WOST 2019 - Simulative validation of automated driver assistance systems using reliability analysis

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Mercedes-Benz
Das Beste oder nichts.

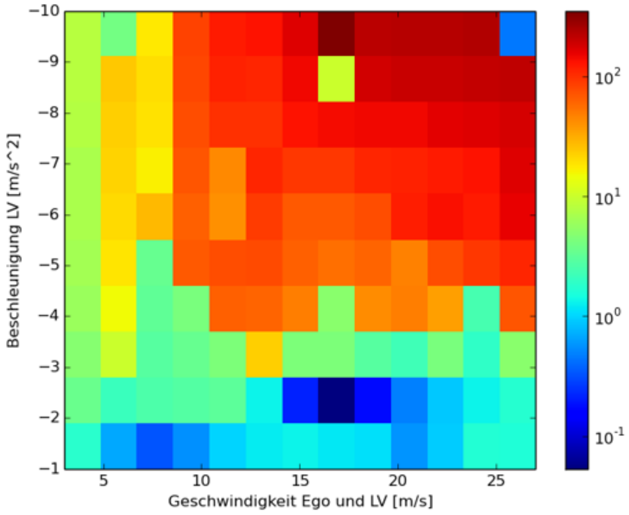
Highly Automated Driving

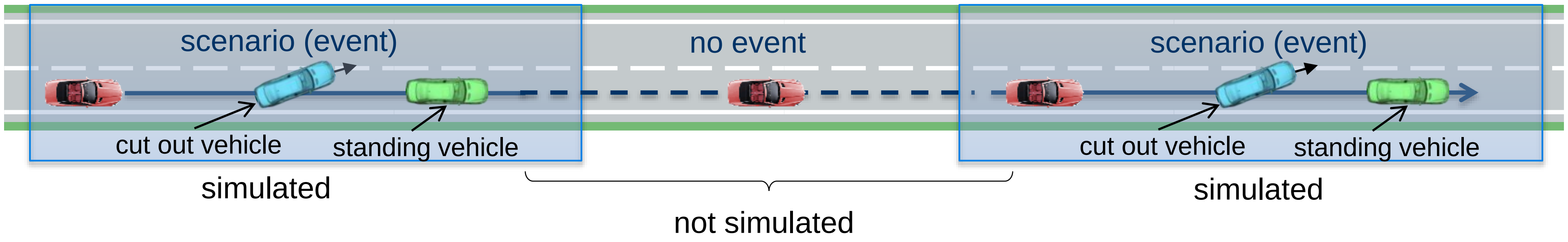
Level 0	Level1	Level 2	Level 3	Level 4	Level 5
Driver	Feets off	Hands off	Eyes off	Attention off	Passenger
					
No Automation	Driver Assistance	Partial Automation	Conditional Automation	High Automation	Full Automation

Human | Transition of responsibility | Machine

Simulative validation of HAD

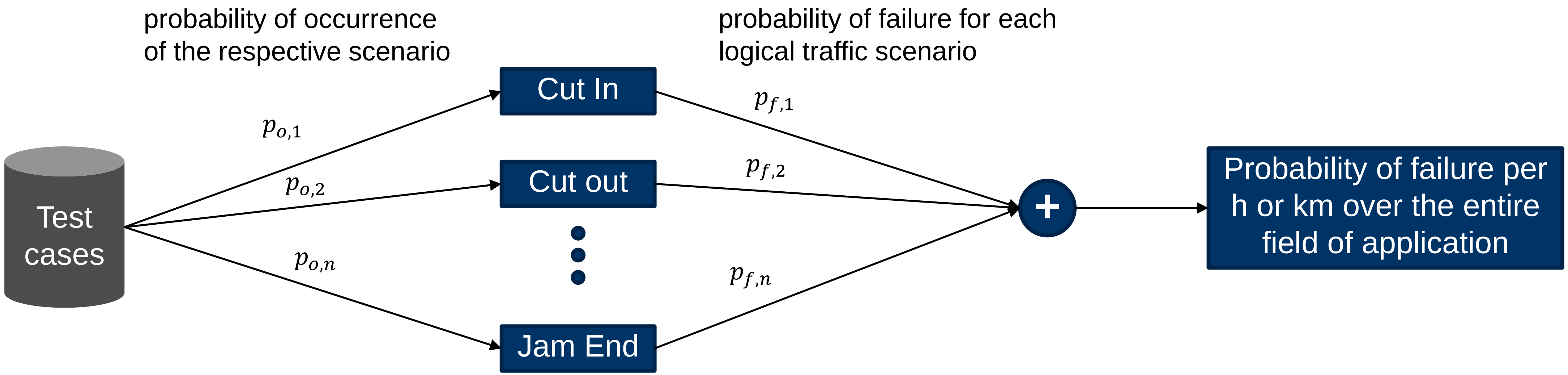
- Required mileage needed to proof the probability of failure of the system is impossible to reach in field operational tests [Winner]
- **The goal of simulative validation:** Find collision-relevant scenario characteristics
- The quality of validating HAD can be improved by the virtual variation of traffic scenarios
- Pure simulation is not enough!
- Solution: Only critical situations are simulated
  - Scenario-based approach





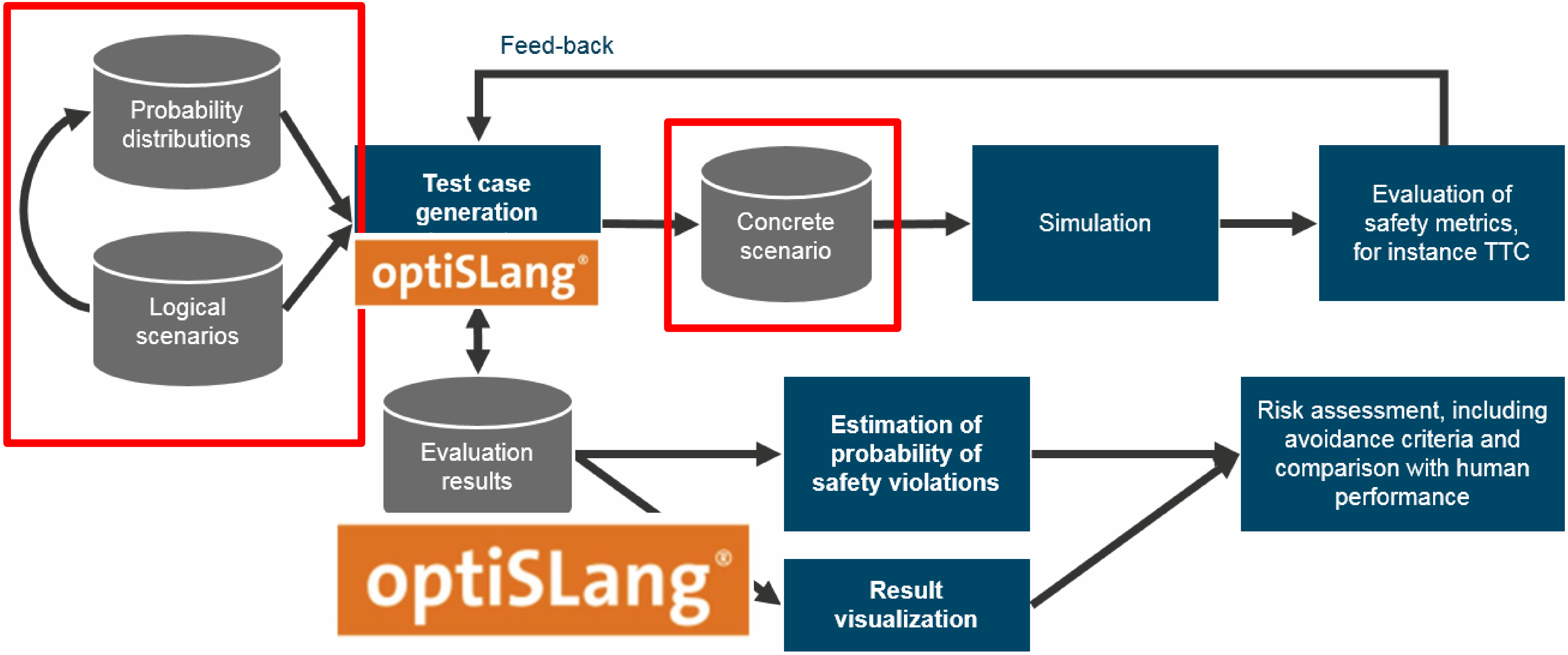
Methodology

- The diversity of traffic scenarios and their probability of occurrence enables a safety assessment of the overall system for the respective scenario

