

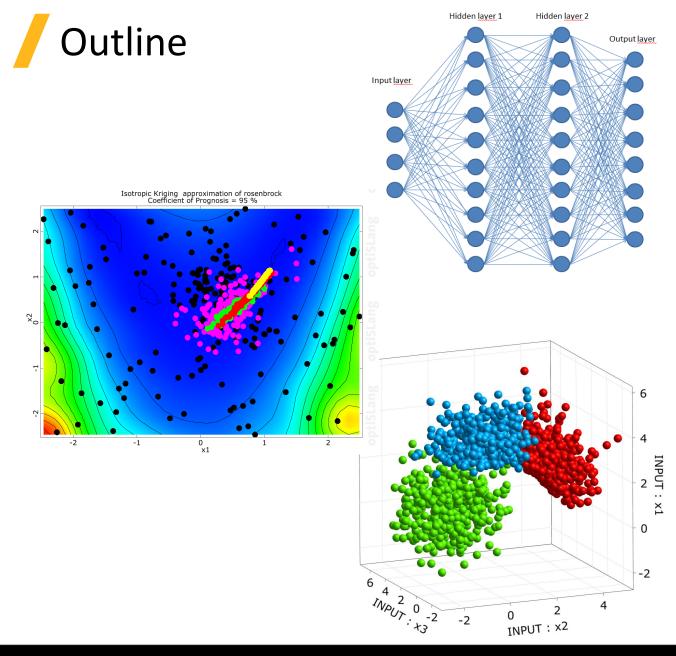
CONFERENCE

Recent Developments in Metamodeling, Optimization, and Uncertainty Quantification in the optiSLang product line

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ANSYS Dynardo, Weimar, Germany





Meta-Modeling & Data Mining

- Meta-model availability
- Deep feed-forward networks
- Residual plot
- Cluster analysis

Single & Multi-Objective Optimization

- Optimization Wizard Update
- New Nature Inspired Optimization
- Multi-objective AMOP
- Derivative-based optimizer for HFSS

Reliability Analysis

- Multiple FORM and ISPUD
- Reliability Importance Measures



Meta-modeling &

Data mining





MOP- Approximation Models

Premium license

- Polynomials
- Moving Least Squares
- Kriging
- Genetic Aggregation Response Surface (DX)
- Support Vector Regression (DX)

Enterprise license

- Deep Feed-Forward Network
- Signal MOP

DX models, Signal MOP and DFFN are included in optiSLang and ANSYS installers

Property		Value		
~ M	✓ 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 Respon			
	Use	False		
~	Support Vector Regression	_		
	Use	False		
~	beep recurrent and network			
	Use	False		
~	Signal MOP			
	Use	False		
✓ External				
	ASCMO	False		



MOP- New Presets (2021 R2)

Tested metamodels

- Polynomial
- Polynomial + MLS+ isotropic Kriging
- **Polynomial + DFFN** (requires Enterprise)
- All internal metamodels (incl. DX, Signal MOP)

Variable reduction

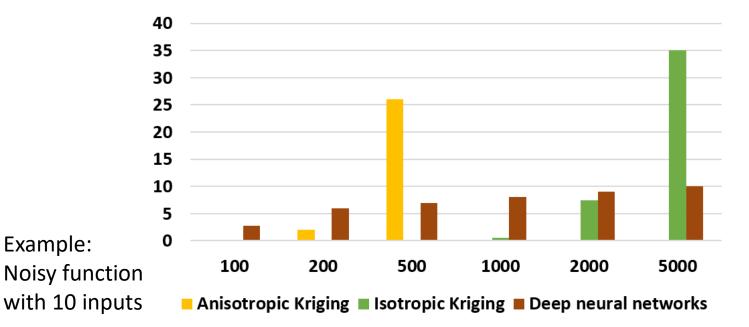
- No reduction (all inputs are mandatory)
- Filter unimportant (delta CoP = 0.001)
- Filter minor important (delta CoP = 0.01)
- User defined

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Set	tings Mes	sage log					
Use advanced settings							
Tested metamodels Polynomial + Deep Feed Forward Network							
Variable reduction Filter minor important			ant				•
		No reduction Filter unimportant					
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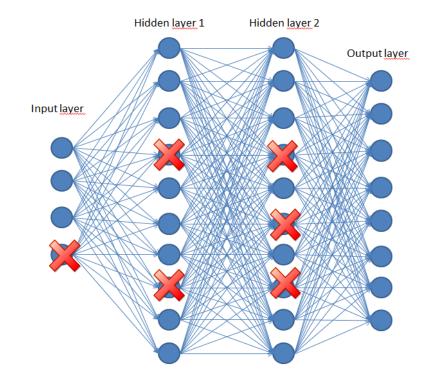


