New Reliability Methodologies for Driving Scenarios

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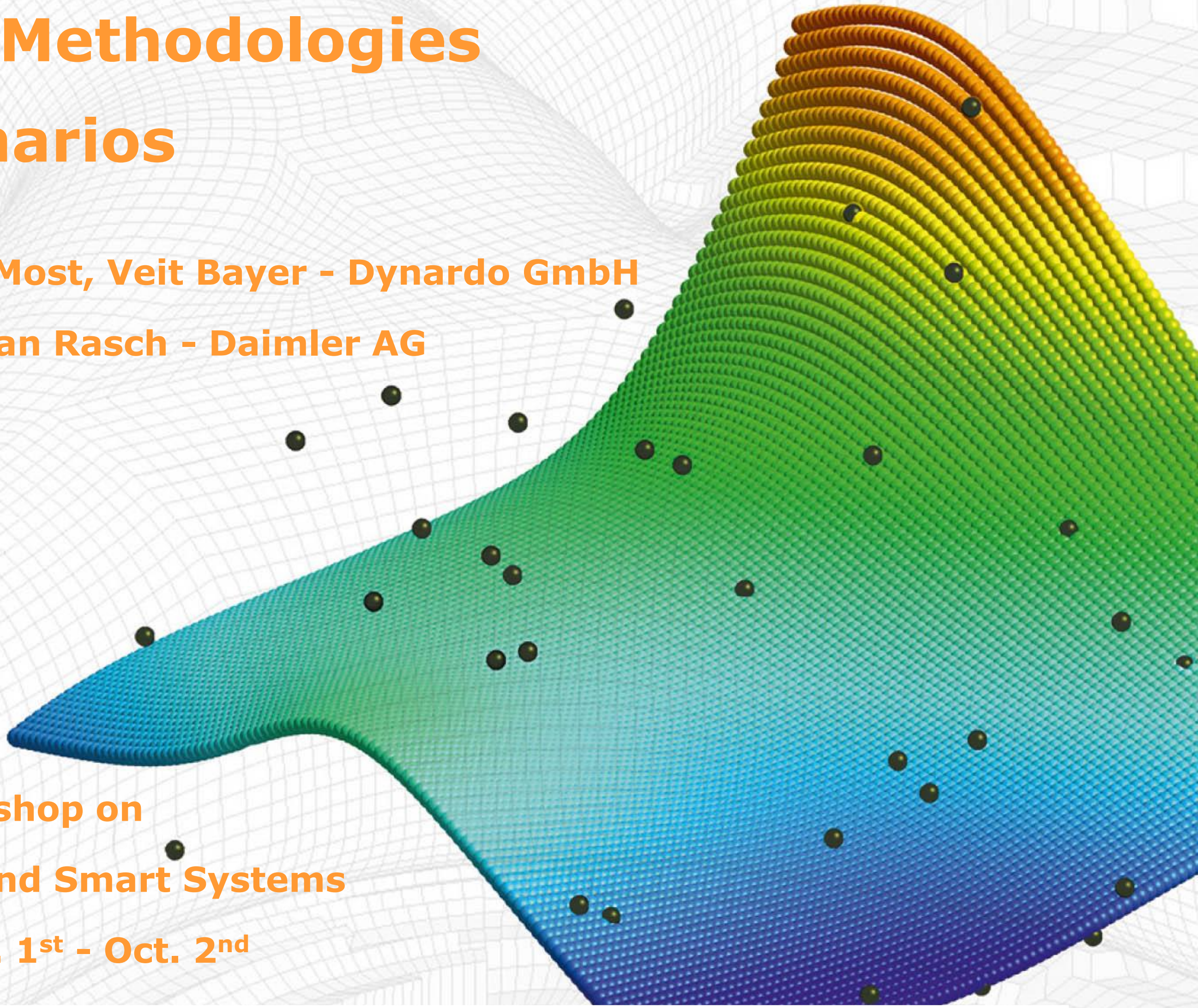

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How many miles ...

Table 1. Examples of Miles and Years Needed to Demonstrate Autonomous Vehicle Reliability