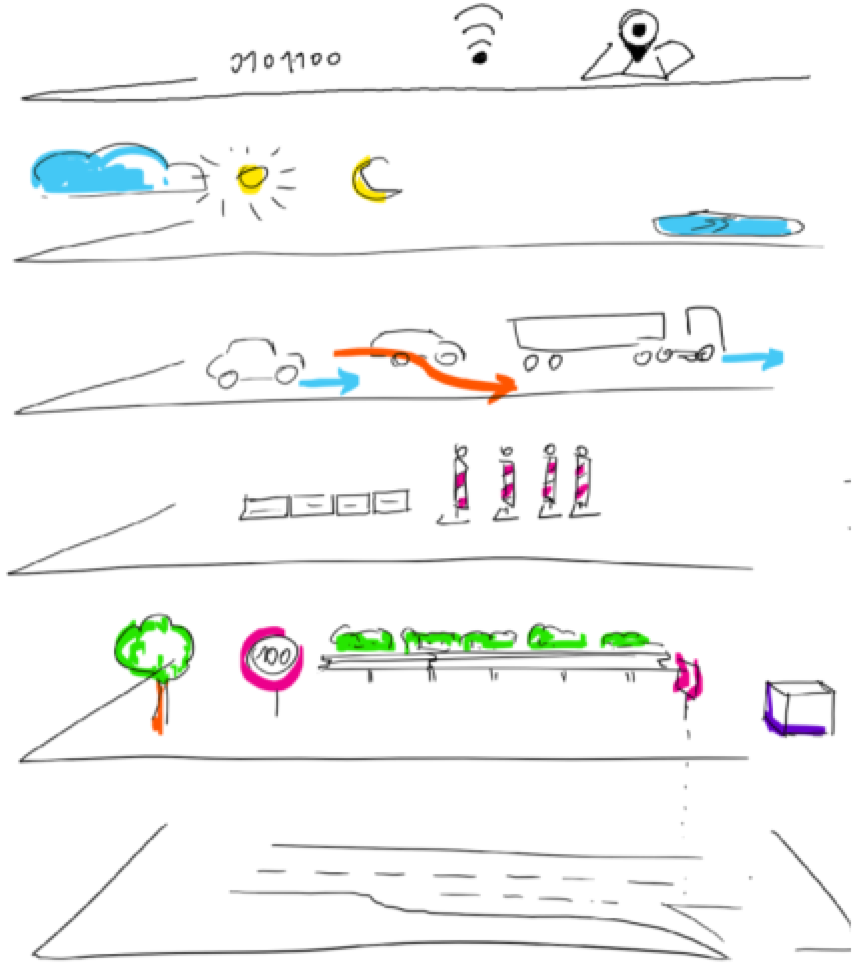


- → With the methods of the reliability analysis the probability of failure for each logical traffic scenario can be calculated

Simulation-based assessment of vehicle functions for logical scenarios



6-Layer model



Layer 6 — **Digital information:**
e.g. V2X information on traffic signals, digital map data
=> *Availability and quality of information communicated to own ship*

Layer 5 — **Environmental conditions**
Light situation, weather (rain, snow, fog…) temperature
=> *environmental influences on system performance*

Layer 4 — **Moving objects**
Vehicles, pedestrians moving relatively to own ship
=> *relevant traffic participants and their motion incl. dependencies*

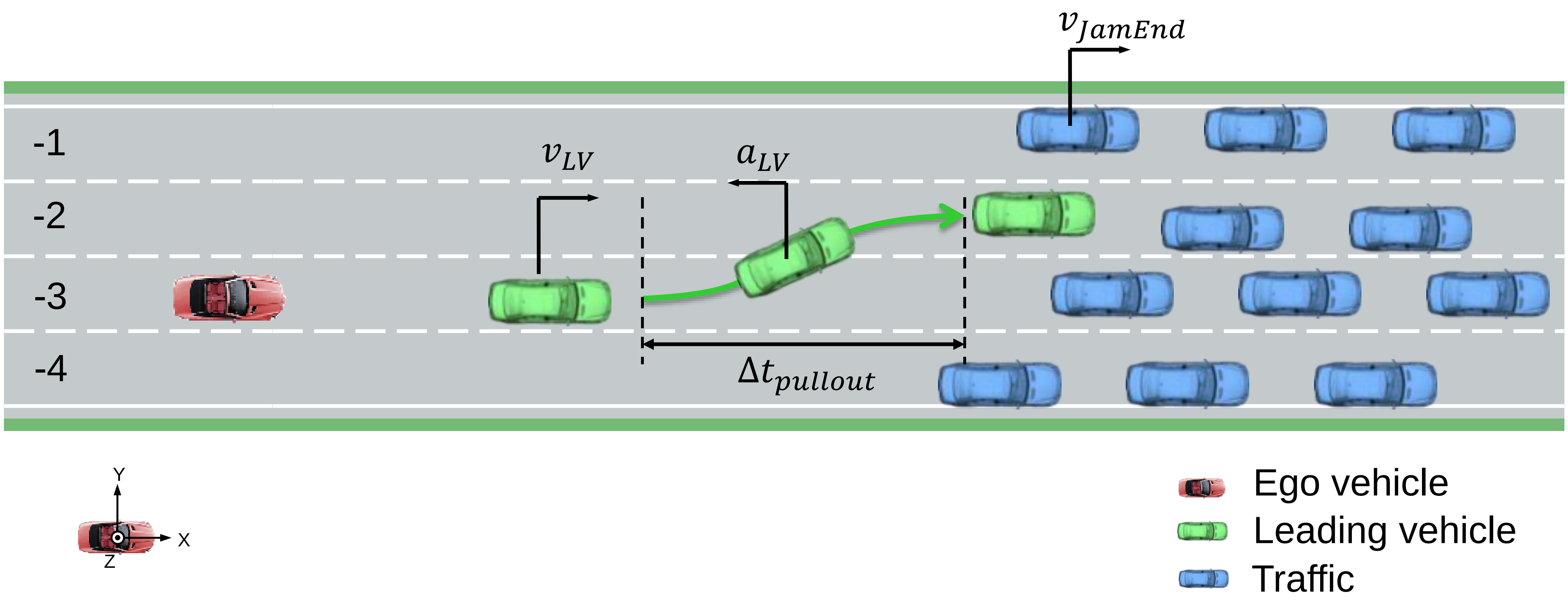
Layer 3 — **Temporal modifications and events**
Road construction, lost cargo, fallen trees, dead animal
=> *temporary objects minimizing / influencing the driving space*