Deep Feed Forward Networks (2021 R2)

- Smart Layout Automatic network configuration
- Simplified settings
- Training time increases linearly with # of samples
- ➢ Efficient especially for larger data sets





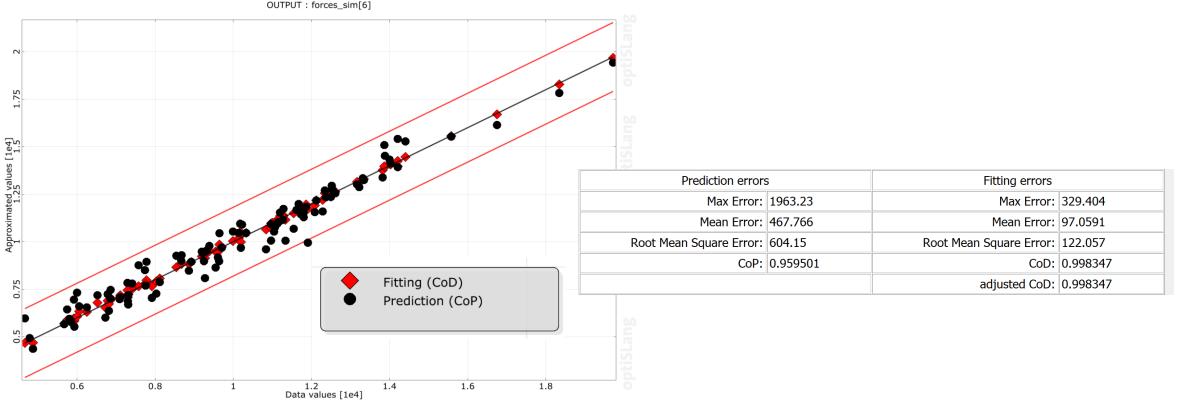


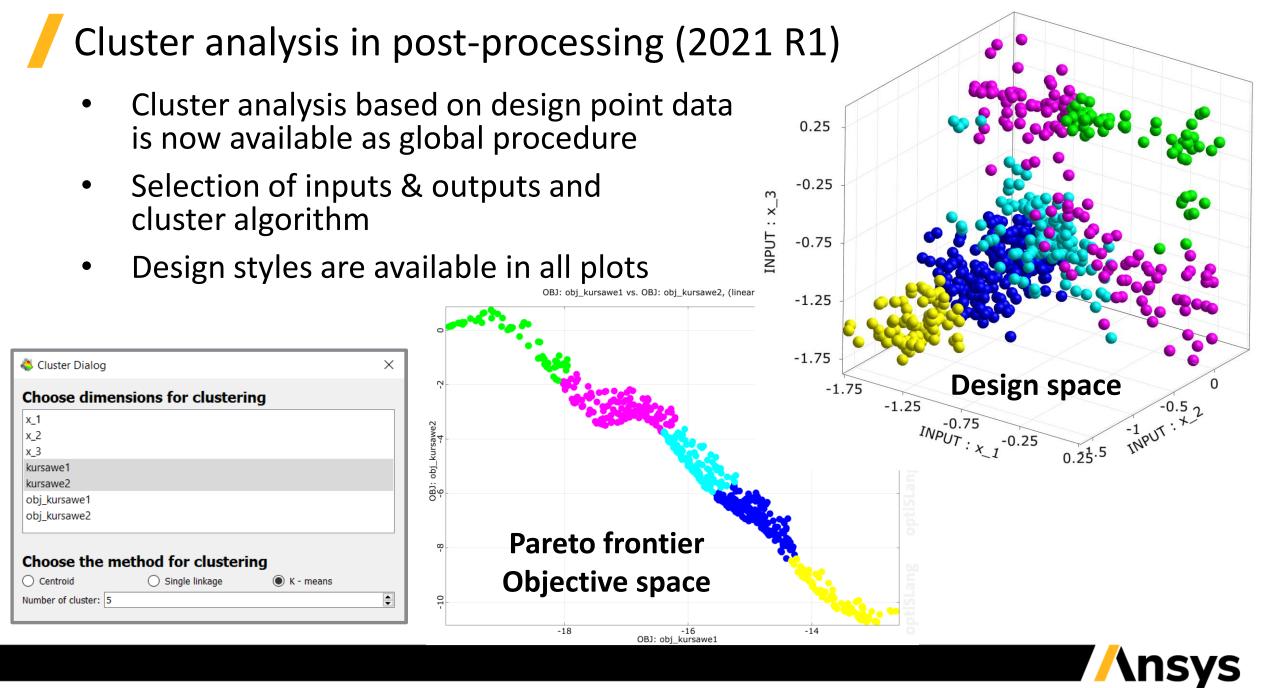
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2 🔹
30 🔹
2



