SCENARIO-BASED UNCERTAINTY QUANTIFICATION FOR THE DESIGN OF RELIABLE AUTOMATED DRIVER ASSISTANCE SYSTEMS

Simulation-Based Optimization, London, UK, October 15-16

L. Graening, Th. Most, R. Niemeier

NAFEMS

Dynardo GmbH

- Founded: 2001
- More than 60 employees, offices at Weimar, Vienna and San Francisco
- Providing Robust Design Optimization based on Stochastic Analysis to leading technology companies like Bosch, Continental, Daimler, EADS, Shell, Siemens, …

Software Development

optiSLang: Robust Design Optimization
SoS: Random Fields
multiPlas: Elasto-Plastic Modeling

CAE-Consulting

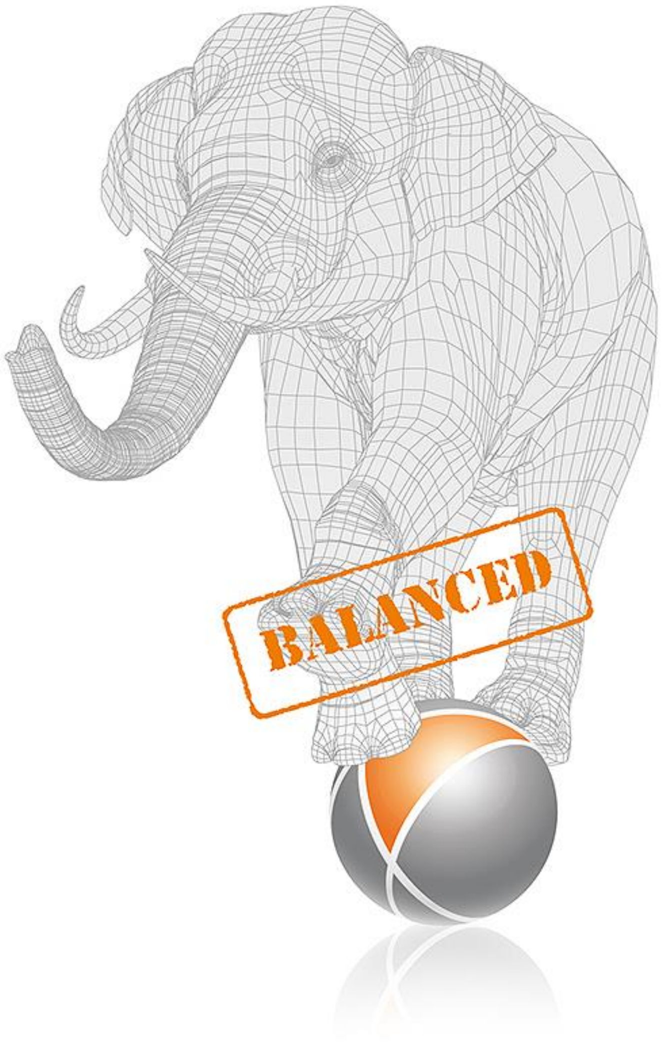
- Mechanical engineering
- Civil engineering & Geomechanics
- Automotive industry
- Consumer goods industry
- Power generation

optiSLang®

Is a general purpose tool for variation analysis
using CAE-based design sets (and/or data sets)
for the purpose of

- sensitivity analysis
- design/data exploration
- calibration of virtual models to tests
- optimization of product performance
- quantification of product robustness and product reliability
- Robust Design Optimization (RDO) and Design for Six Sigma (DFSS)

serves arbitrary CAX tools with
→ **support of process integration**
→ **workflow generation**
→ **process automation**



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Motivation for Automated Driving Functions (ADF)

Comfort

Source: cars.usnews.com

Safety

Source: insurancejournal.com

Motivation for Automated Driving Functions (ADF)

US National Highway Traffic Safety Administration (NHTSA):
94% of serious vehicle crashes in the US are caused by human error (NCSA, 2015, p. 142)

Autonomous vehicles are never drunk, distracted, or tired; these factors are involved in 41 percent, 10 percent, and 2.5 percent of all fatal crashes, respectively (National Highway Traffic Safety Administration, 2011; Bureau of Transportation Statistics, 2014b; U.S. Department of Transportation, 2015).

For instance, inclement weather and complex driving environments pose challenges for autonomous vehicles, as well as for human drivers, and
autonomous vehicles might perform worse than human drivers in some cases (Gomes, 2014).

⇨ *Requirement: Extensive validation of the automated driving functions*

Confidence

Americans drive nearly **3 trillion miles every year** (Bureau of Transportation Statistics, 2015). The 2.3 million reported injuries in 2013 correspond to a failure rate of **77 reported injuries per 100 million miles**. The 32,719 fatalities in 2013 correspond to a failure rate of **1.09 fatalities per 100 million miles**.