Layer 2 — **Road furniture and Rules**
traffic signs, rail guards, lane markings, bot dots, police instructions
=> *including rules, where to drive how*

Layer 1 — **Road layer**
road geometry. Road unevenness (openCRG),
=> *physical description, no scenario logics*

6-layer-model to structure scenarios based on Schuldt (2017), Bagschik et al. (2018) and Bock et al. (2018)

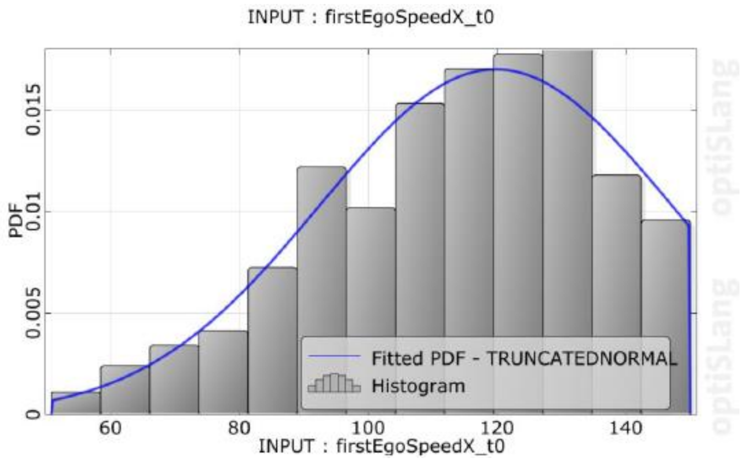
Example Scenarios with parameters



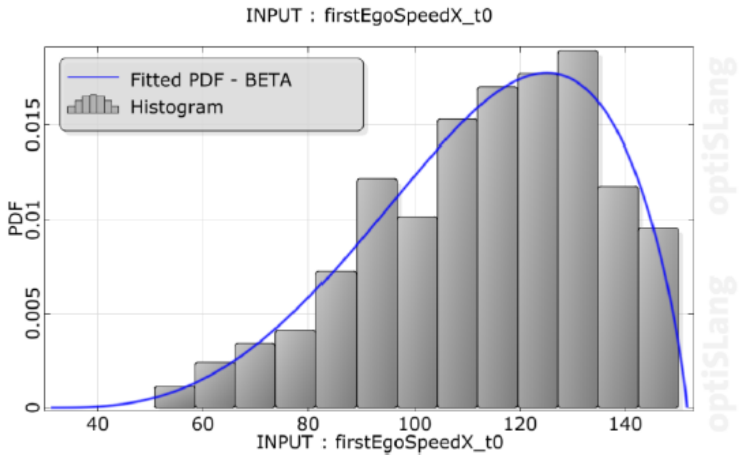
Parameter distributions

- Probability distributions determined on the basis of real measured data and by using the PEGASUS database
- Correlations between parameters have to be considered