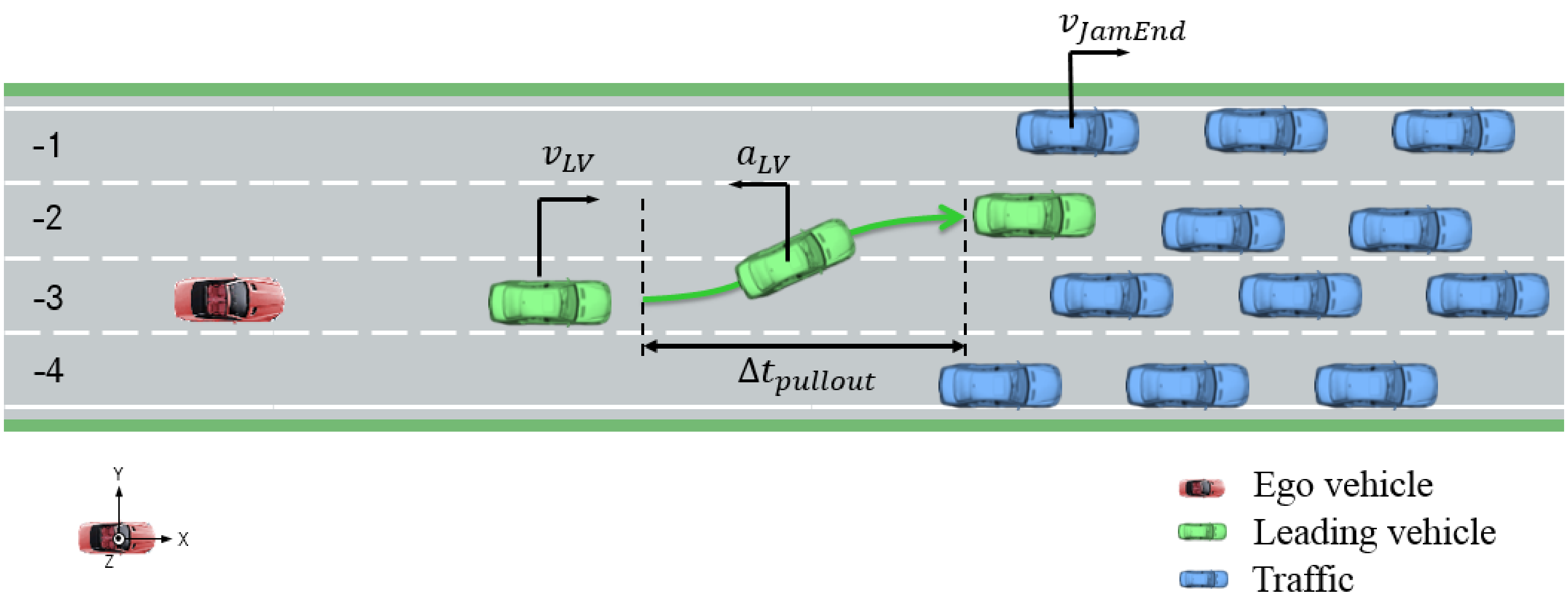
Statistical Question	Benchmark Failure Rate		
How many miles (years[a]) would autonomous vehicles have to be driven...	**(A) 1.09 fatalities per 100 million miles?**	**(B) 77 reported injuries per 100 million miles?**	**(C) 190 reported crashes per 100 million miles?**
(1) without failure to demonstrate with 95% confidence that their failure rate is at most...	275 million miles (12.5 years)	3.9 million miles (2 months)	1.6 million miles (1 month)
(2) to demonstrate with 95% confidence their failure rate to within 20% of the true rate of...	8.8 billion miles (400 years)	125 million miles (5.7 years)	51 million miles (2.3 years)
(3) to demonstrate with 95% confidence and 80% power that their failure rate is 20% better than the human driver failure rate of...	11 billion miles (500 years)	161 million miles (7.3 years)	65 million miles (3 years)

[a] We assess the time it would take to compete the requisite miles with a fleet of 100 autonomous vehicles (larger than any known existing fleet) driving 24 hours a day, 365 days a year, at an average speed of 25 miles per hour.

Source: Nidhi Kalra, Susan M. Paddock: Driving to Safety, www.rand.org

➡ **There is a crucial Need for Smart Reliability Methods for Driving Scenarios**

A typical driving scenario: approaching a jam tail with a lane change of the vehicle in front of the driver

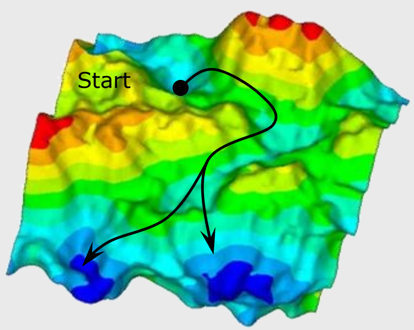


Robust Design Optimization

Optimization

Sensitivity Analysis

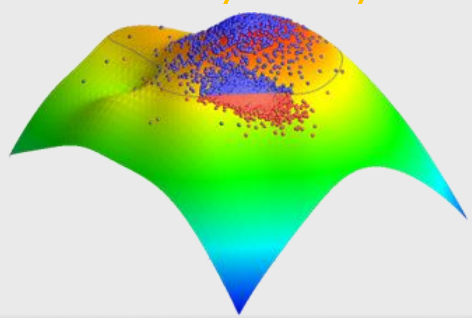
Single- & Multi-Objective (Pareto) Optimization



Robust Design

Variance-Based Robustness Evaluation

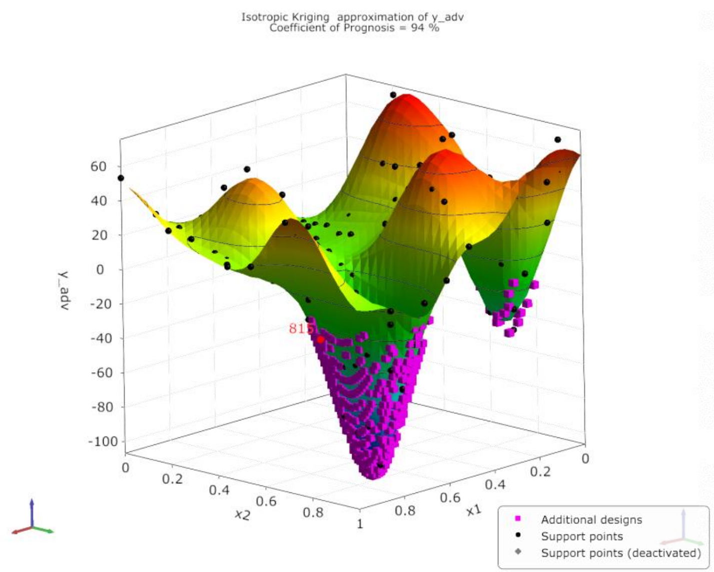
Probability-Based Reliability Analysis

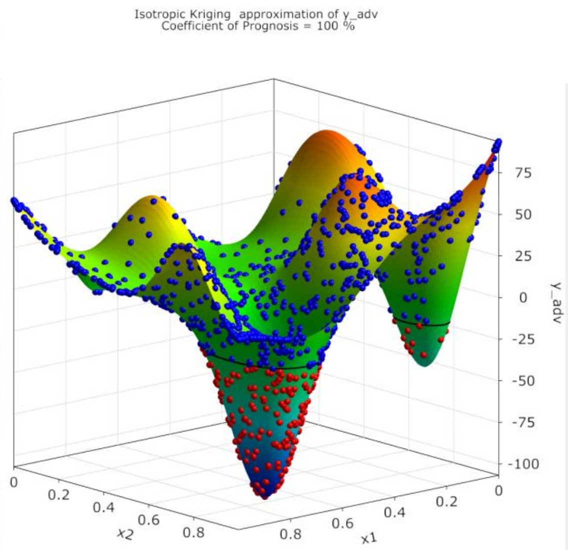


CAE process (FEM, CFD, MBD, Excel, Matlab, etc.)