To demonstrate that fully autonomous vehicles have a fatality rate of 1.09 fatalities per 100 million miles (R=99.9999989%) with a **C=95% confidence level**, the vehicles would have to be driven **275 million failure-free miles**. With a fleet of **100 autonomous vehicles** being test-driven **24 hours a day, 365 days a year** at an average speed of 25 miles per hour, this would take about …

… 12.5 years.

Kalra & Paddock, Driving to Safety, 2016

Homologation trap of autonomous driving!

Source: https://www.automotivetestingtechnologyinternational.com

Szenario-Based Validation

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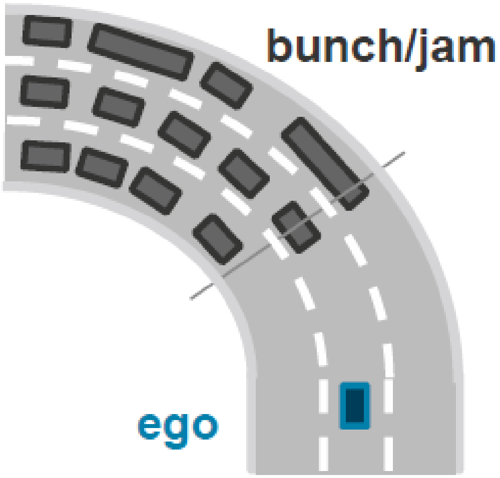
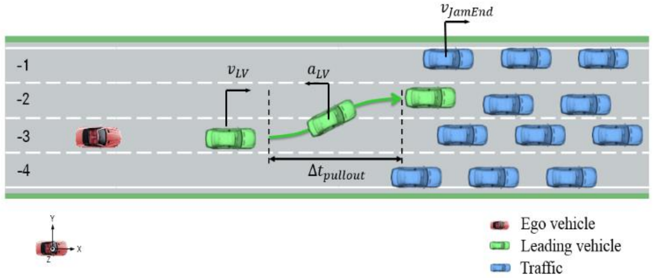


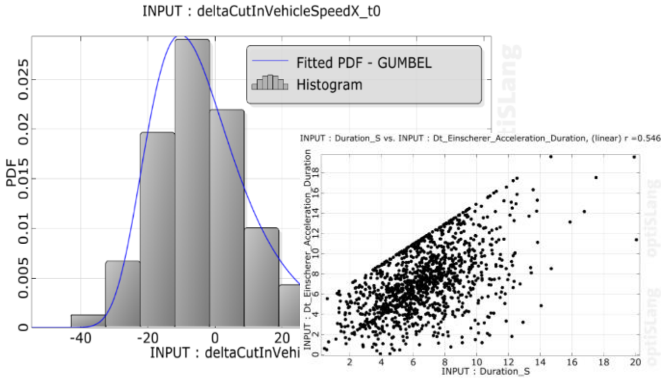
Functional scenarios	Logic scenarios
Basis road: highway in bend	Basis road: number of lanes [2..4] curve radius [0,6..0,9] kph
Stationary objects: -	Stationary objects: -
Movable objects: ego, jam; interaction: ego approaches end of jam	Movable objects: End of jam position [10..200] m jam speed [0..30] kph ego distance [50..300] m ego speed [80..130] kph
Environment: summer, rain	Environment: temperature [10..40] °C droplet size [20..100] µm rain amount [0,1..10] mm/h