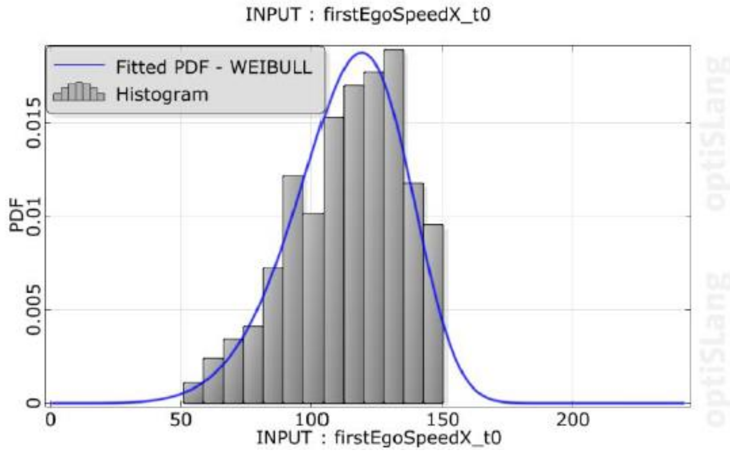
Truncated normal



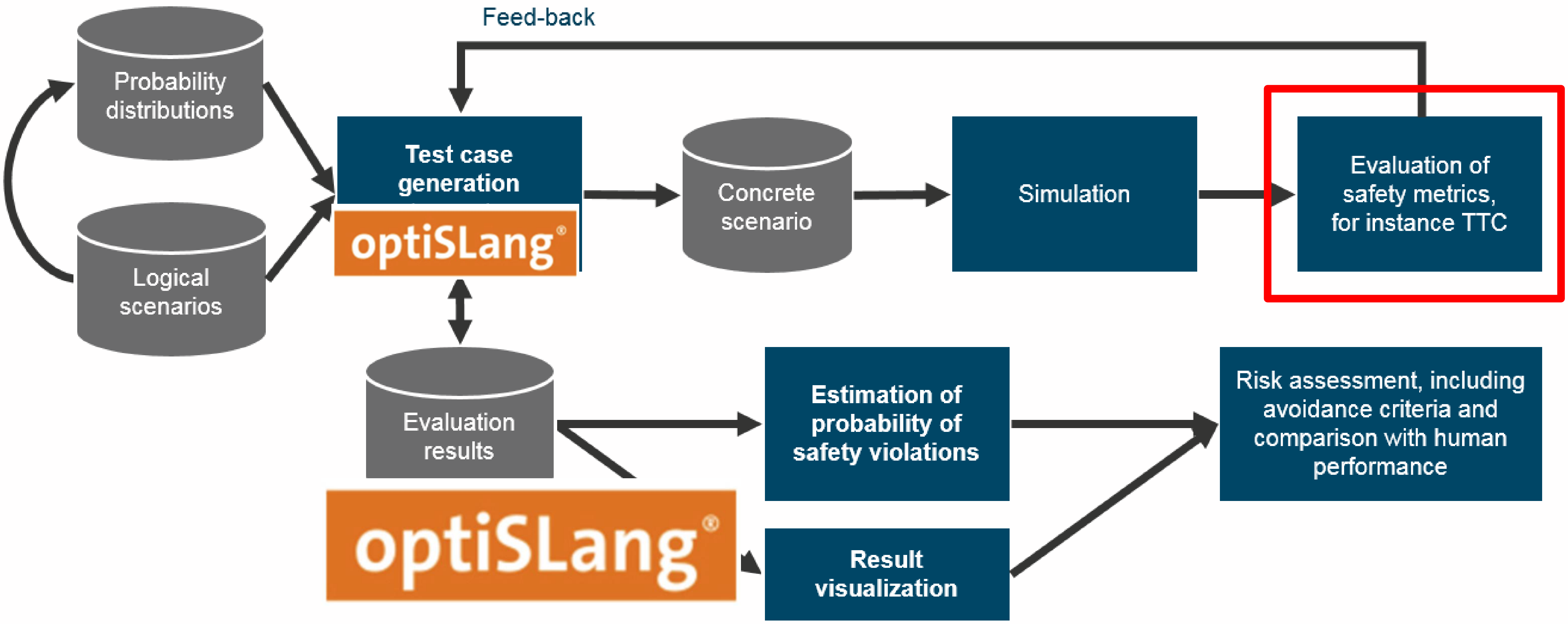
Beta



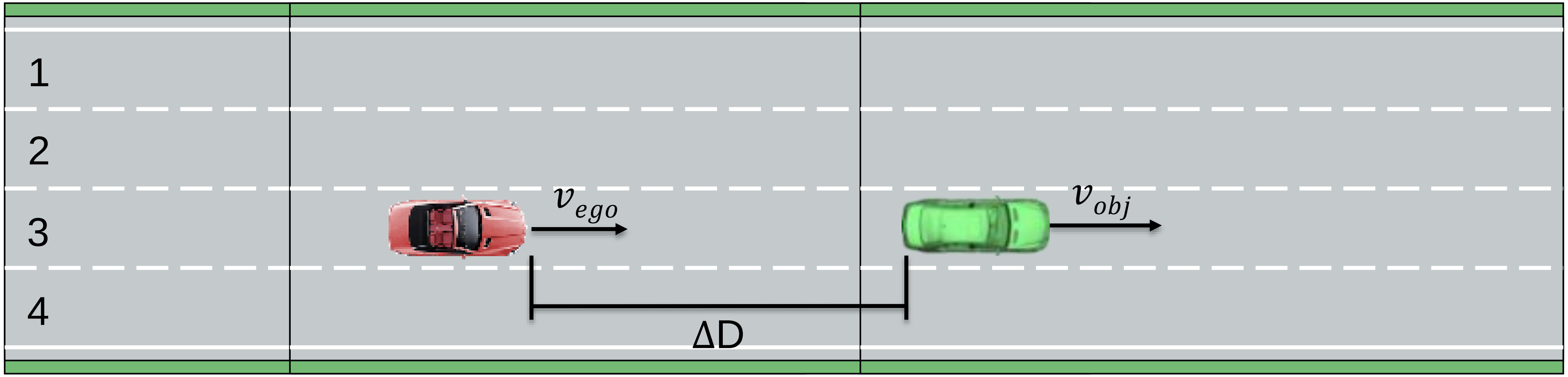
Weibull



Simulation-based assessment of vehicle functions for logical scenarios



Evaluating criteria



$$\text{TTC} = \frac{\Delta D}{V_{ego} - V_{obj}}$$

$$\text{THW} = \frac{\Delta D}{V_{ego}}$$

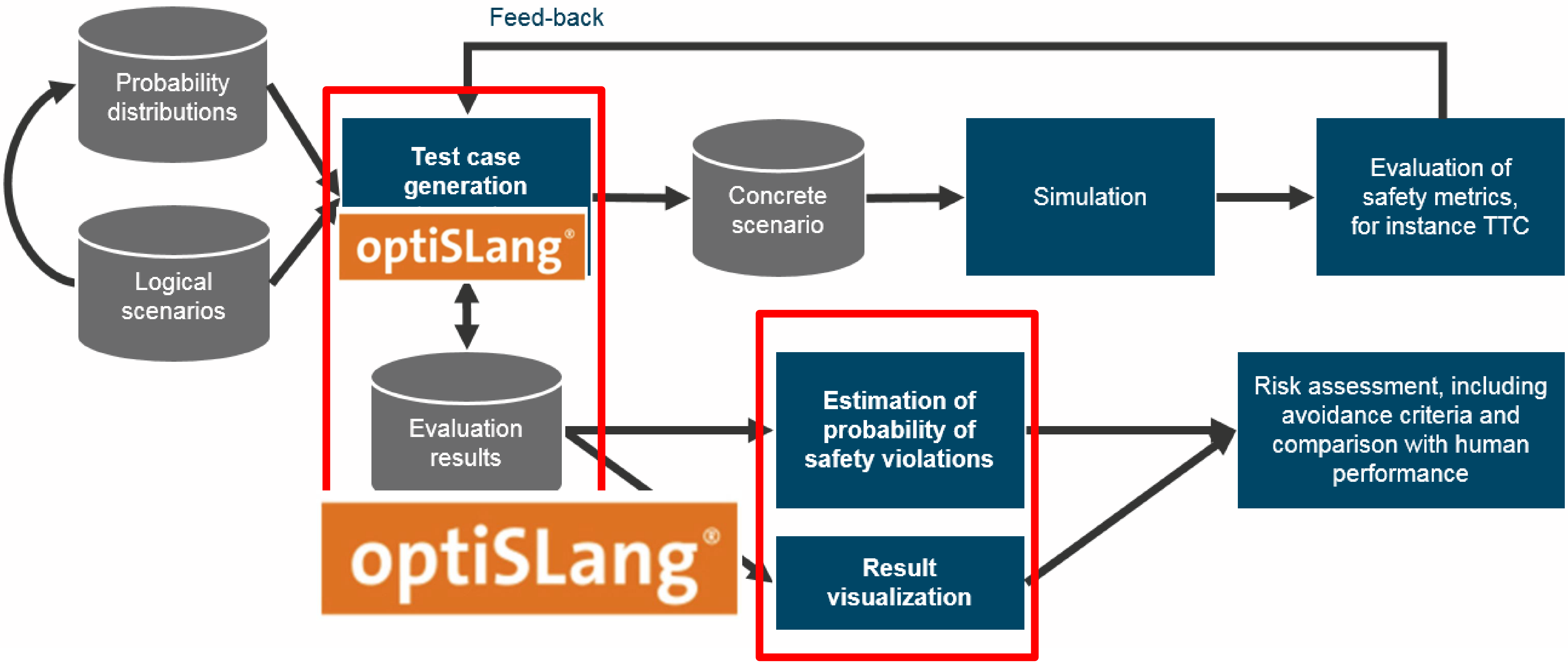
…

$$V_{coll} = V_{coll\,Ego} - V_{coll\,Obj}$$

alternative Criticallity =

$$\min\left(\frac{TTC}{TTC_{grenz}}; \frac{THW}{THW_{grenz}}; \frac{\Delta D}{\Delta D_{grenz}}; -\frac{V_{coll}}{V_{collgrenz}}\right)$$

Simulation-based assessment of vehicle functions for logical scenarios



Challenges using Reliability Analysis for ADAS

- Very low probability of failure → $p_f < 10^{-6}$
- Big parameter space → more than 50 parameters possible
- No linear system → difficult to calculate a MOP
- Limited computer power → efficient methods
- Near realtime simulation → efficient methods
- Discrete parameters
- Possibility of more then one failure area

→ Improved Adaptive Importance Sampling

→ Importance Sampling Using Design Points

Improved Adaptive Importance Sampling

1. Characterization of the parameter space with Latin hypercube sampling
2. Calculation of a Metamodel (MOP)
3. Identification of the relevant parameter / Determination of the model quality
4. Determination of the probability of failure by using Adaptive Importance Sampling

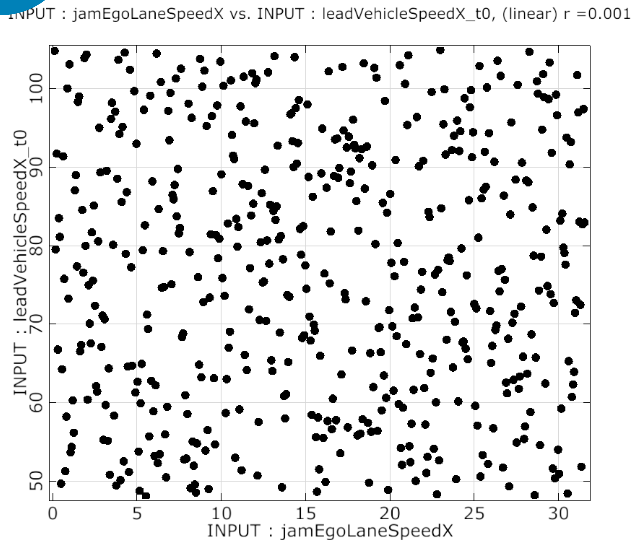
Steps 1–3: **Sensitivity Analysis**

Step 4: **Reliability Analysis**

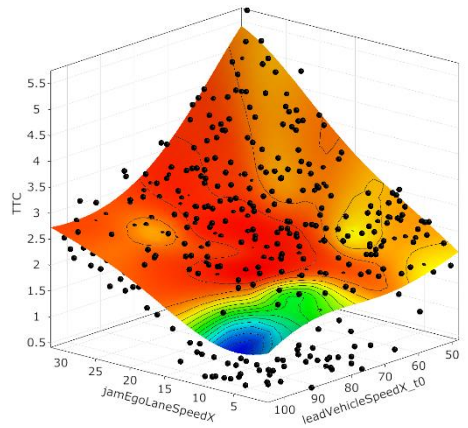
Parameter reduction by sensitivity analysis

