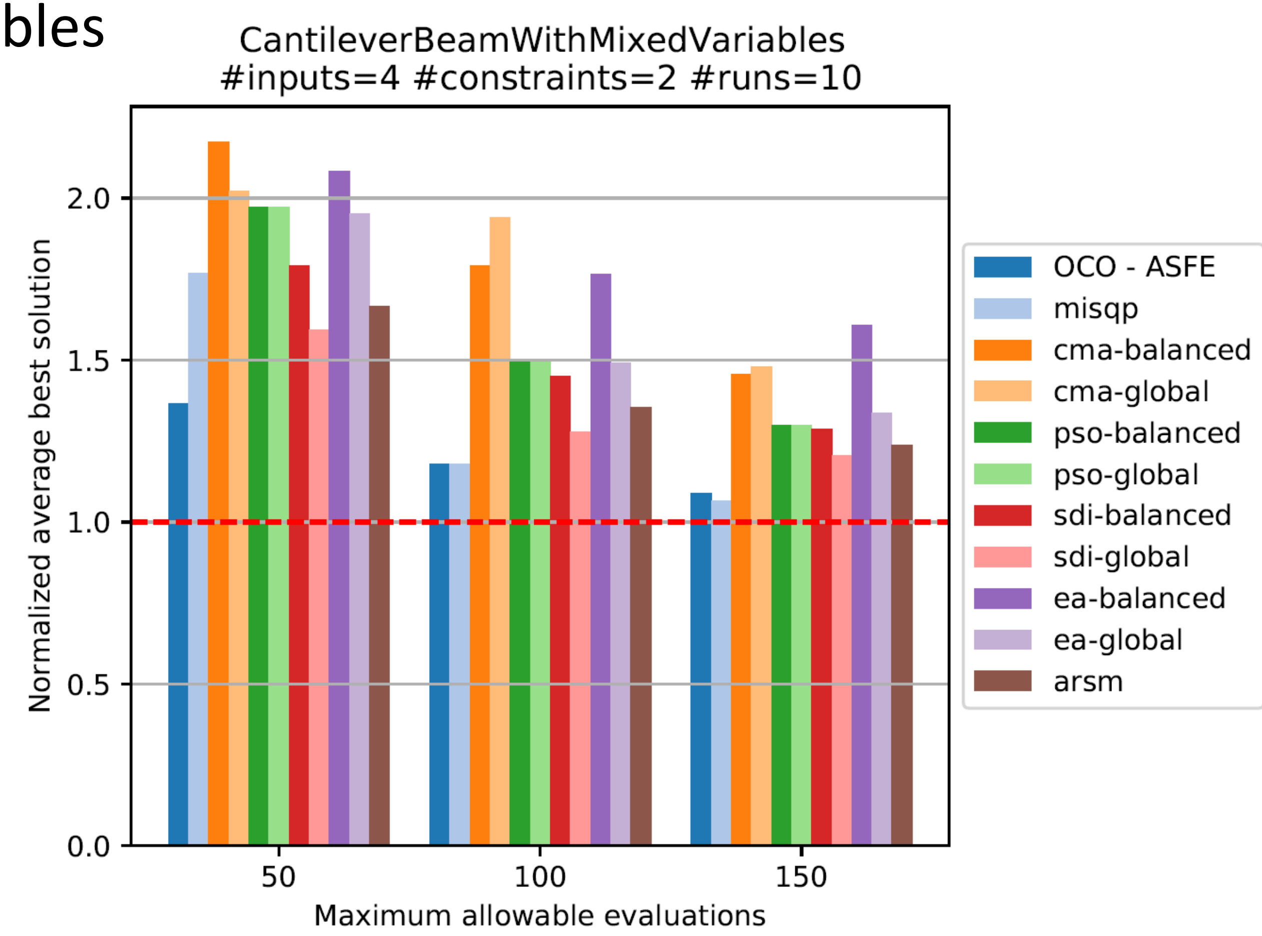


Figure 12. Cross-sectional shape variables in the cantilevered I-beam with a tip load.