Szenario Definition & Parametrization

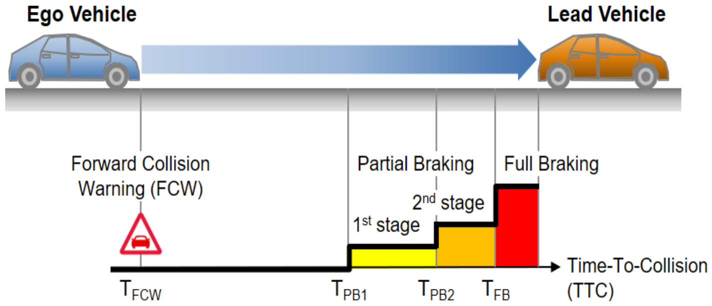
1. Define scenario parametric



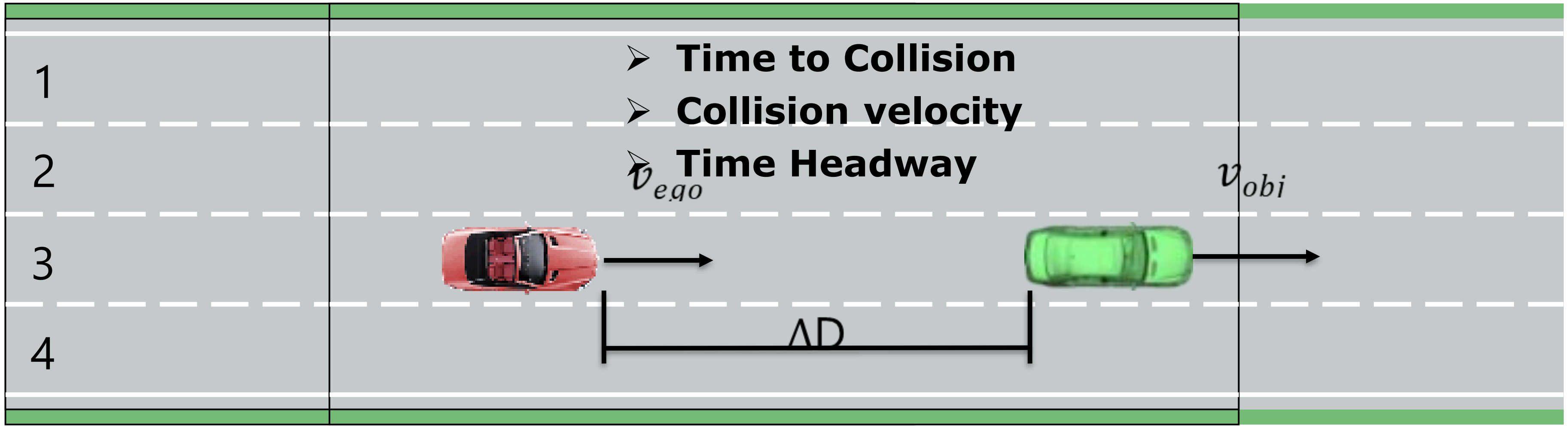
2. Derive parameter scatter and correlation from data



3. Define criticality by means of available KPIs



Criticality & KPI estimation



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

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

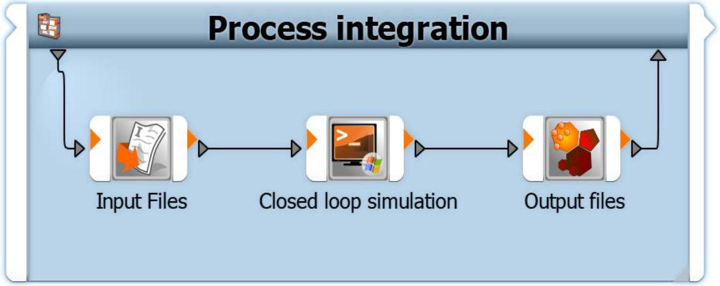
$$THW = \frac{\Delta D}{V_{ego}}$$

alternative Criticallity =

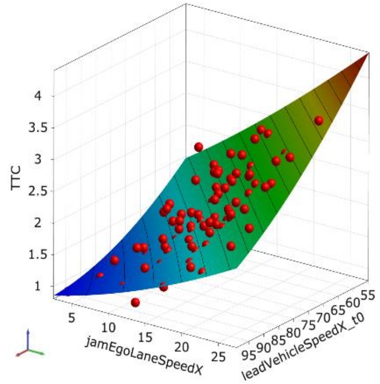
$$\min\left(\frac{TTC}{TTC_{grenz}}; \frac{THW}{THW_{grenz}}; \frac{\Delta D}{\Delta D_{grenz}}; -\frac{V_{coll}}{V_{collgrenz}}\right)$$

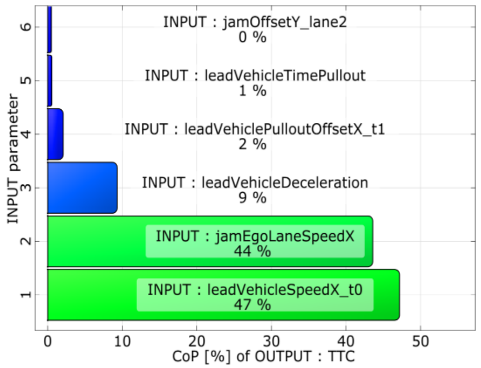
Szenario Variation & Uncertainty Quantification