Residual Plot – Prediction vs. Fitting Errors (2021 R1)

- Prediction errors from cross validation (default until 2020 R2) are shown in comparison to fitting errors
- Statistical values show both, which is equivalent of contribution to CoP and CoD





Single- and Multi-Objective Optimization





Optimization Wizard Update (2021 R2)

Classical algorithms

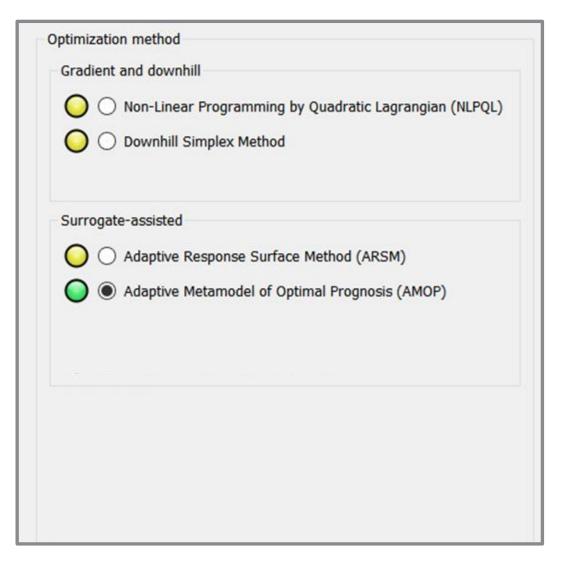
- NLPQL
- Downhill Simplex
- ARSM
- AMOP

New NOA algorithms

- Evolutionary Algorithm
- Particle Swarm Optimization
- Covariance Matrix Adaptation

DX algorithms

- Mixed-Integer MISQP
- Adaptive Single-Objective
- Adaptive Multi-Objective



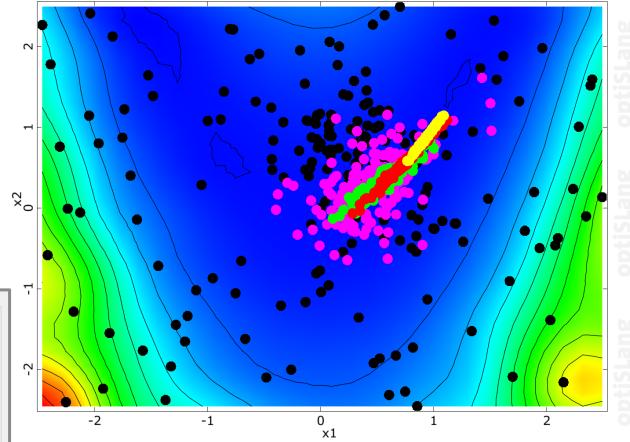


Covariance Matrix Adaptation Evolutionary Strategy (2021 R1)

- New algorithm in NOA toolbox
- Automatic adjustment of sampling/mutation density to objective and constraints
- State-of-the-art in benchmarking and evolutionary research

Nature Inspired Optimization			
Algorithm type:	Covariance M	atrix Adaptation	•
Maximum number of samples:	500		
Search strategy:	local	balanced	global

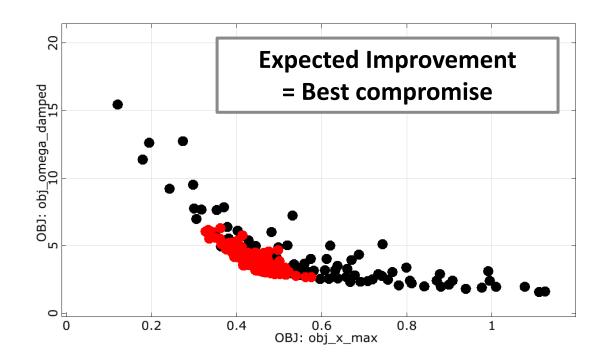
Isotropic Kriging approximation of rosenbrock Coefficient of Prognosis = 95 %