Mishra's Bird Function

Test function used for events in advanced driver assistance systems





Method : Adaptive Sampling (AS)

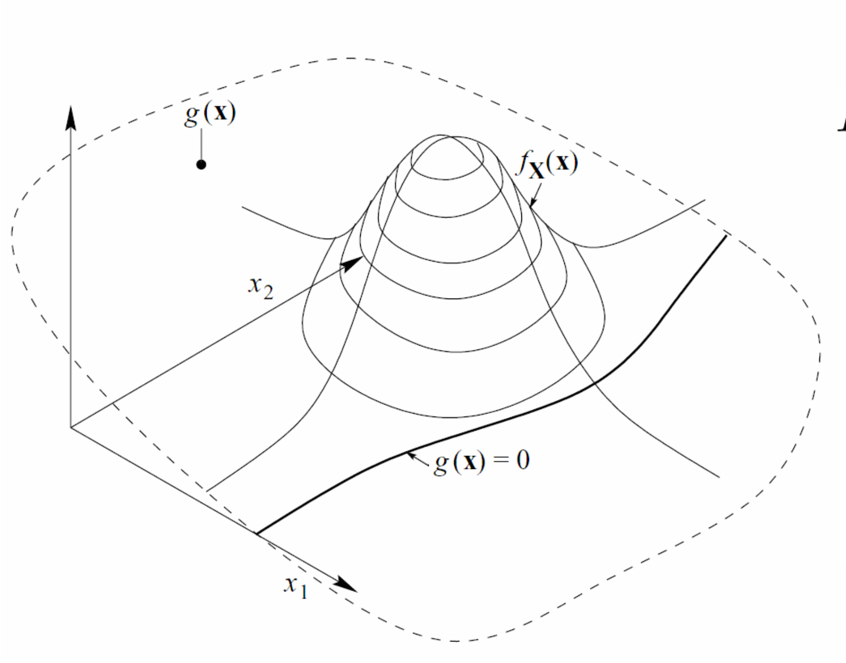
Complete iterations : 3 / 3
Selected data : All designs

Probability of Failure : 0.110101
Standard deviation error : 0.0102236
Reliability Index : 1.22599

Number of designs
Total : 1200
Safe domain : 953
Unsafe domain : 247
Failure strings : 0
Failed : 0

Comparison of Monte Carlo based Failure Probability calculation with Adaptive Sampling method helped to reduce simulations runs from about 500.000 to 3.000

Failure Probability



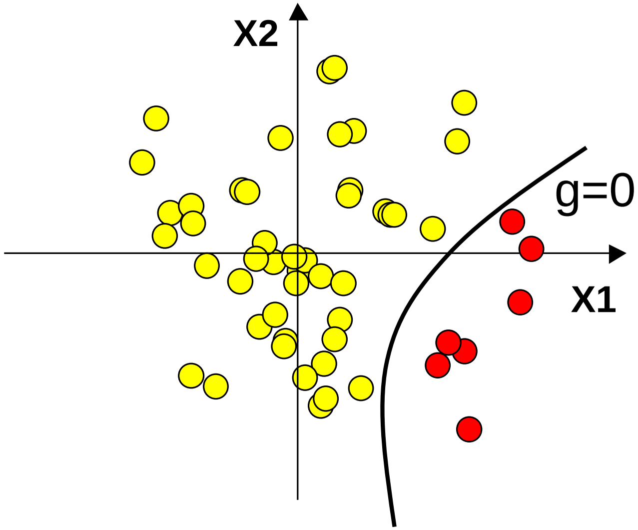
$$P_F = P\left[\mathbf{X} : g(\mathbf{X}) \leq 0\right]$$
$$= \int \cdots \int_{g(\mathbf{x}) \leq 0} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$
$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} I\left(g(\mathbf{x})\right) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$

- The probability of failure is the integral of the joint probability density function over the failure domain
- By introducing an indicator function

$$I\big(g(\mathbf{x})\big) = 1 \text{ if } \left(g(\mathbf{x})\right) < 0, \qquad I\left(g(\mathbf{x})\right) = 0 \text{ else}$$

this can be computed as the expected value of I

Monte Carlo Simulation



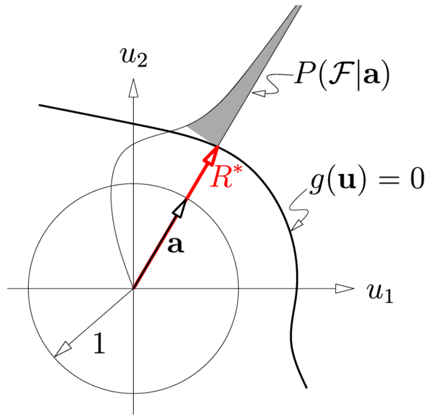
Sigma level	P_F	N for cov(P_F) = 10%
2	2.3E-2	4 400
3	1.3E-3	74 000
4.5	3.4E-6	29 500 000

$$\hat{P}_F = \frac{1}{N} \sum_{i=1}^{N} I\left(g(\mathbf{x}_i)\right) \qquad \hat{\sigma}_{P_F} = \sqrt{\frac{\hat{P}_F}{N}}$$