$3.0 \leq H \leq 7.0$
h1 in {0.1, 0.25, 0.35, 0.5, 0.65, 0.75, 0.9, 1.0}
$2.0 \leq b1 \leq 12.0$
$0.1 \leq b2 \leq 2.0$

The global minimum has a value f = 92.77 at the location H = 7.0, h_1 = 0.1, b_1 = 9.48482, b_2 =0.1.



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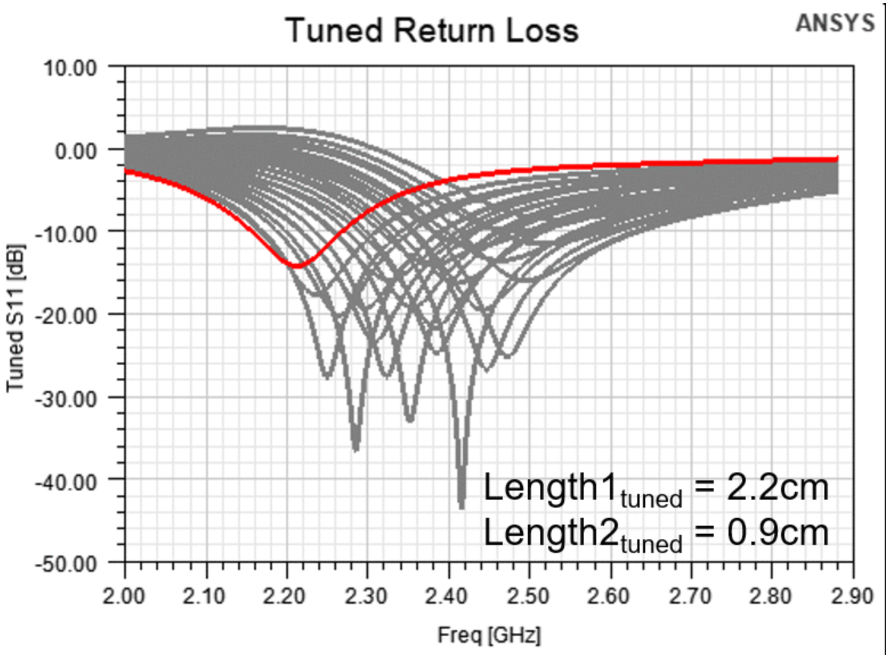
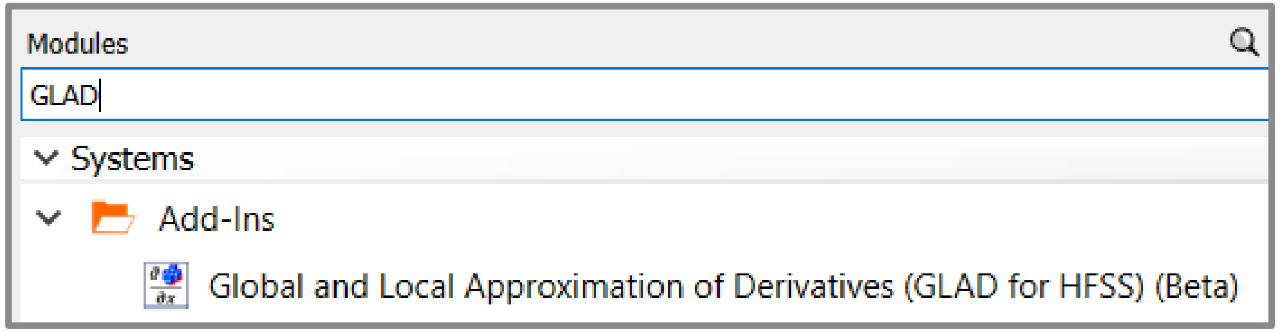
GLAD - Global and Local Approximation of Derivatives

HFSS optimizer finalization 2022 R1

- Introduced at WOST 2021
- Considers the HFSS derivatives of signal responses for more efficient optimization
- Setup of integration is supported by an AEDT wizard
- Delivered as beta feature in 2022 R1