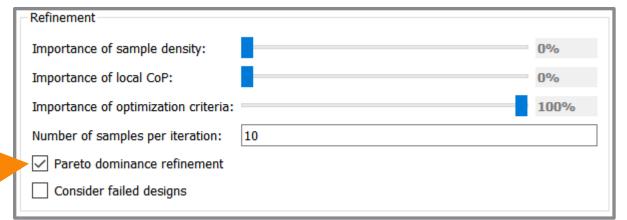


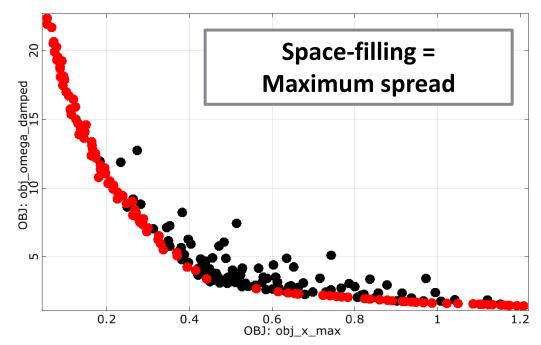


Adaptive MOP – Improved Multi-objective Optimization (2021 R1)

- Adaptive MOP uses now new NOA for multi-objective refinement
- Space-filling criterion for maximum spread of Pareto frontier

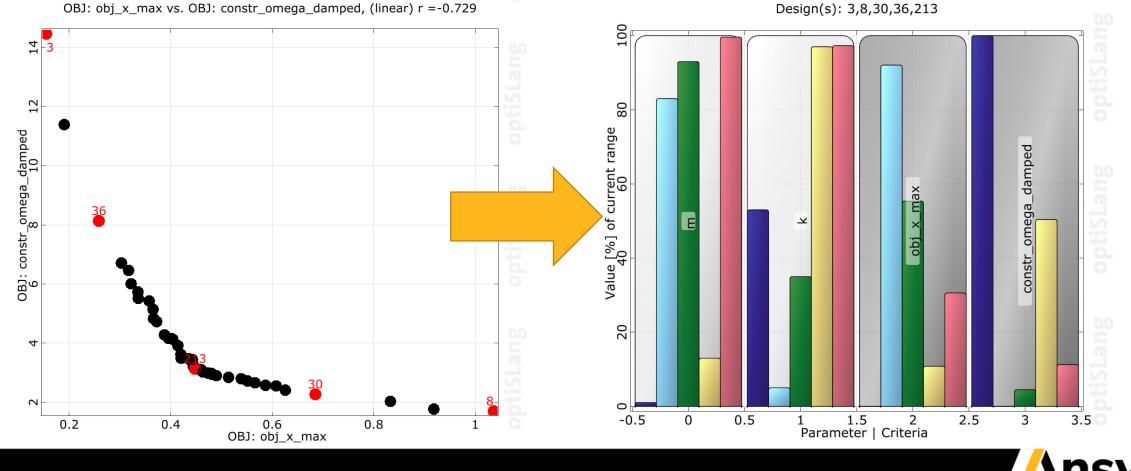






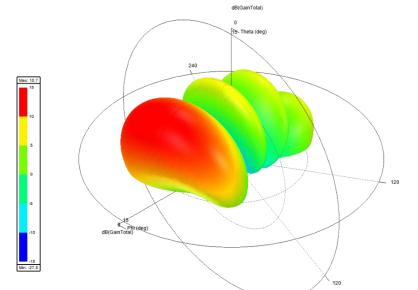
Design Comparison Plot (2021 R1)

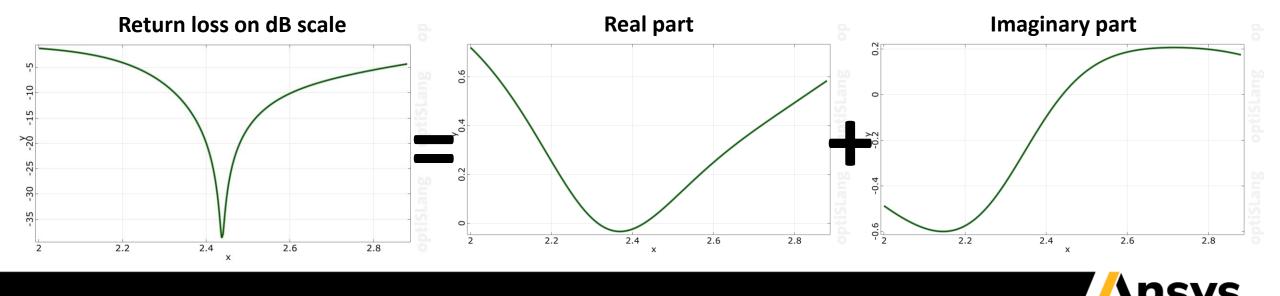
- Directly compares input, response and criteria values of selected designs
- E.g. for comparison of initial vs. optimized designs, different Pareto designs