4. Integrate closed loop simulation in automated workflow

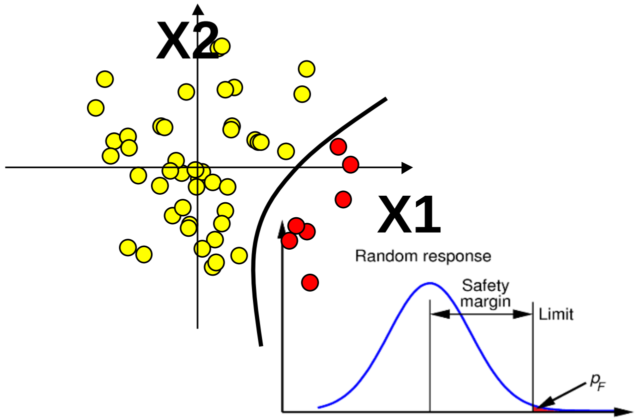


5. Get parameter importance by robustness/sensitivity analysis



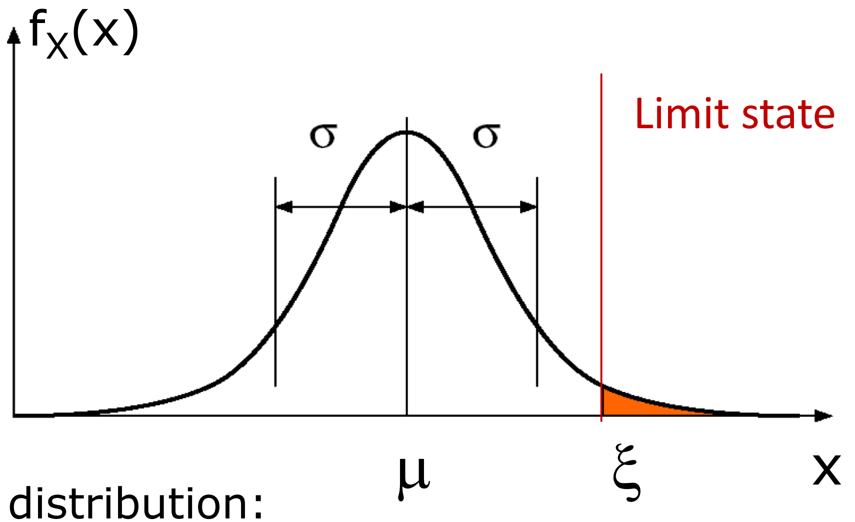


6. Uncertainty quantification



Uncertainty Quantification

- Probability of reaching values above a limit



Exceedance Probability

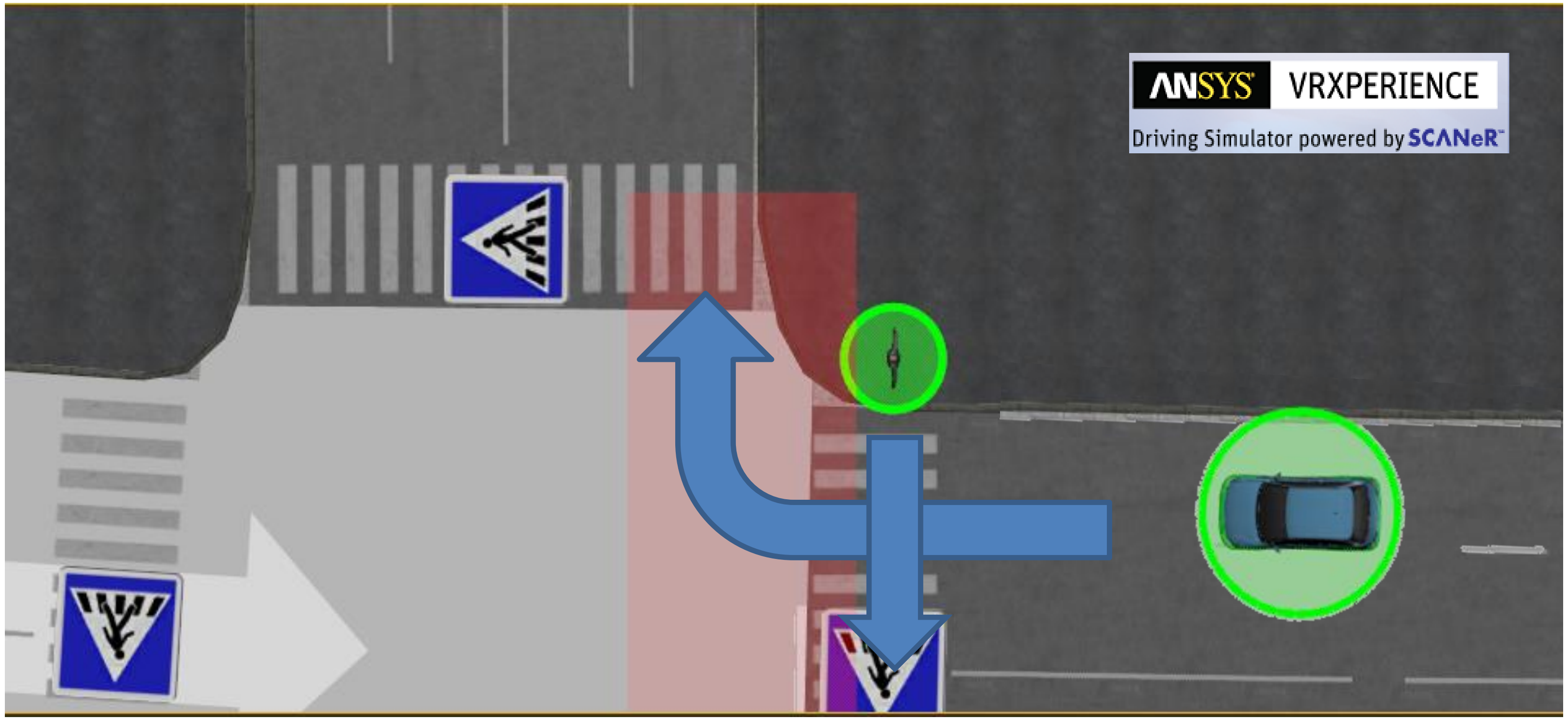
e.g. probability exceeding a critical TTC