Parameter	Responses
gap2 * 1.5	StFeed_T1Feed_T1_dB [1:1]
ws * 25	StFeed_T1Feed_T1_der_im_gap2 [1:1]
	StFeed_T1Feed_T1_der_im_ws [1:1]
	StFeed_T1Feed_T1_der_re_gap2 [1:1]
	StFeed_T1Feed_T1_der_re_ws [1:1]
	StFeed_T1Feed_T1_im [1:1]
	StFeed_T1Feed_T1_re [1:1]



GLAD - Global and Local Approximation of Derivatives

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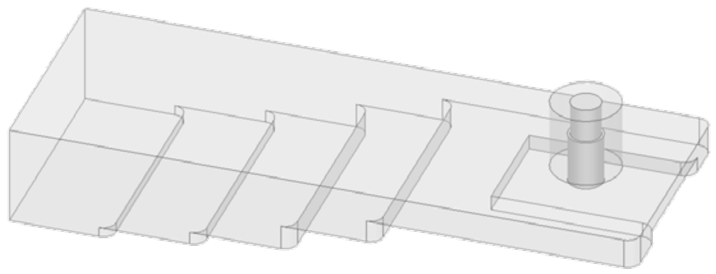
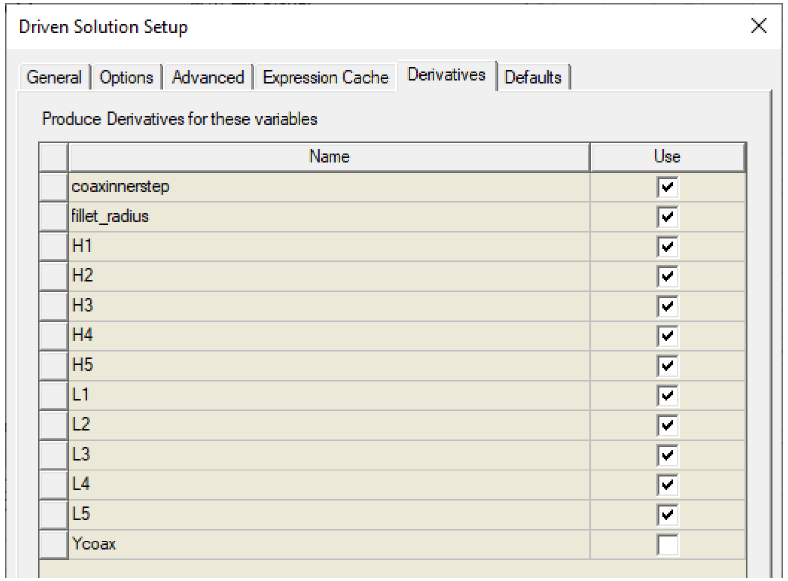
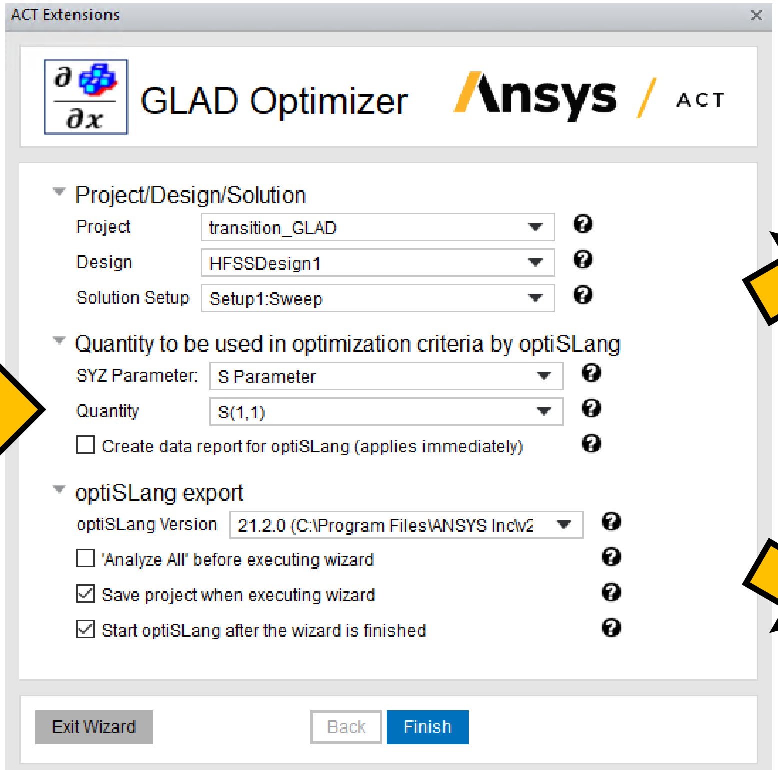
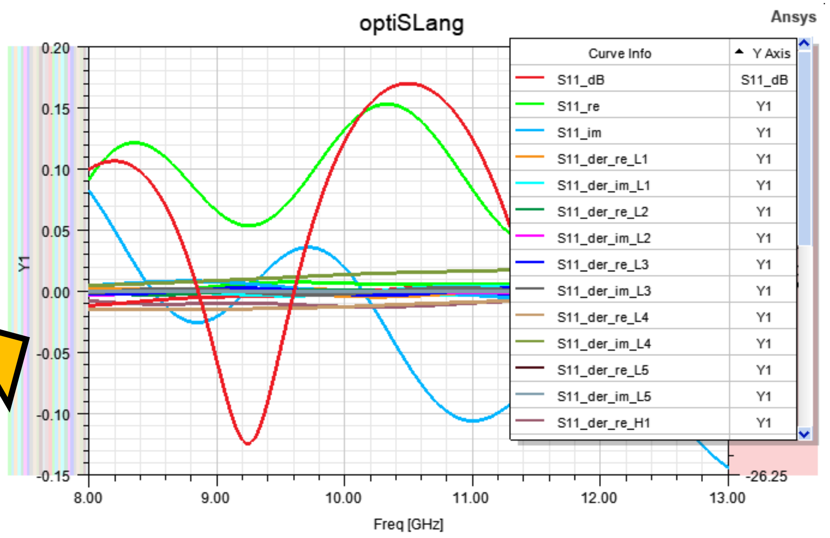