Ansys HFSS: 3D high frequency electromagnetic solver Gam Piot

- HFSS for antenna simulations
 - Common outputs: S-parameters, antenna impedance, radiation patterns, etc.
- HFSS can calculate partial derivatives of antenna responses w.r.t. optimization parameters such as geometry and material properties

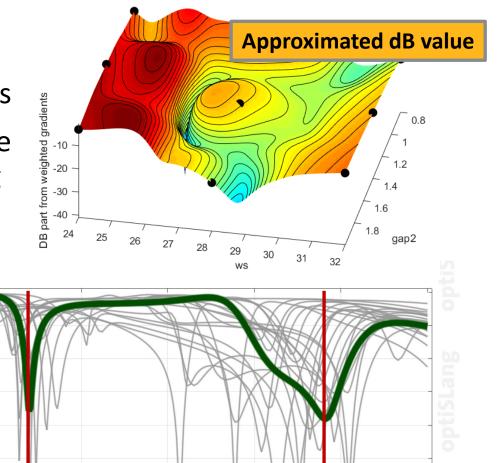


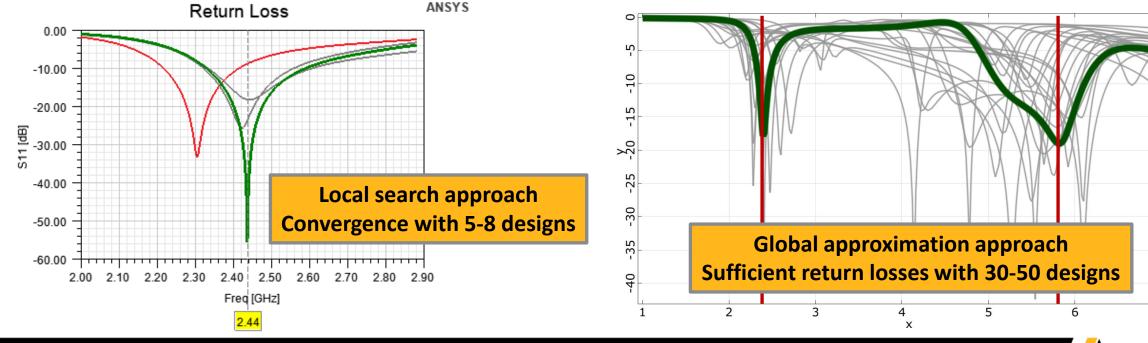


Derivative based approximation model

- Using partial derivatives, S-parameters can be predicted locally for tuned optimization parameters
- The real and imaginary parts of the HFSS signals are approximated in a global meta-model by weighting the individual local values and gradients of all available data points

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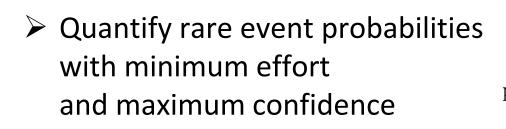
Uncertainty Quantification