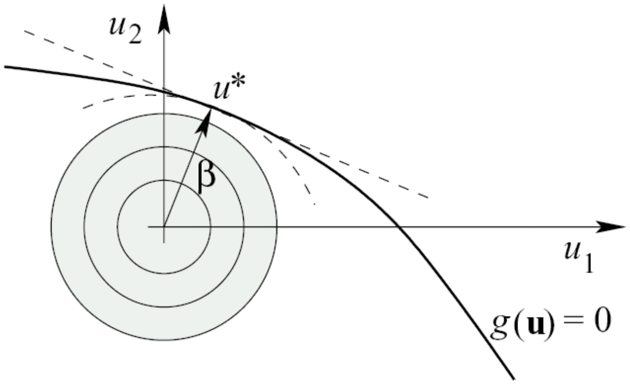
- Robust for arbitrary limit state functions
- Confidence of the estimate is very low for small failure probabilities
- ➢ Sigma level ≤ 2
- ➢ Independent of number of random variables

Some advanced methods for reliability analysis

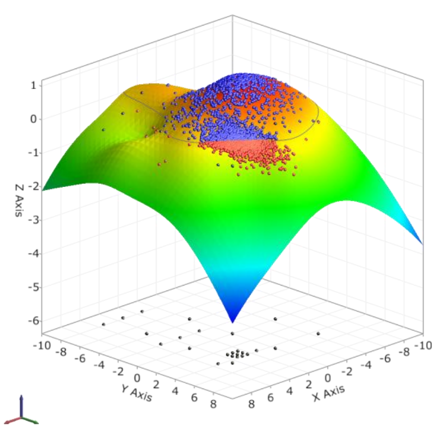
Directional Sampling



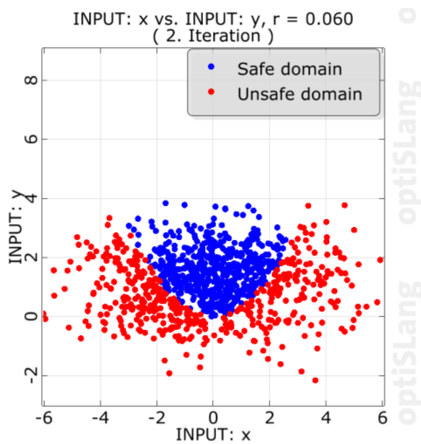