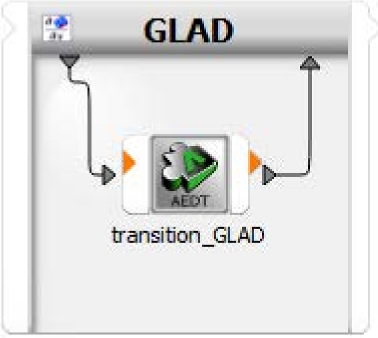


Define variables for derivative study



ACT Wizard helps setup reports and create optiSLang project

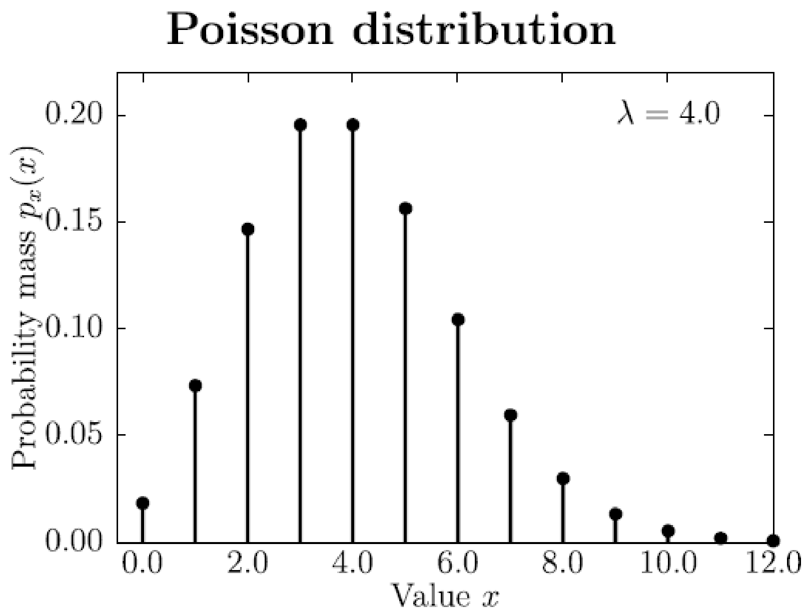




Robustness & Reliability Analysis

Poisson Distribution for Stochastic Parameters

- Simulated values can only be natural numbers 0,1,2,3,…
- Only one distribution parameter, which is equivalent to mean and variance
- PDF does not exist, PMF is implemented instead
- CDF and inverse CDF are step-wise, similar as for Bernoulli and Discrete distributions