- Gaussian distribution:

$$P_\xi = P[X \geq \xi]$$

ξ	μ	$\mu + \sigma$	$\mu + 2\sigma$	$\mu + 3\sigma$	$\mu + 4\sigma$
P_ξ	$5 \cdot 10^{-1}$	$1.6 \cdot 10^{-1}$	$2.3 \cdot 10^{-2}$	$1.4 \cdot 10^{-3}$	$3.2 \cdot 10^{-5}$

Automated Emergency Breaking (AEB)



Together with Manh Tuan Bui, Product expert in ANSYS SBU Optic

System Simulation

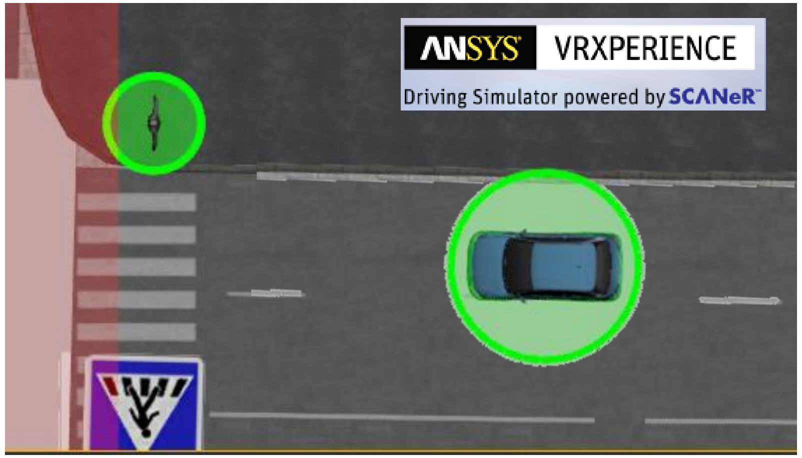
Sensors

Camera
(VRXPERIENC Lighting
and Sensors)