First Order Reliability Method



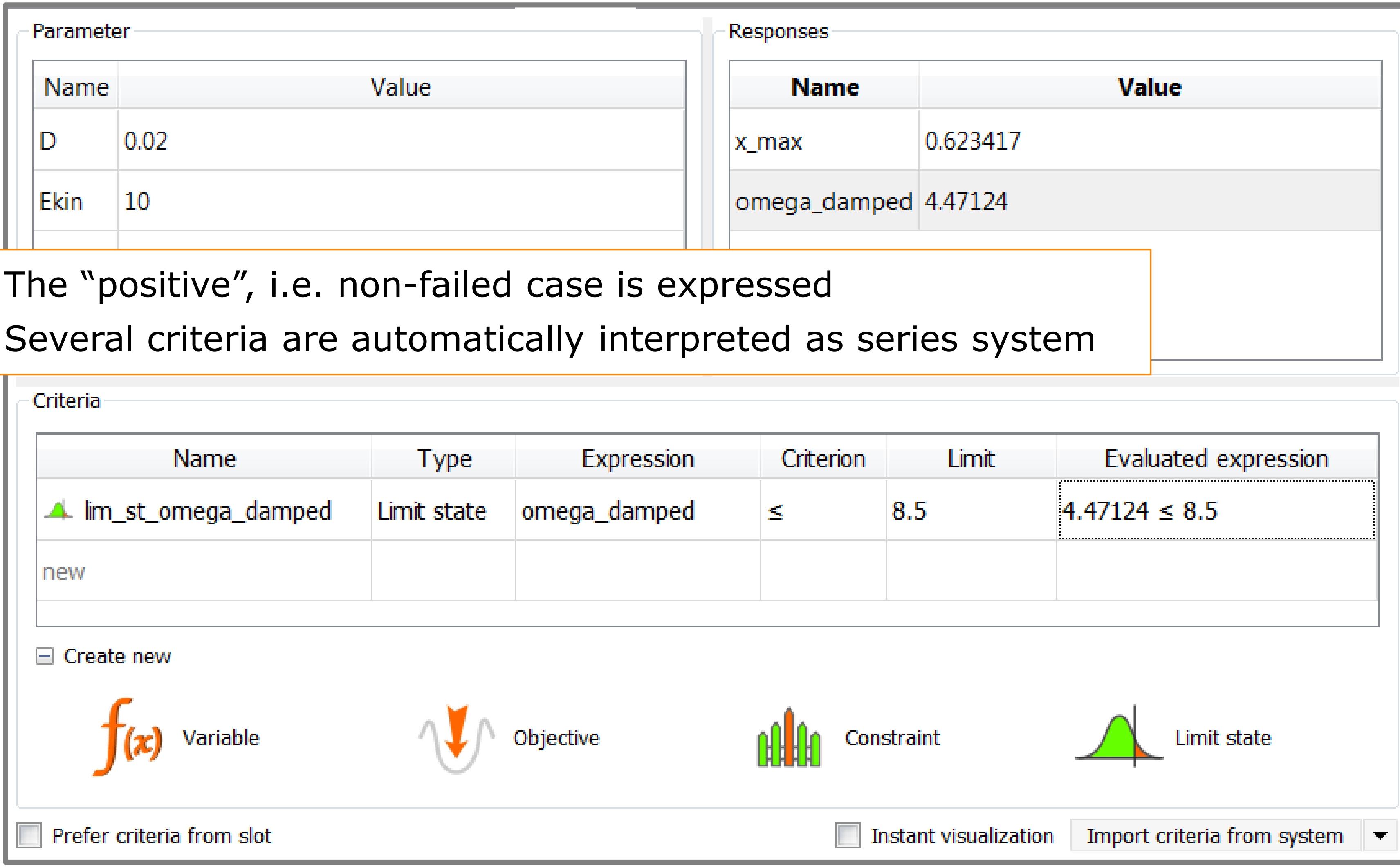
Adaptive RSM



Adaptive Importance Sampling



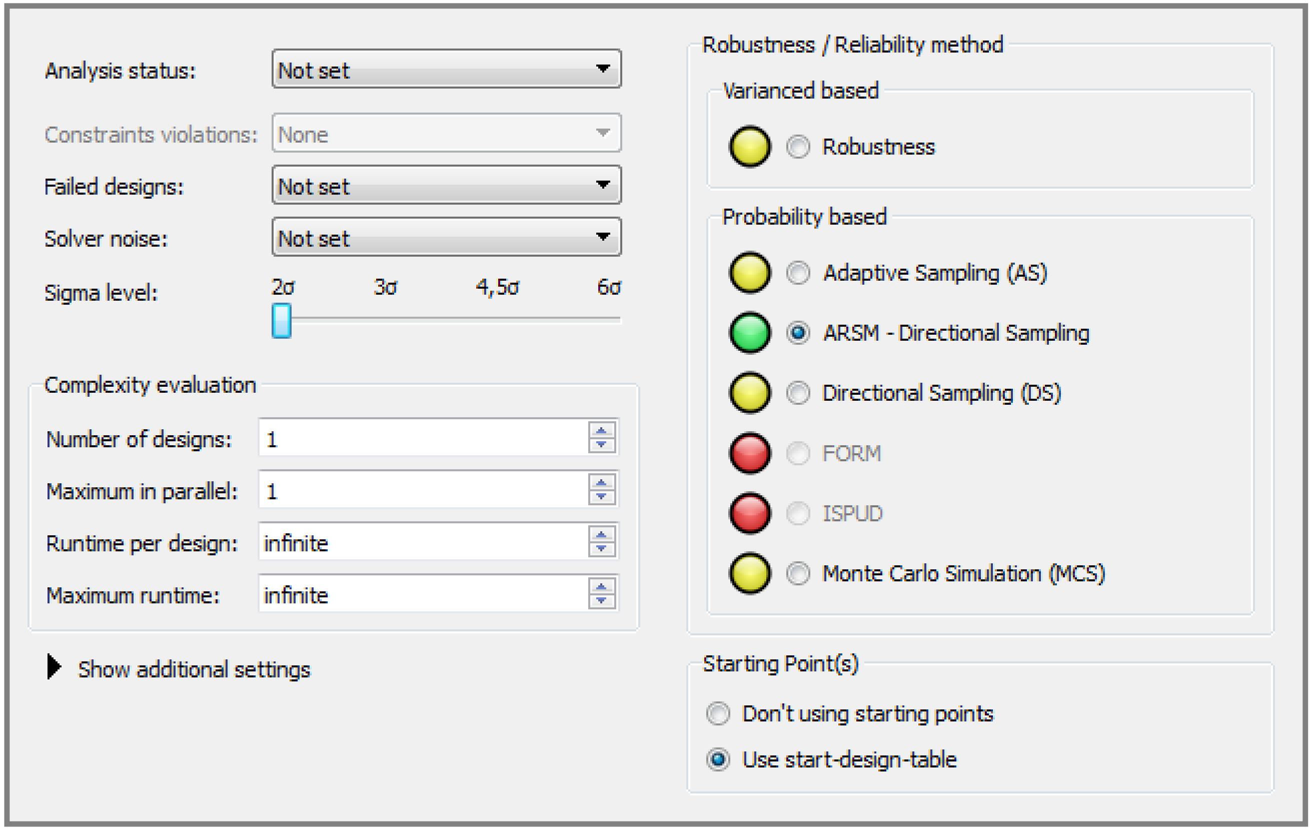
Define Limit State in optiSLang



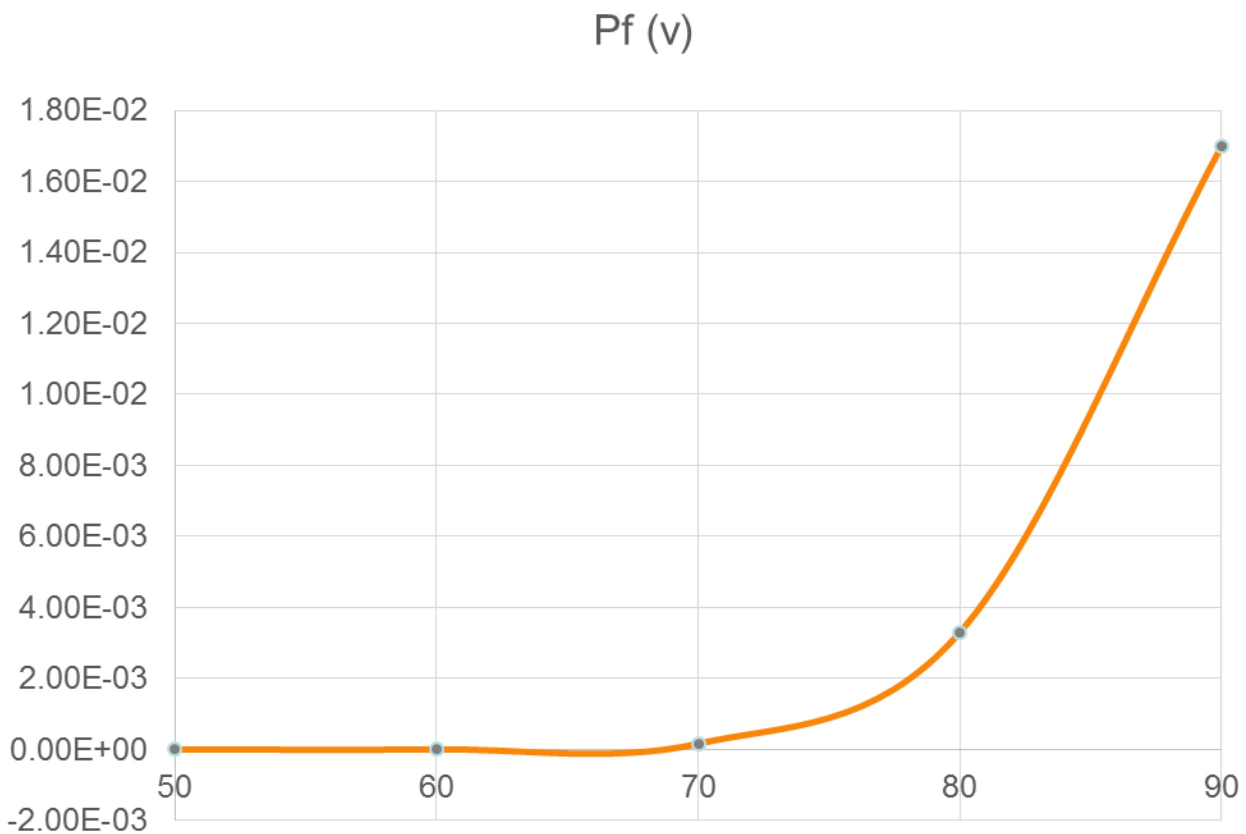
- The “positive”, i.e. non-failed case is expressed
- Several criteria are automatically interpreted as series system