- Creating a DoE with equally distributed parameter space (500 - 1000 designs)
- Determine the design results through simulation
- Calculate meta-models to determine the sensitivity of the parameters
- Selection of the most sensitive parameters for the following reliability analysis

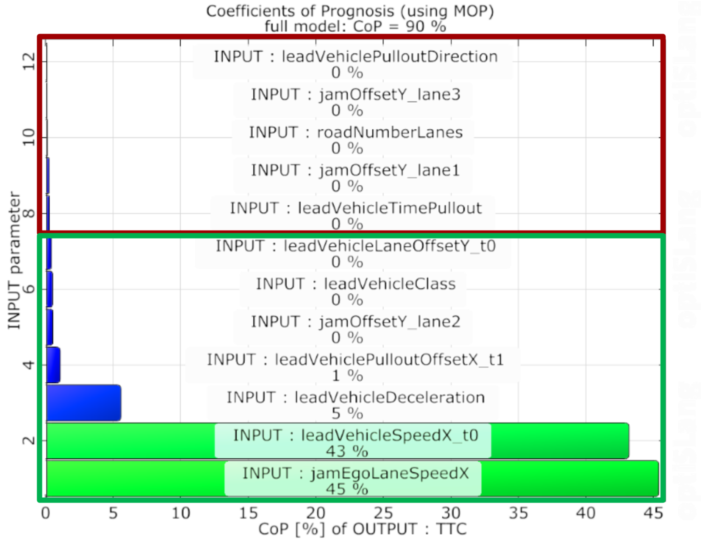
1 Design of Experiments



2 Mathematical regression model



3 Sensitivity of the parameters



Improved Adaptive Importance Sampling

1. Characterization of the parameter space with Latin hypercube sampling
2. Calculation of a Metamodel (MOP)
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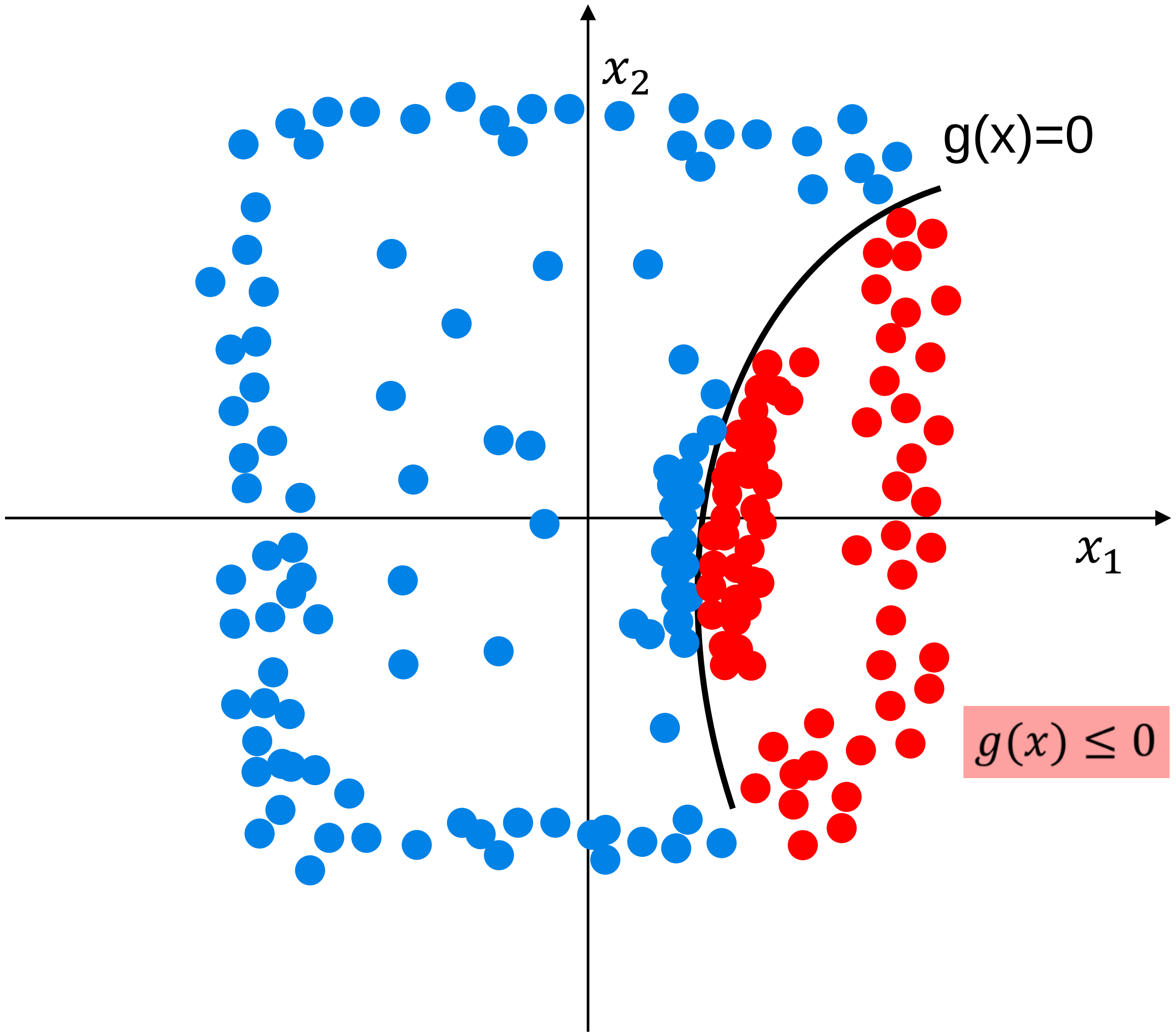
Sensitivity Analysis (steps 1–3)

Reliability Analysis (step 4)

Adaptive Importance Sampling



1. First iteration Monte Carlo sampling with scaling factor to place samples in the border areas

2. Sampling density is adapted from the found samples in the failure domain by estimating mean and covariance

$$E[Y] = E[X|g(\boldsymbol{X}) \leq 0]$$
$$E[YY^T] = E[XX^T|g(\boldsymbol{X}) \leq 0]$$