Reliability Analysis

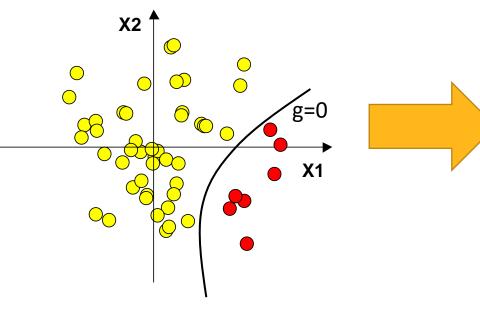


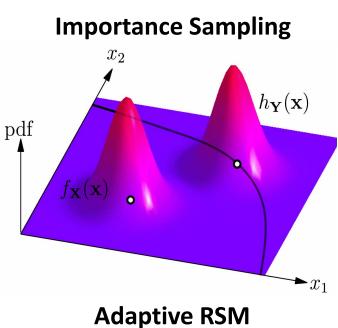


Reliability based Robustness Analysis

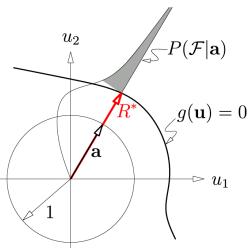


Monte Carlo Sampling

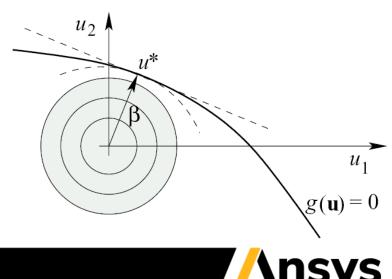




Directional Sampling

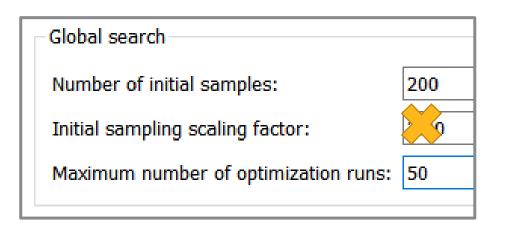


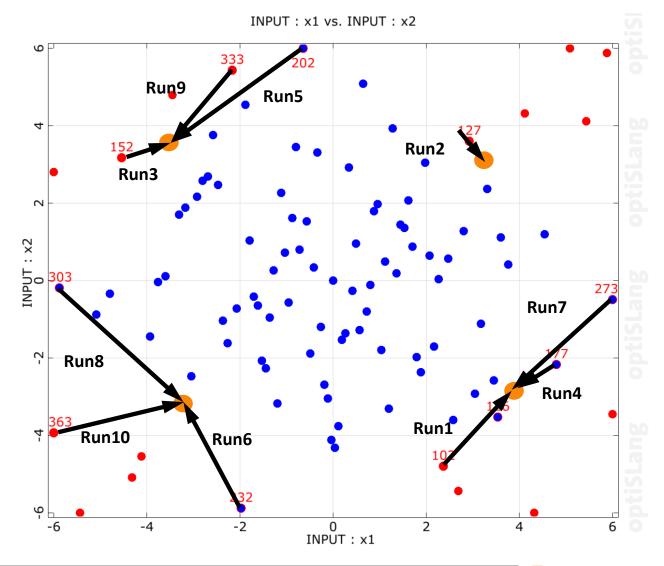
First Order Reliability Method



First Order Reliability Method (FORM)

- Multiple design point search is done be NLPQL optimizer with different start points
- This approach detects local optima and different failure regions
- New start design sampling (2021 R2)
- Scaling factor becomes obsolete

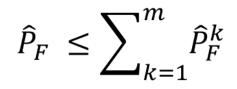




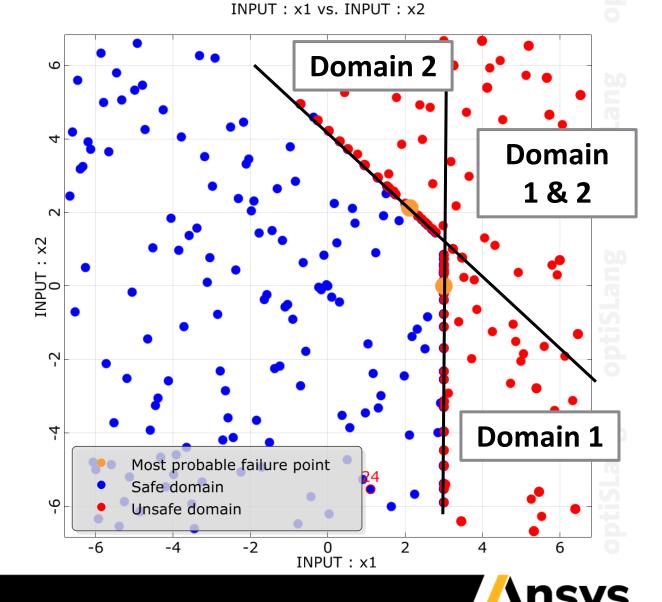


Improved calculation of failure probability in FORM (2021 R2)

• Calculation of failure probability for multiple failure regions now considers the over-lapping of the estimated linearized regions



Method : First Order Reliability Method (FORM)				
Probability of Failure : 0.00244219 Reliability Index : 2.81456				
Most probable failure point(s)				
ID:	677	733		
Input parameter values				
x1 :	2.12132	3		
x2 :	2.12132	1.31347e-07		
Reliability index (FORM) :	3	3		
Probability of failure (FORM) :	0.0013499	0.0013499		



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Importance Sampling Using multiple Design Points (2021 R2)