$x \in \{0, 1, 2, 3, \ldots\}, \quad \lambda > 0$

Distribution parameter

- Expected number of events $\lambda > 0$

Mean value & standard deviation

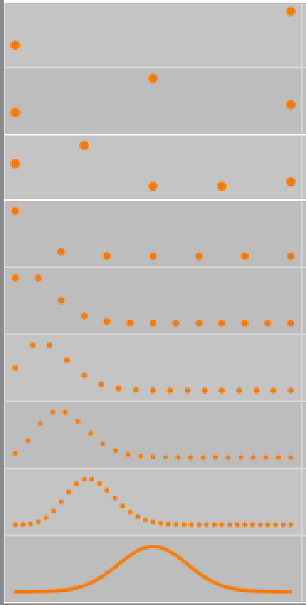
- $\bar{X} = \lambda$
- $\sigma_X = \sqrt{\lambda}$

Probability mass function

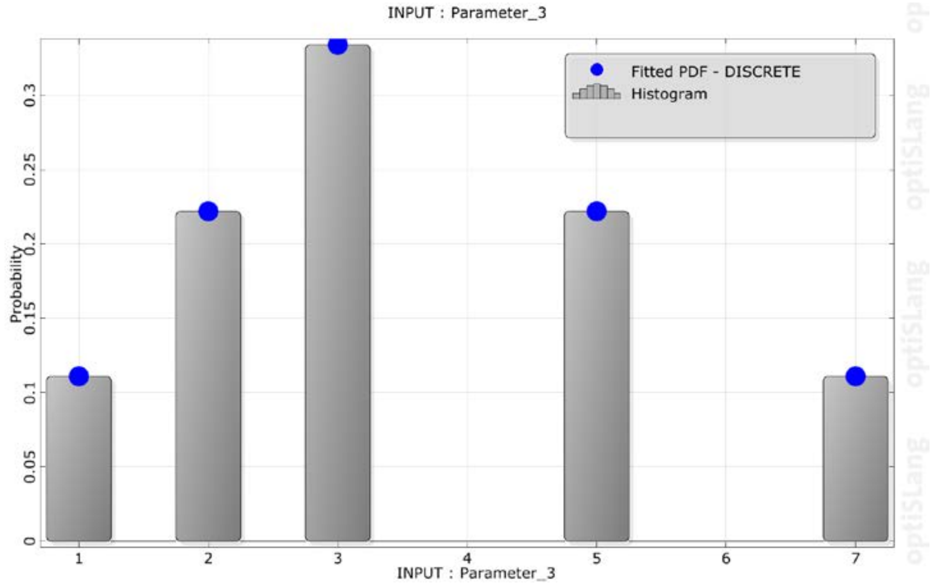
- $p_X(x) = \begin{cases} \frac{\lambda^x \cdot e^{-\lambda}}{x!} & \text{if } x \in \{0, 1, 2, 3, \ldots\} \\ 0 & \text{otherwise} \end{cases}$