- Exposure
- Field of view

Co-Simulation

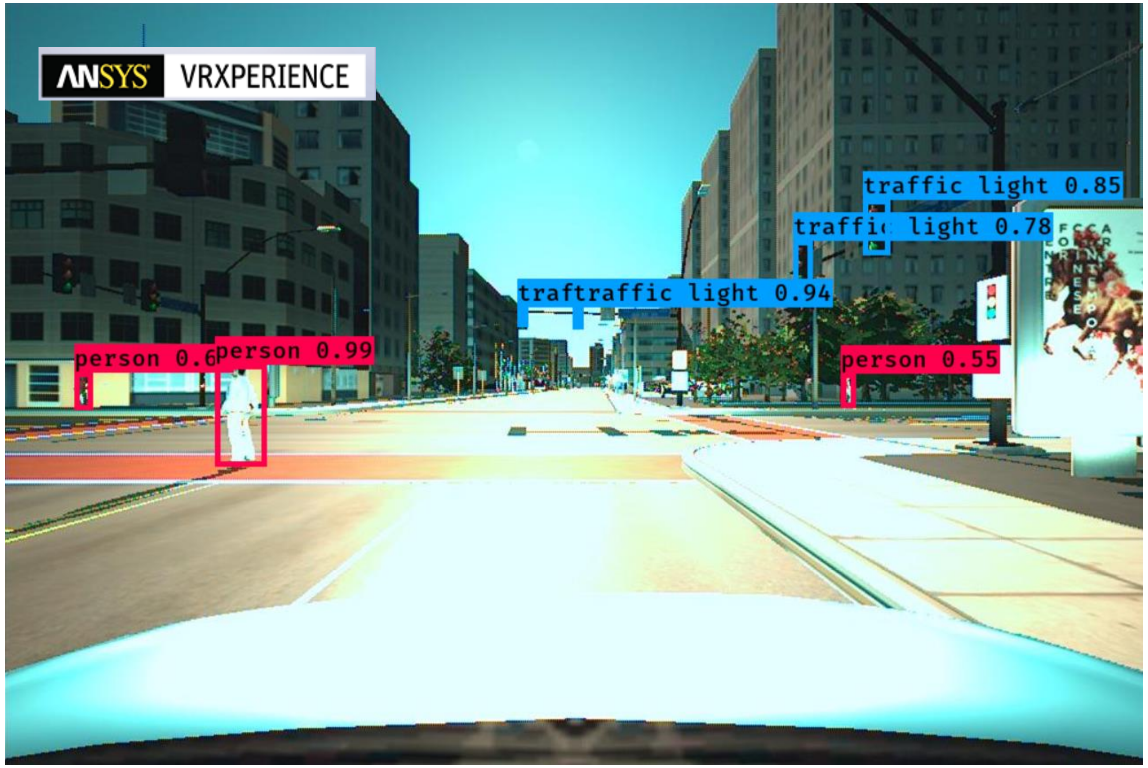
Scenario



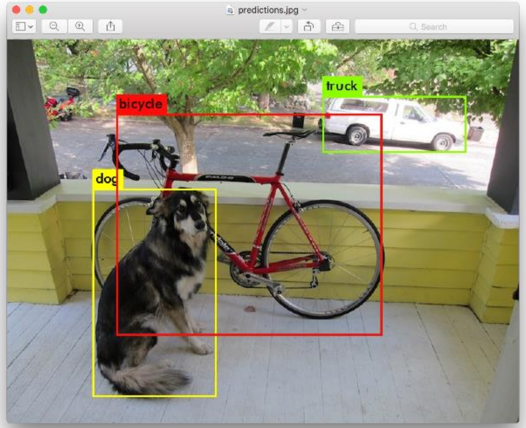
Pedestrian
- Start moment in TTC
- Walking speed

Ego-vehicle
- Initial speed

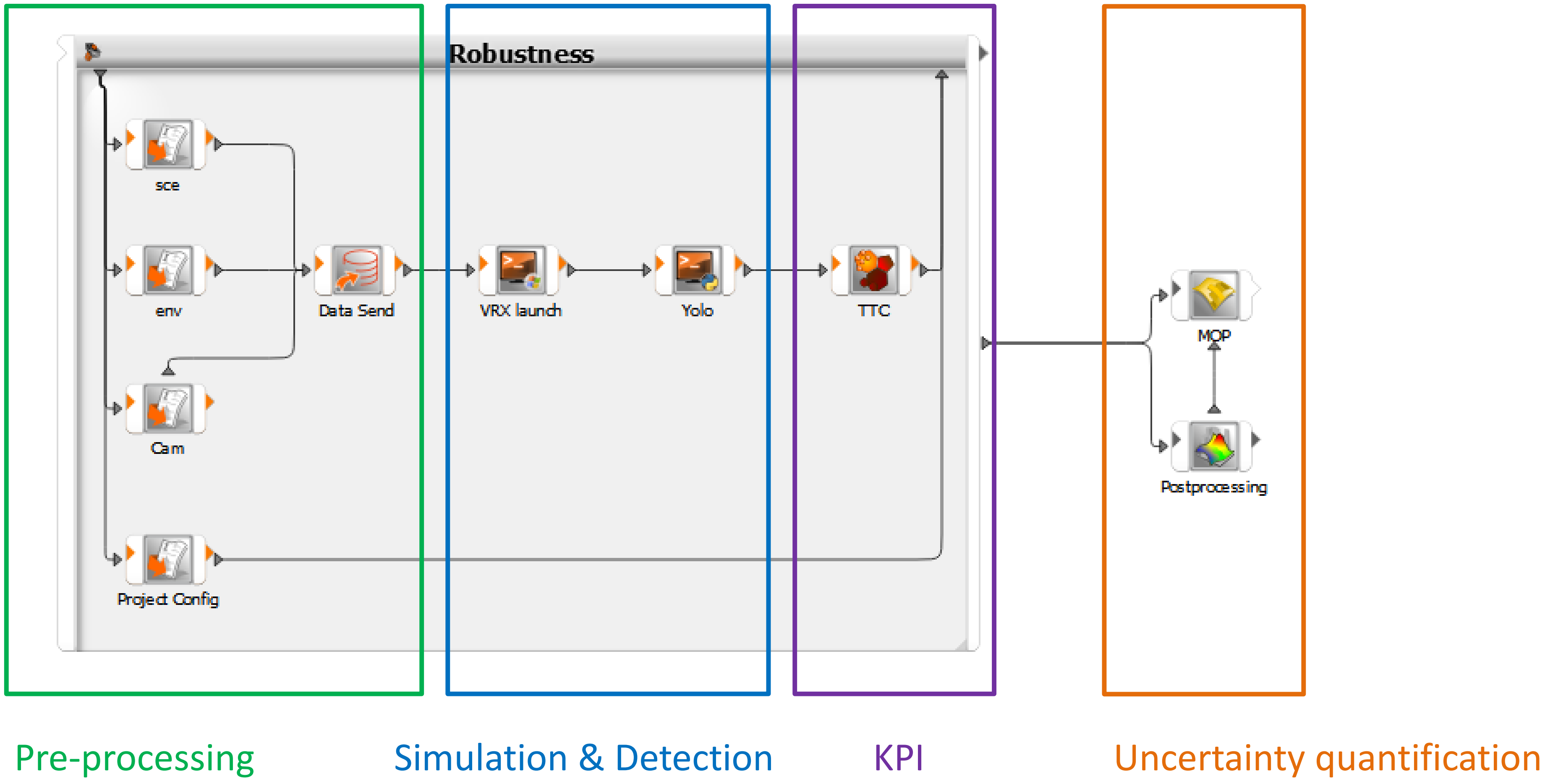
Pedestrian detection with Yolo: Real Time Object Detection