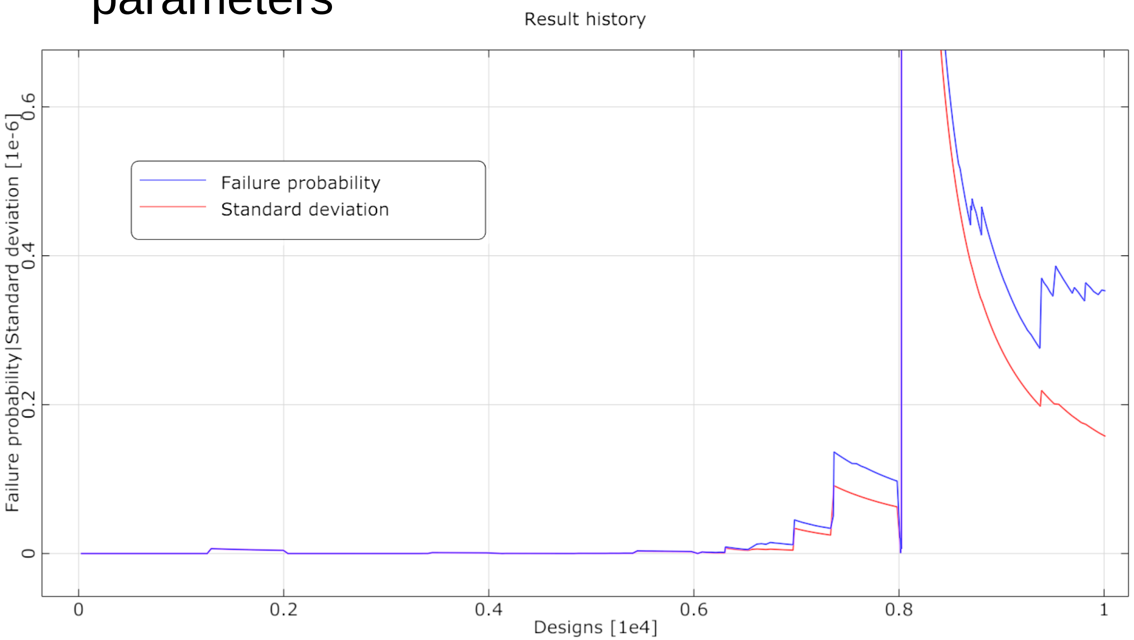
3. A weighting function $h_Y(x)$ is formed and the new probability of failure is calculated

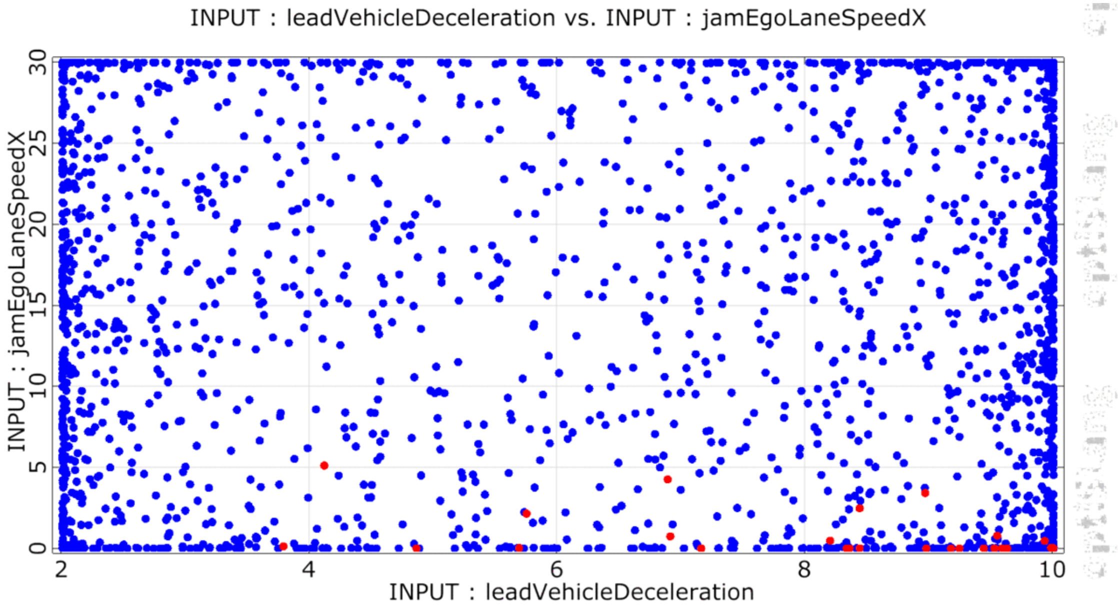
$$P_F = \frac{1}{N} \sum_{i=1}^{N} \frac{f_X(x_i)}{h_Y(x_i)} I(g(x_i))$$

4. Steps 2 and 3 are repeated any number of times

Adaptive Sampling using jam end scenario

- 5 iterations à 2000 samples with 13 parameters



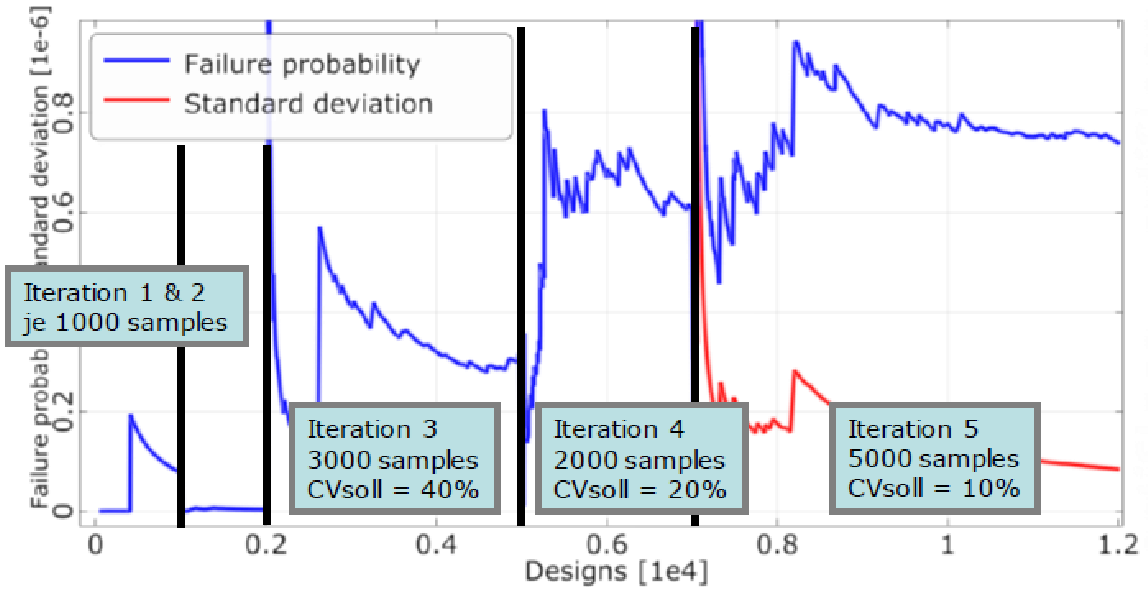


Pf= 3.5E-07, cov(Pf) = 46% → too high

→ too few samples in the failure area

Improved Adaptive Importance Sampling

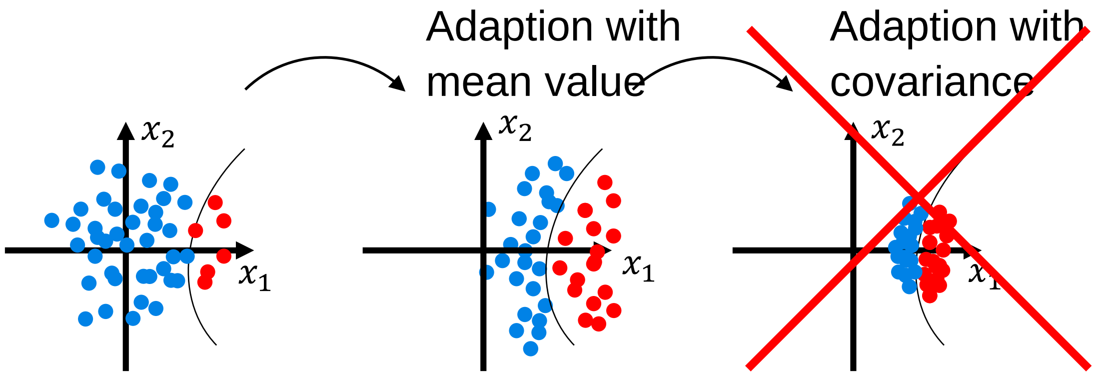
- Improvement of the Adaptive Sampling in OptiSlang
- Automatic sampling procedure that generates samples until required accuracy is achieved