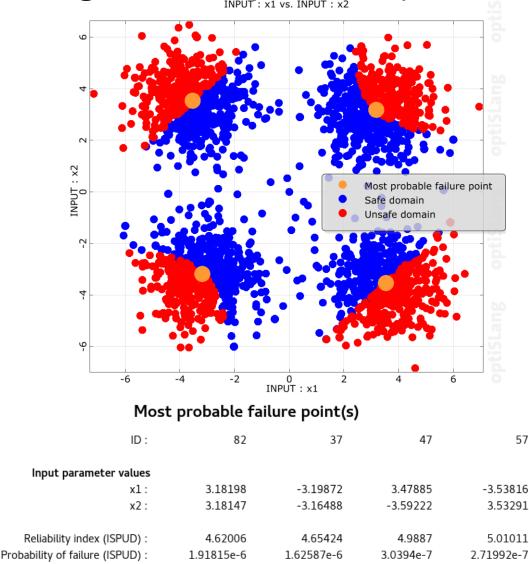
 Probability of failure is now estimated for each sampling density by considering the weights of only these samples, which belong to this single sampling density

$$\widehat{P}_F^k = \frac{1}{N} \sum_{i=1}^{N_k} w(x_i^k) I(g(x_i^k))$$

• Sum of individual failure probabilities is equal to global probability

$$\hat{P}_F = \sum_{k=1}^m \hat{P}_F^k$$

 Center points (design points) of sampling densities and belonging failure probabilities are indicated in the post-processing





Reliability Sensitivity

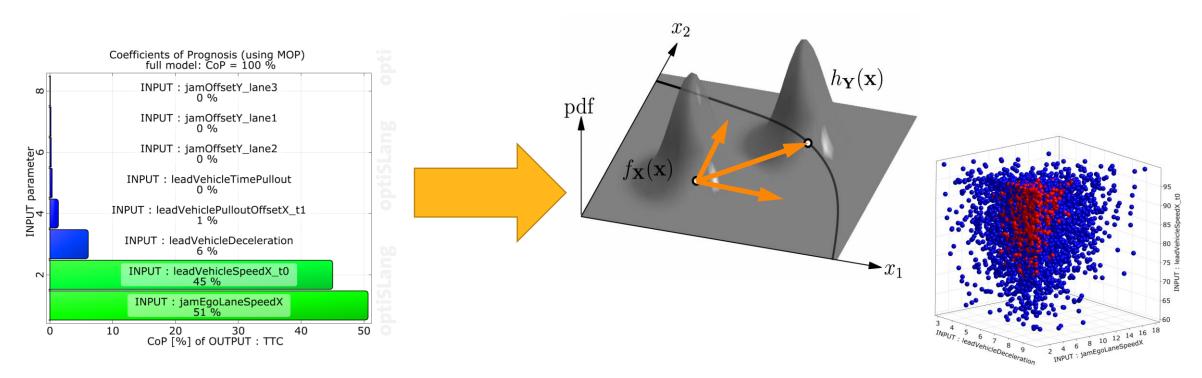
Measures





Reliability Sensitivity Measures

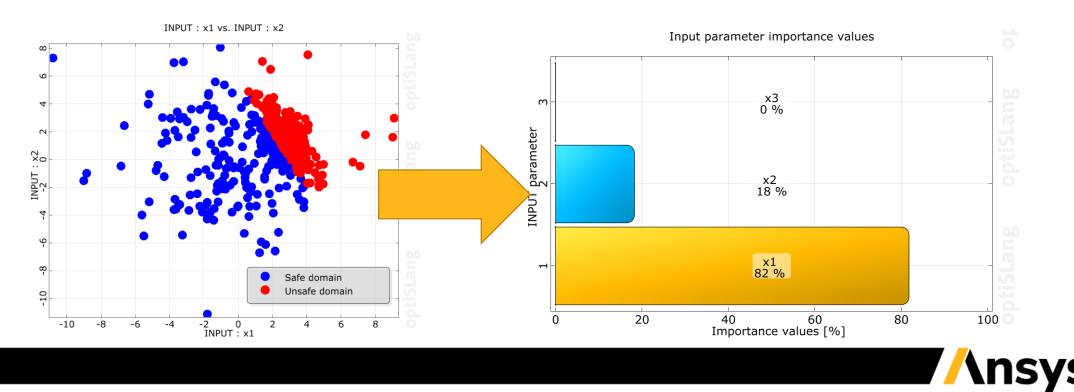
- Today, correlation and variance-based sensitivity analysis can assess the variable influence only around the mean!
- Sensitivities w.r.t. failure mechanisms are required!