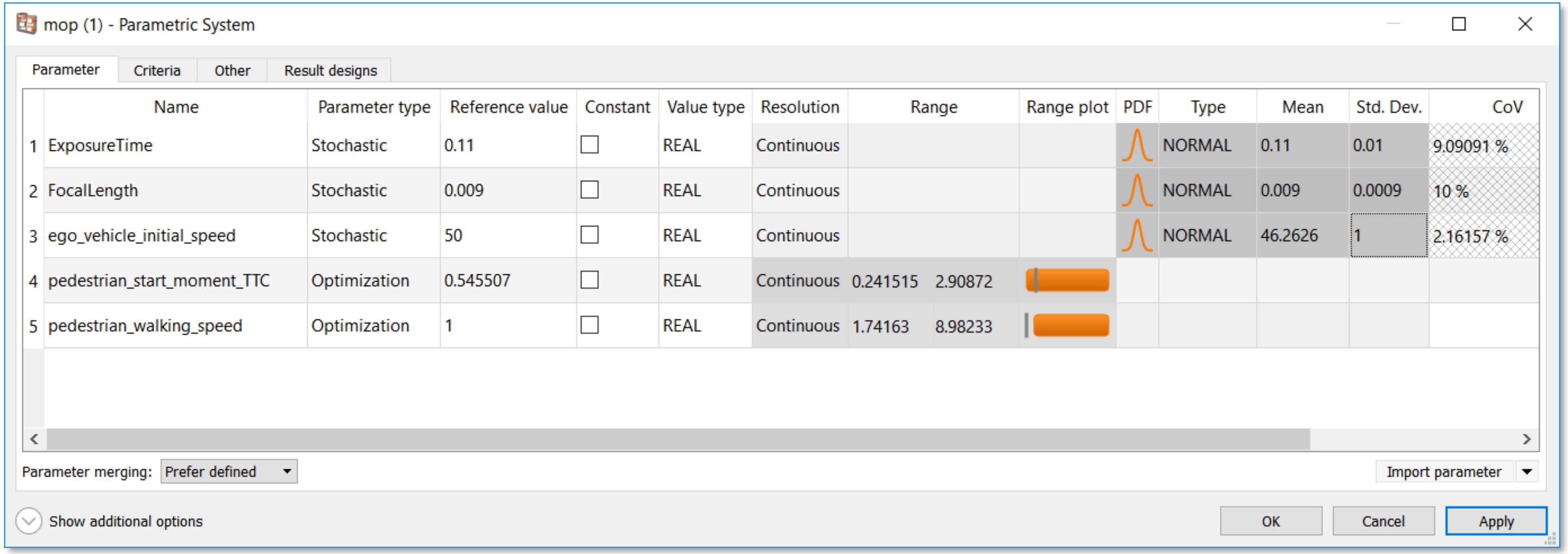
- Yolo: Neural Network based object detection algorithm (https://pjreddie.com/darknet/yolo/)
- Predicting bounding boxes and probabilities