- Adaptation of the sampling density only with the mean value → Covariance is no longer considered

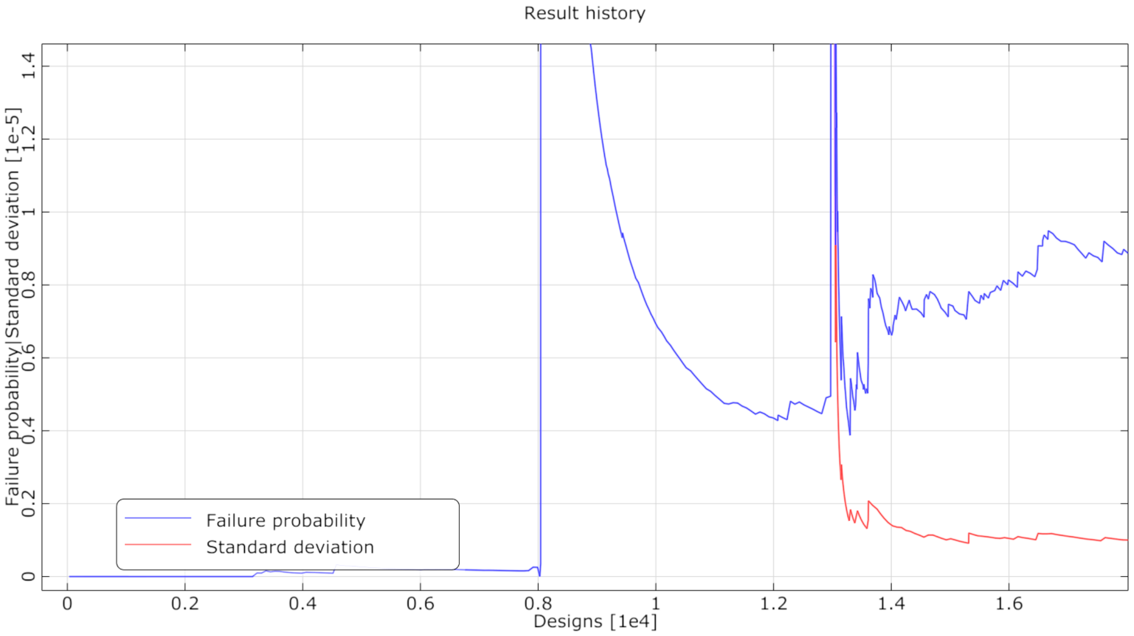
$$E[Y] = E[X|g(\boldsymbol{X}) \leq 0]$$

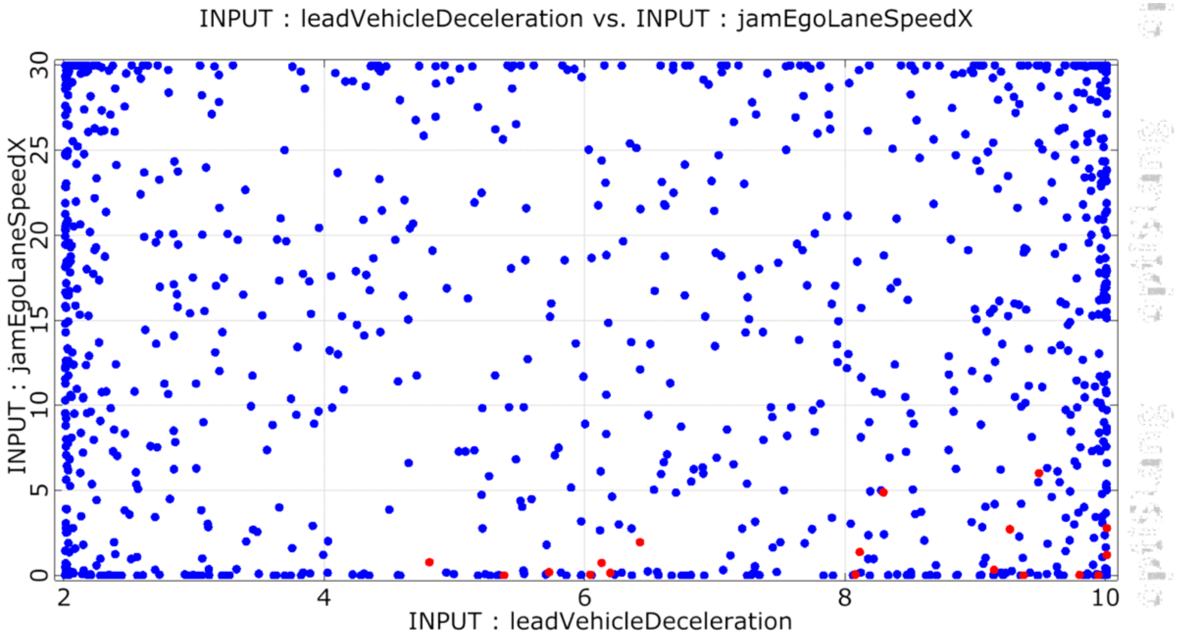
~~$E[YY^T] = E[XX^T|g(\boldsymbol{X}) \leq 0]$~~



Improved Adaptive Importance Sampling

- 5 iterations (1000/2000/5000/5000/5000) with 13 parameters





Pf= 8,7E-06, cov(Pf) = 11,3% → good accuracy

→a lot of samples in the failure area

Importance Sampling using Design Points

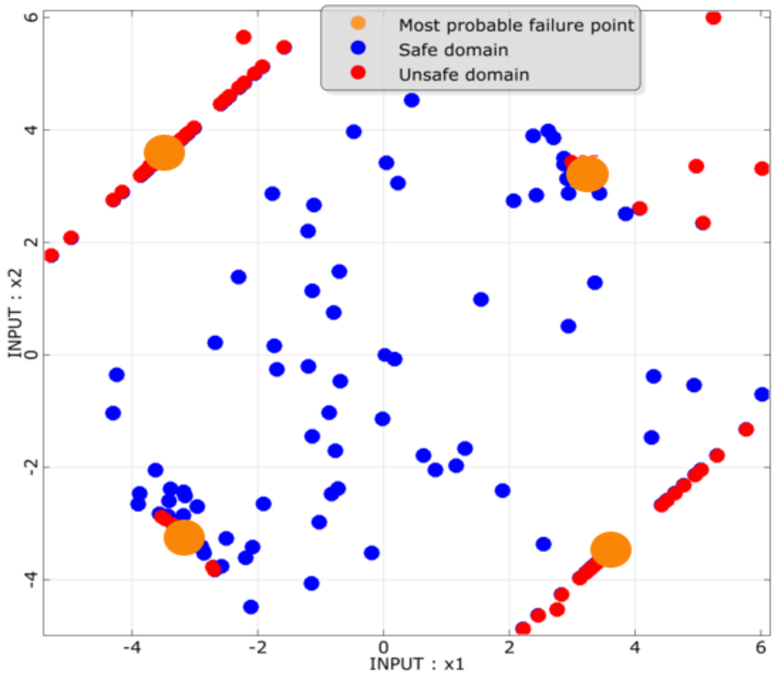
1. Characterization of the parameter space with Latin hypercube sampling
2. Calculation of a Metamodel (MOP)
3. Identification of the relevant parameter / Determination of the model quality
4. Determination of the design points by using FORM on the MOP
5. Determination of the probability of failure by using ISPUD with all parameters