Robustness & Reliability – Decision Tree

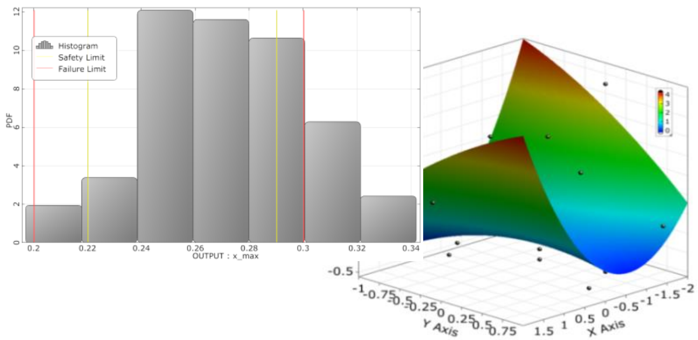
- optiSLang automatically suggests a robustness approach depending on the parameter properties, the defined criteria and user specified settings



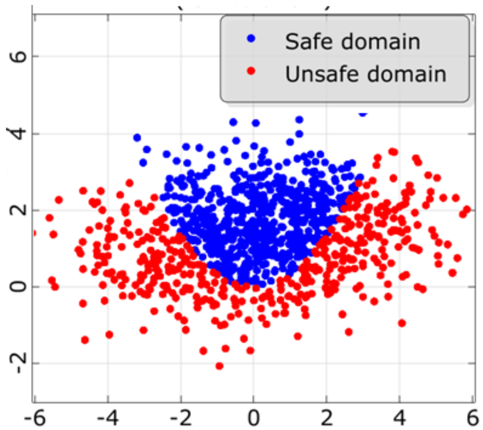
Probability of Failures and Fragility Curves