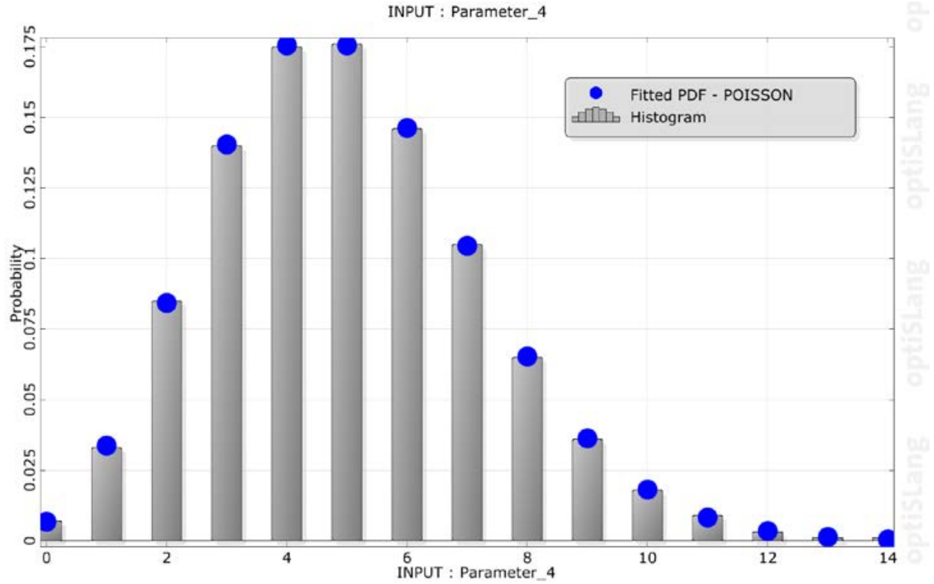
Visualization of Discrete Distributions

- Point-wise Probability Mass Function instead of PDF
- Ordinate shows probability values, since no “density” exists
- Implemented for Bernoulli, Discrete and Poisson
- Automatic fit allows fitting of discrete distributions only for discrete data



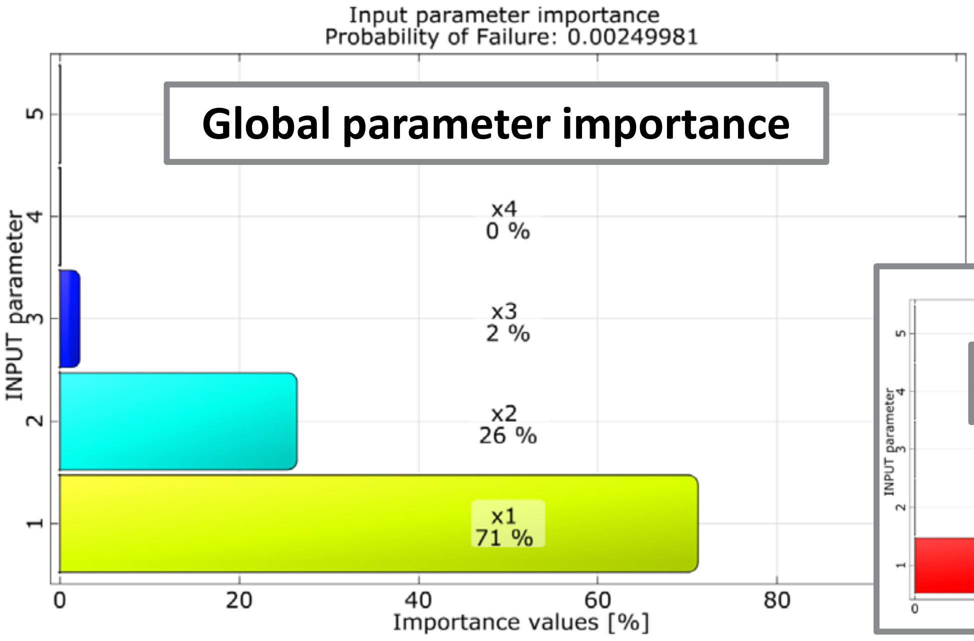
PDF	Type	Distribution parameter
	BERNOULLI	0.8
	DISCRETE	-1; 0.15; 1; 0.6; 1.8; 0.25
	DISCRETE	1; 0.3; 2; 0.5; 4; 0.05; 7; 0.05; 8; 0.1
	POISSON	0.1
	POISSON	1
	POISSON	2
	POISSON	4
	POISSON	10
	TRUNCATEDNORMAL	0; 1.60678; -10; 10