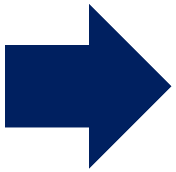
Sensitivity Analysis (steps 1–3)

Reliability Analysis (steps 4–5)

Importance Sampling using Design Points

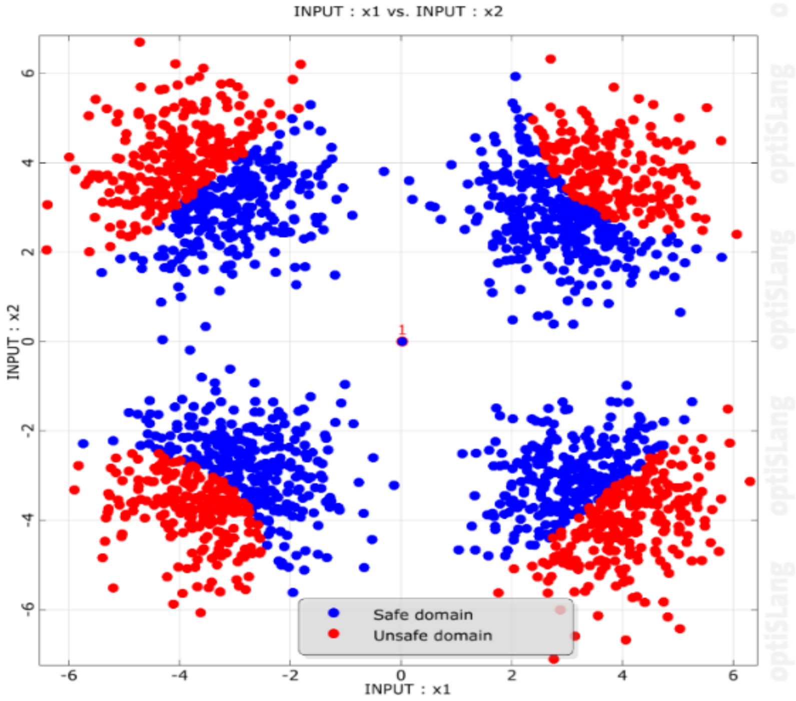
4 → Multiple FORM for detecting multiple failure areas





Design Points

5 → Multimodal Importance Sampling for calculating the probability of failure

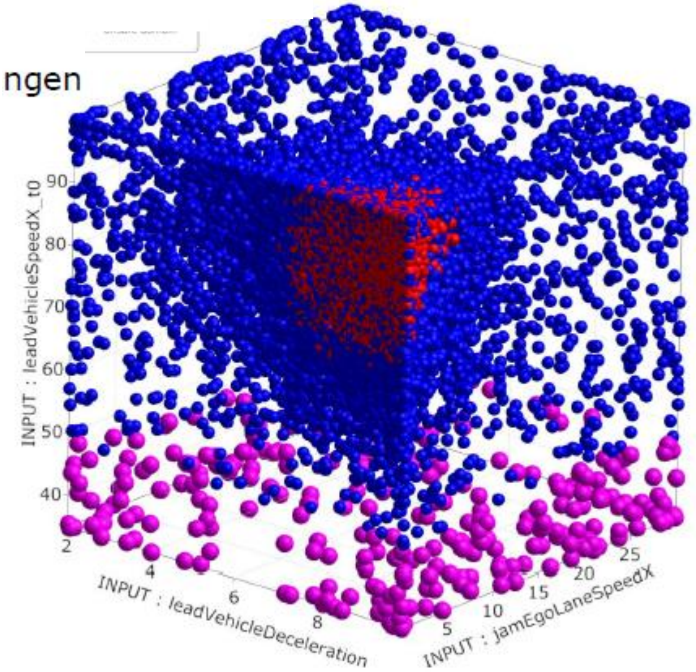


Results

- Jam end scenario with 13 parameters
- Methods like Adapive Sampling or ISPUD can reduce the required samples

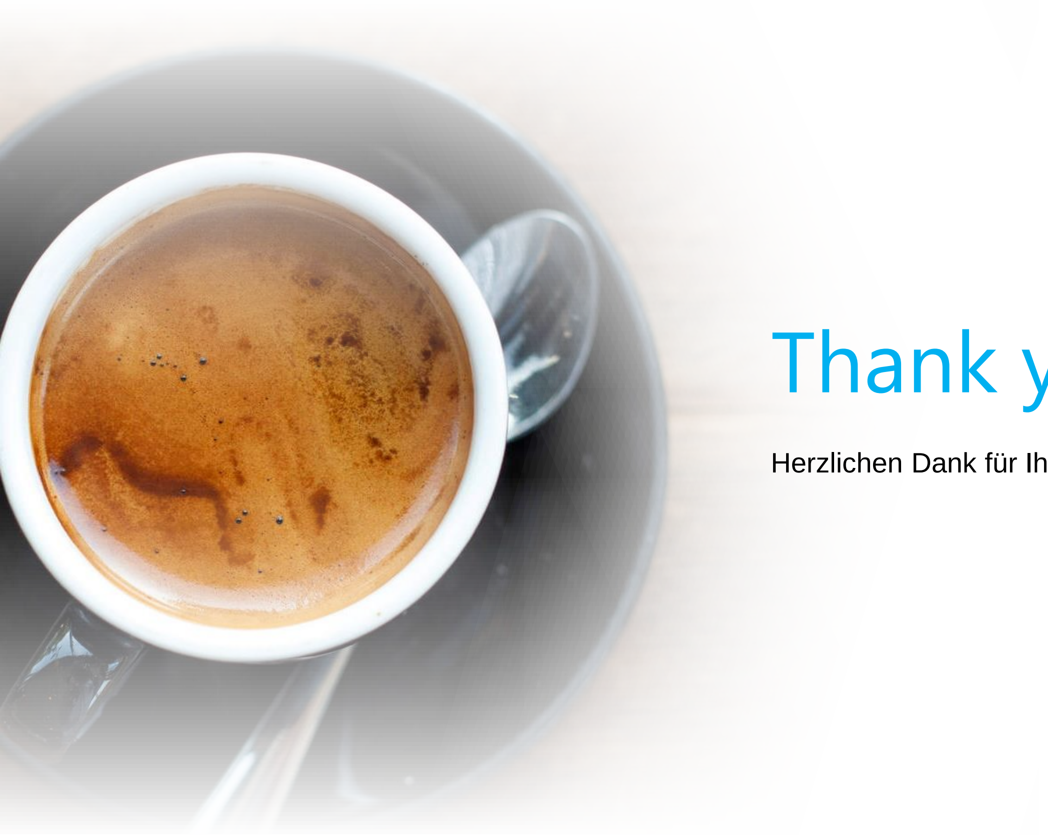
→ Reliability Analysis using meta-model

TTC = 0.4	Samples	Pf	CoV	Beta
MCS	39.420.000	2.54E-6	10.0%	4.56
AS	16.000	2.81E-6	9.1%	4.54
ISPUD+FORM	7.000+5.500	2.31E-6	9.5%	4.58



→ Reliability Analysis using the traffic simulation tool

TTC = 0.5	Samples	Pf	CoV	Beta
MCS	Not possible	-	-	-
AS	22.000	5.30E-3	9.2%	2.55
ISPUD+FORM	5.000+4.500	4.40E-3	20.1%	2.62



Thank you for your attention!

Herzlichen Dank für Ihre Aufmerksamkeit !