Recommended Workflow



Robustness Sampling/MOP



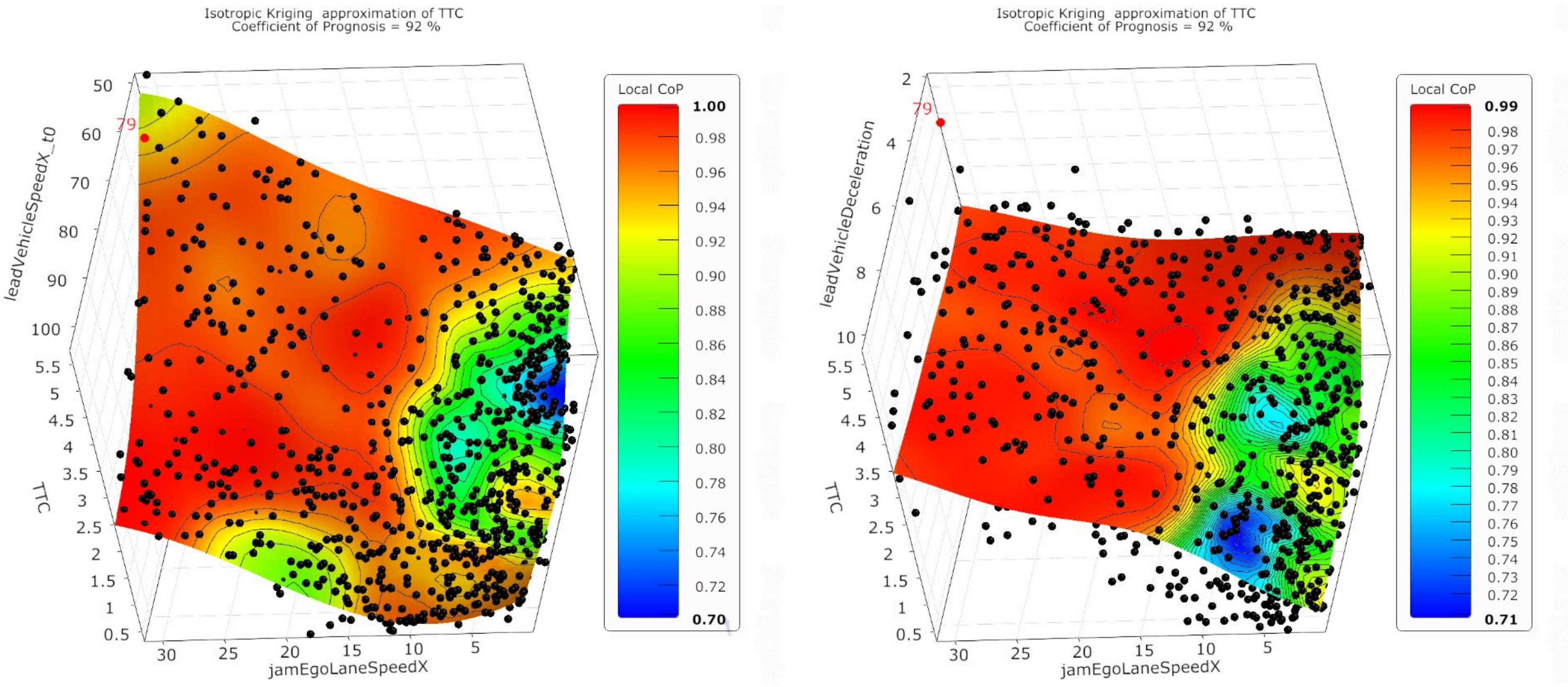
Reliability Analysis

- Check variation of inputs & responses
- Check plausibility in MOP to proof simulation model
- Eventually reduce parameter number
- 200 – 500 samples
- Check different safety limits
- Stop if failure probability is larger as 10%

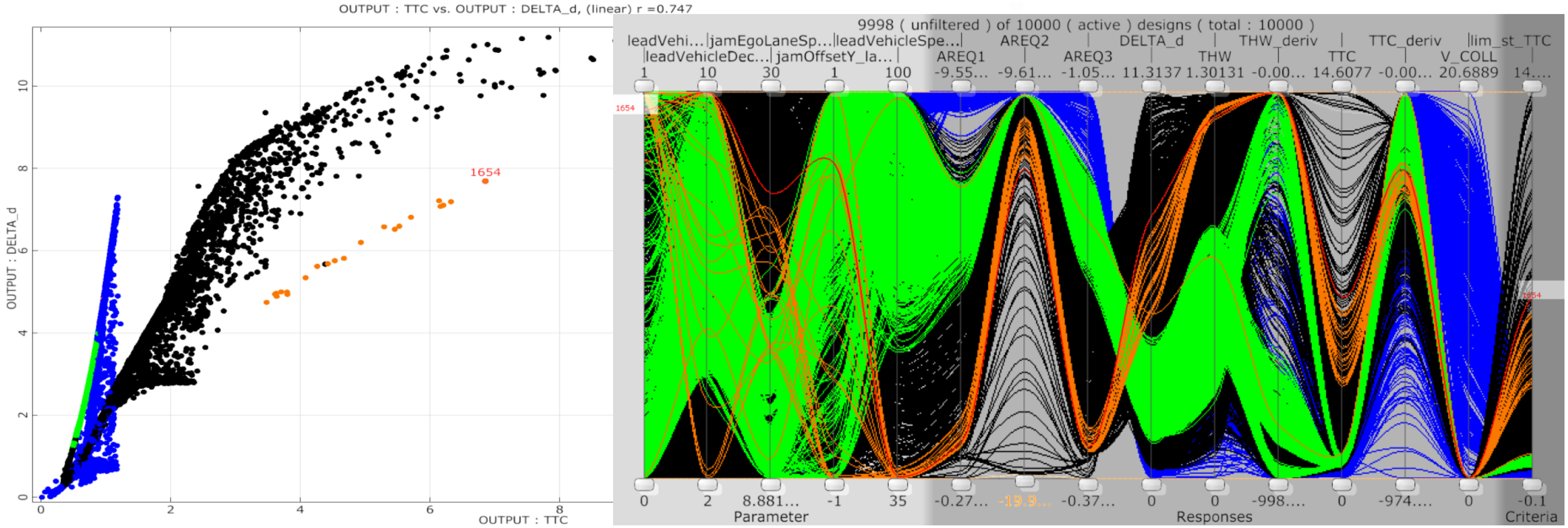
- Perform reliability analysis (e.g. Adaptive Sampling) until defined standard error (e.g. 10%) is reached
- 2000 – 5000 samples
- In case of fulfilled safety requirement: proof the result with different approach (e.g. Directional Sampling)

Analysis based on MOP (Metamodel of Optimal Prognosis)

- Partially low local CoPs (CoP – Coefficient of Prognosis)
- Assumption special physical and control mechanisms in these regions



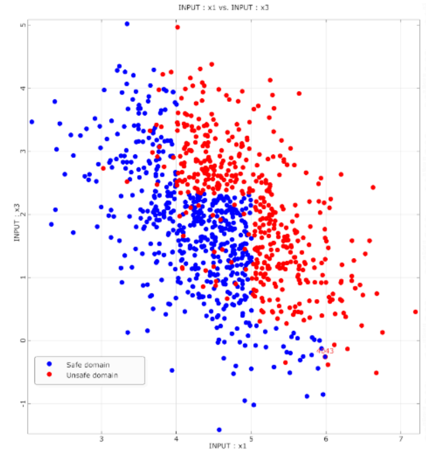
Analysis with Anthill and Parallel Coordinates Plots

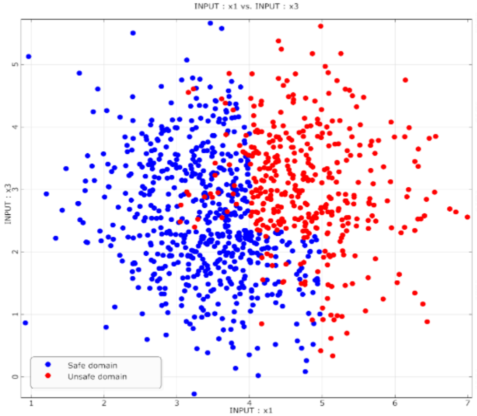


- Some output parameters are used for the steering and therefore have impact on other output parameters
- Analysis provided excellent indication which parameters are used for steering