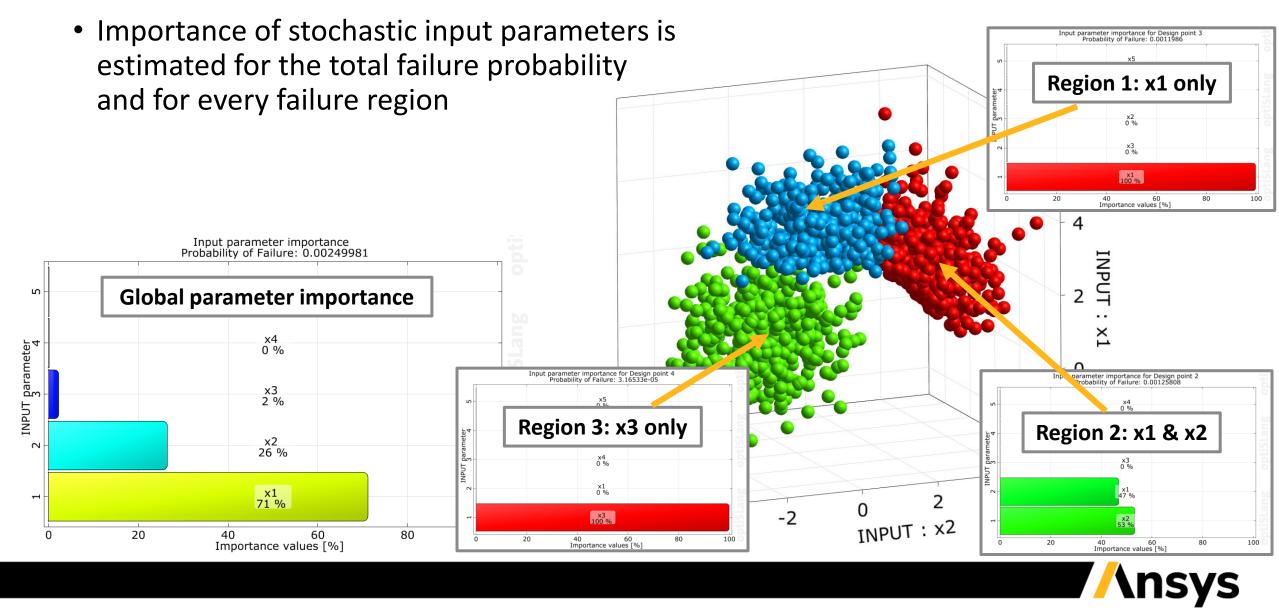


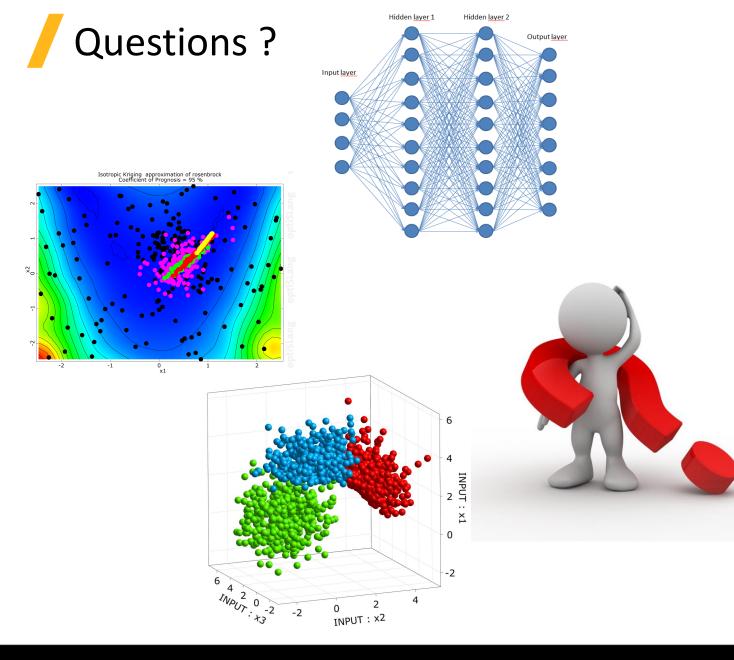
Reliability Importance Plot

- Contribution of variation of stochastic inputs with respect to failure probability
- ✓ Adaptive Sampling in 2021 R1
- ✓ ISPUD with multiple failure regions in 2021 R2



Reliability Importance Plot for multiple failure regions in ISPUD





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