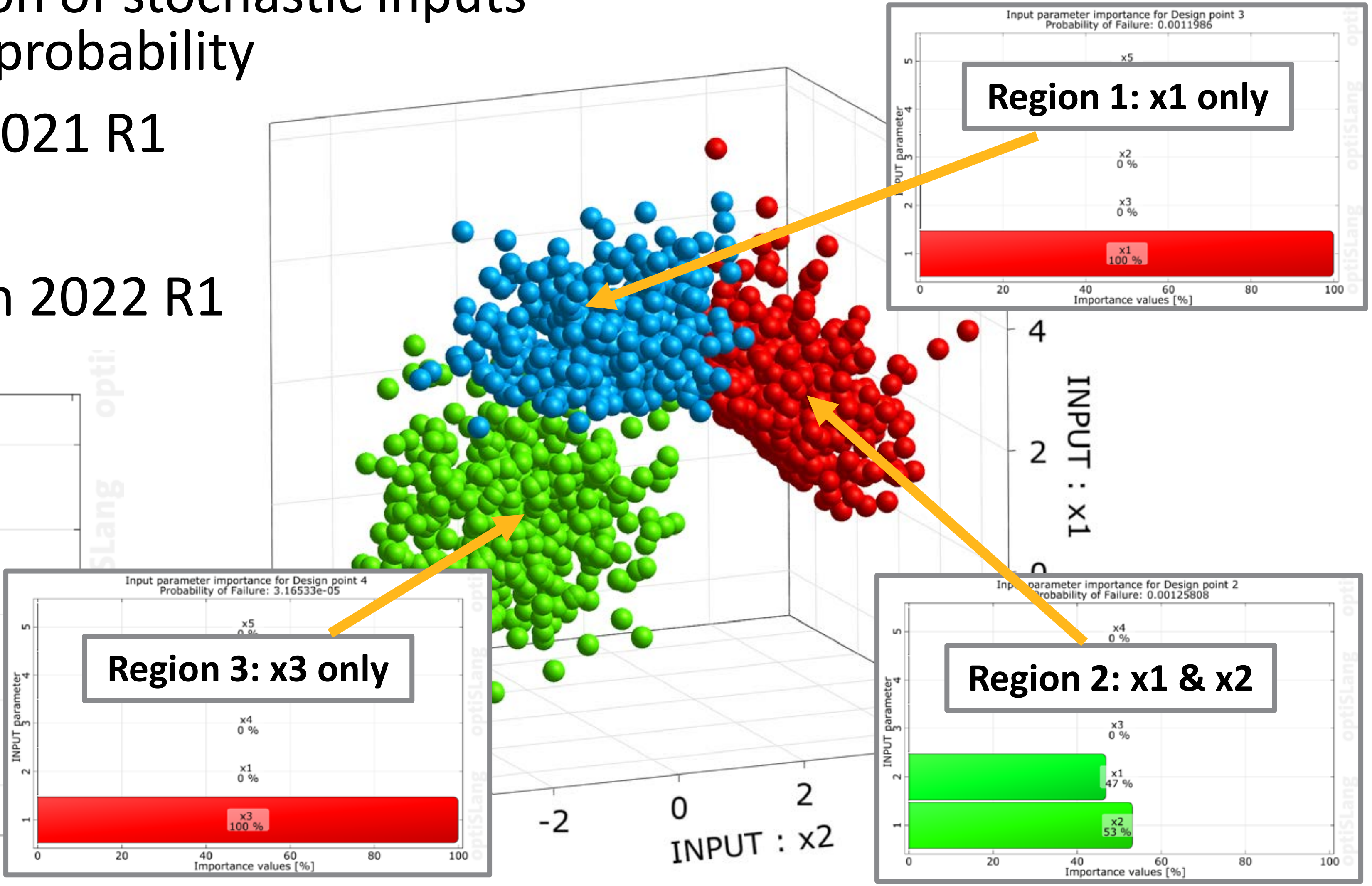




Reliability Importance Plot

- Contribution of variation of stochastic inputs with respect to failure probability
- ✓ Adaptive Sampling in 2021 R1
- ✓ ISPUD in 2021 R2
- ✓ FORM + Monte Carlo in 2022 R1





Questions ?

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