Workflow setup

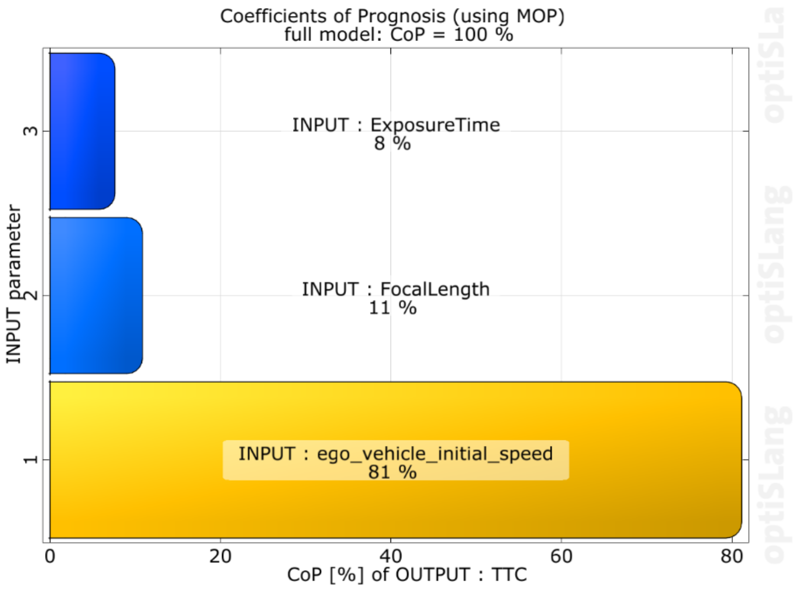


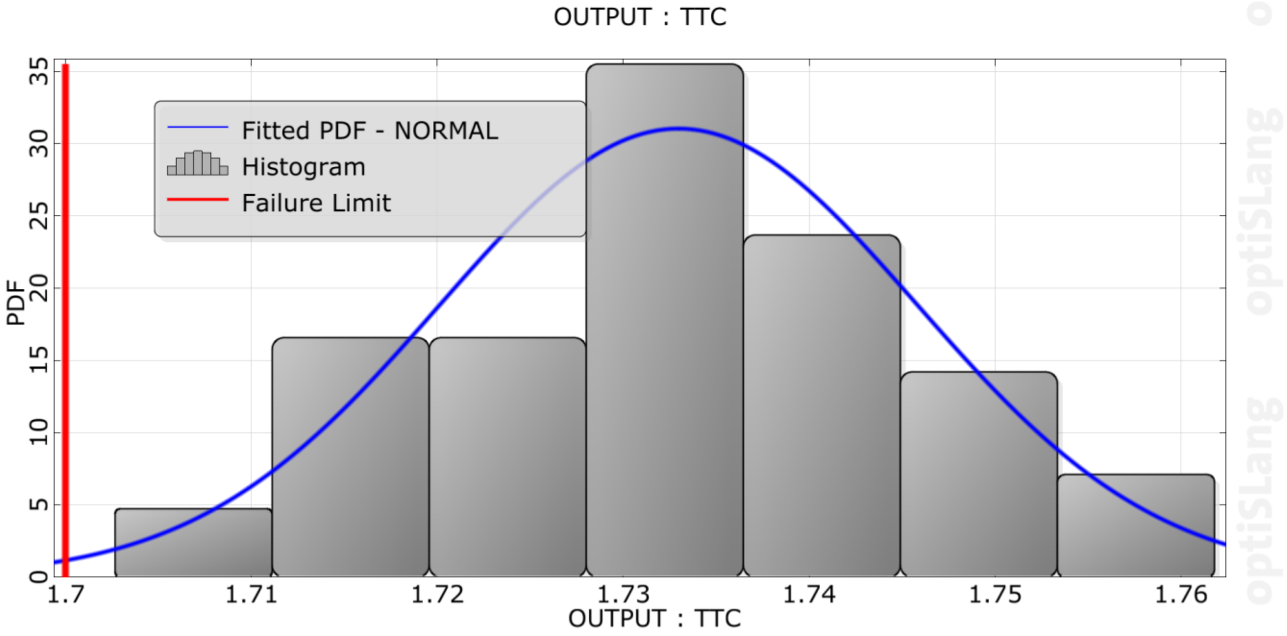
Workflow setup



	Name	Parameter type	Reference value	Constant	Value type	Resolution	Range		Range plot	PDF	Type	Mean	Std. Dev.	CoV
1	ExposureTime	Stochastic	0.11	☐	REAL	Continuous					NORMAL	0.11	0.01	9.09091 %
2	FocalLength	Stochastic	0.009	☐	REAL	Continuous					NORMAL	0.009	0.0009	10 %
3	ego_vehicle_initial_speed	Stochastic	50	☐	REAL	Continuous					NORMAL	46.2626	1	2.16157 %
4	pedestrian_start_moment_TTC	Optimization	0.545507	☐	REAL	Continuous	0.241515	2.90872						
5	pedestrian_walking_speed	Optimization	1	☐	REAL	Continuous	1.74163	8.98233						

Uncertainty in TTC at first detection





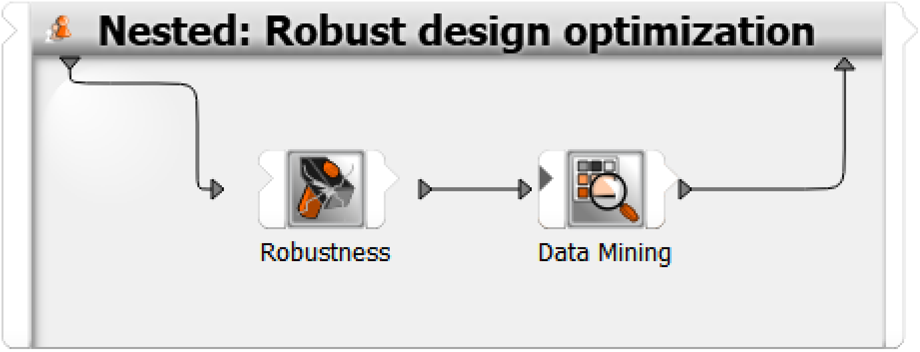
p = 0.5%

Sigma-level = 2.56

Estimation of the likelihood exceeding the safety margin regarding TTC after first detection

Outlook

1. Closing the loop: Detection, (Planning) and Actuation
2. Enhance example, with respect to complexity and to other functional scenarios
3. Exploit uncertainty information for robust design optimization



Thank You for Your Attention!

For more information please visit our booth and homepage:
www.dynardo.com

WOST2020: June 25 - 26