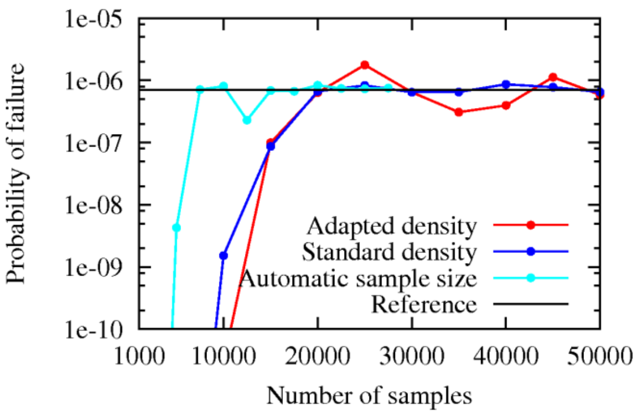
Enhanced Adaptive Sampling

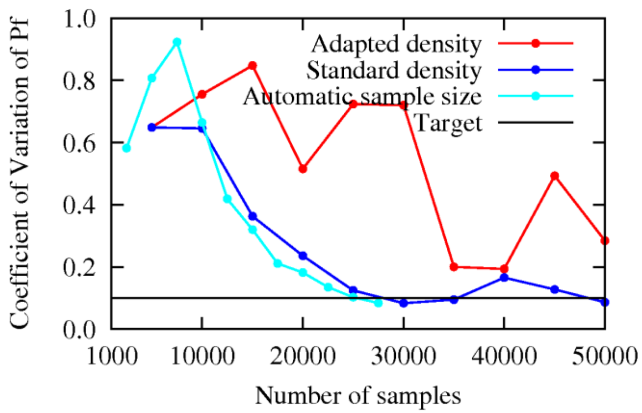
- Adaptation of mean values only, unity covariance matrix in Normal space





- Given a budget (no. of samples), the sample size per iteration is adapted to reach target standard error of results





20 variables,
max. 5000 samples/iteration

Algorithm now integrated in new optiSLang release

Comparision using the Enhanced Adaptive Sampling

- *A factor of 1000 proved to be realistic for the reduction of the necessary simulation runs if using the enhanced adaptive sampling !*

TTC = 1.0	Samples	Pf	CoV	Beta
MCS	30.000	$1.61*10^{-2}$	4.5%	2.14
AS Standard	20.000	$1.55*10^{-2}$	3.2%	2.16
AS Enhanced	8.000	$1.30*10^{-2}$	5.8%	2.22

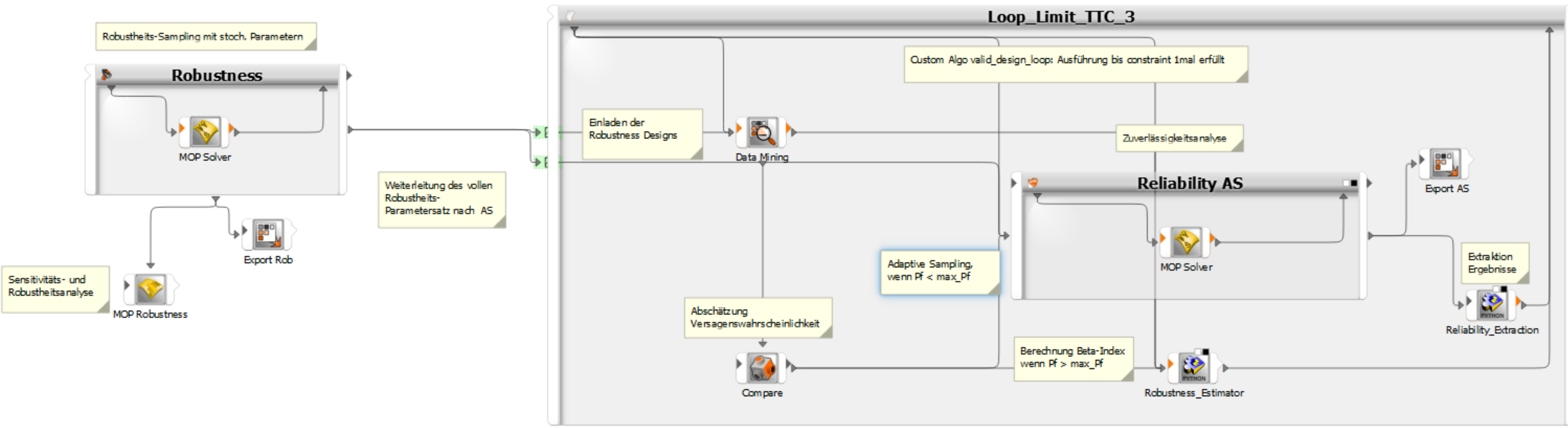
TTC = 0.5	Samples	Pf	CoV	Beta
MCS	14.010.000	$2.86*10^{-5}$	5.0%	4.02
AS Standard	20.000	$2.55*10^{-5}$	5.1%	4.05
AS Enhanced	16.000	$2.85*10^{-5}$	8.4%	4.05

TTC = 0.4	Samples	Pf	CoV	Beta
MCS	39.420.000	$2.54*10^{-6}$	10.0%	4.56
AS Standard	20.000	$3.68*10^{-6}$	23.0%	4.48
AS Enhanced	16.000	$2.81*10^{-6}$	9.1%	4.54

Details to be published with Daimler AG

Automated Process

- Loop over threshold values (fragility curve) by custom algorithm
- Robustness sampling (before the loop)
- Estimate failure probability from robustness sample
- Start reliability analysis only for small probability
- Loop until minimal (target) probability is reached



- *Note: MOP on robustness samples should not be used here for parameter reduction*

Thank you for your attention!