Virtual Testing Validation for ADS

literature review pt. 2

UNECE VMAD SG2, June 30th 2021

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Disclaimer

- No standard validation methodologies exist for ADS virtual testing
- Team defining the validation procedure == team defining requirements
- Presentation's goal:
  - *Not* to force correlation thresholds based on literature survey
  - To give hints on modelling approaches, validation methodologies and obtained correlation

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Virtual validation pipeline

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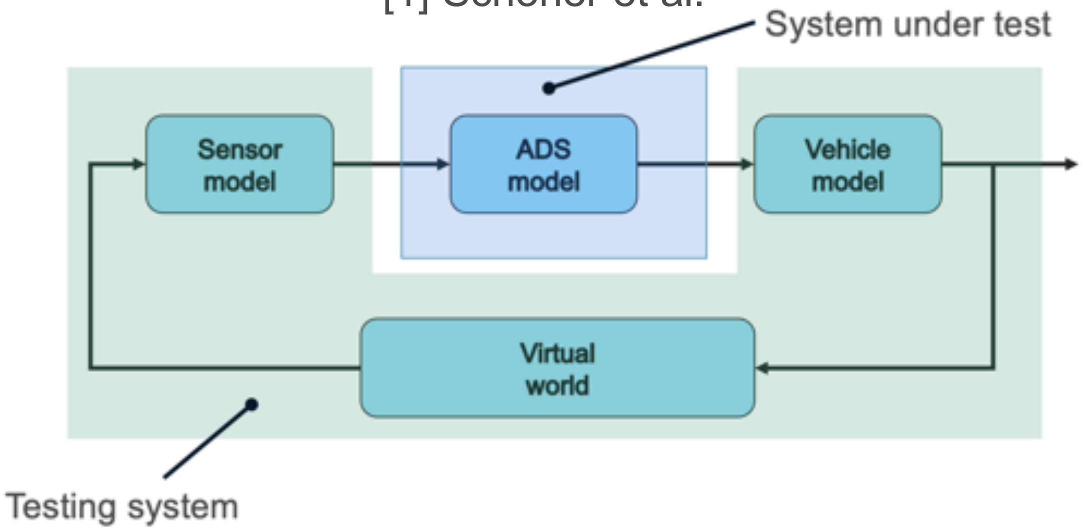
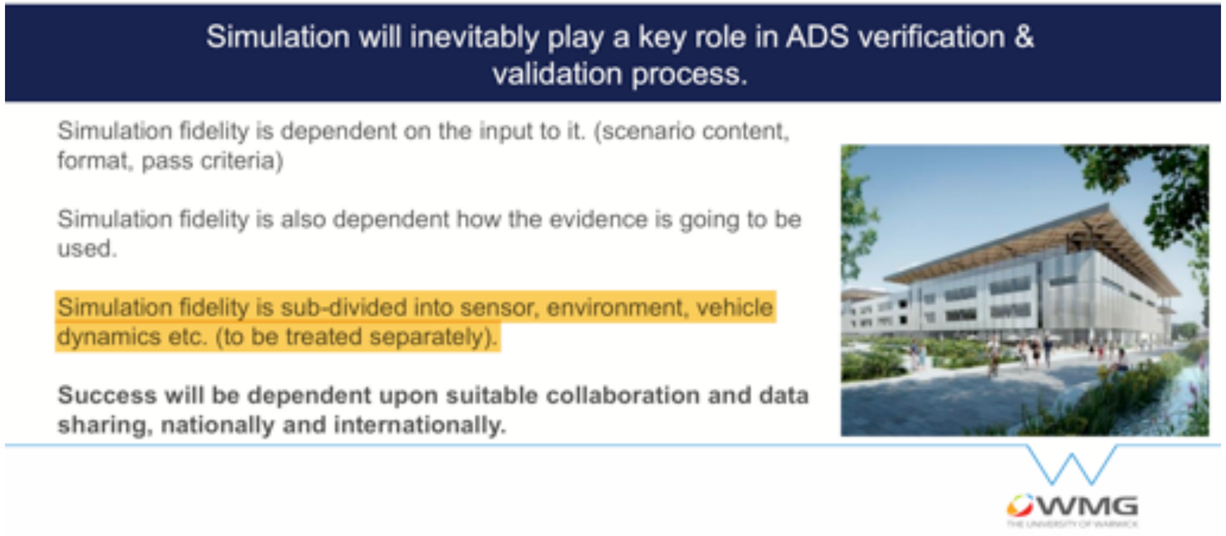
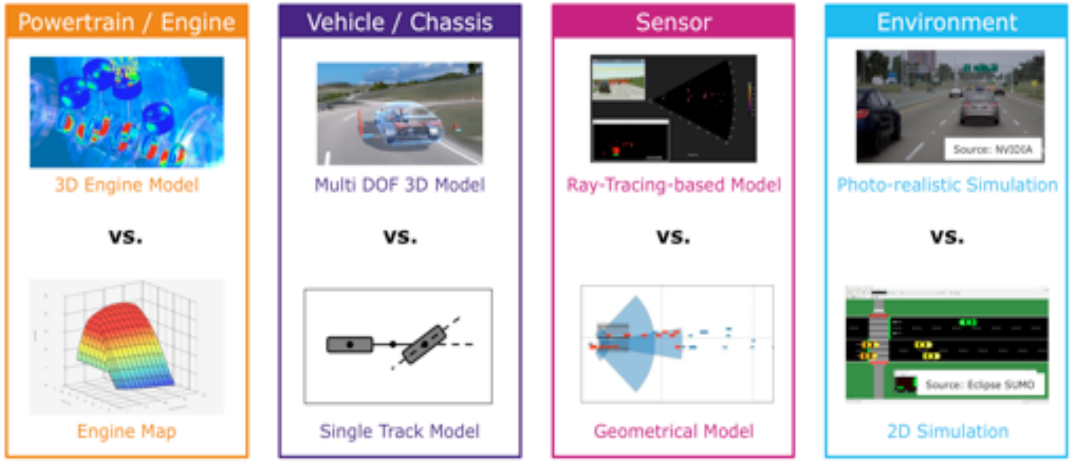
A common modelling framework

[1] Schöner et al.







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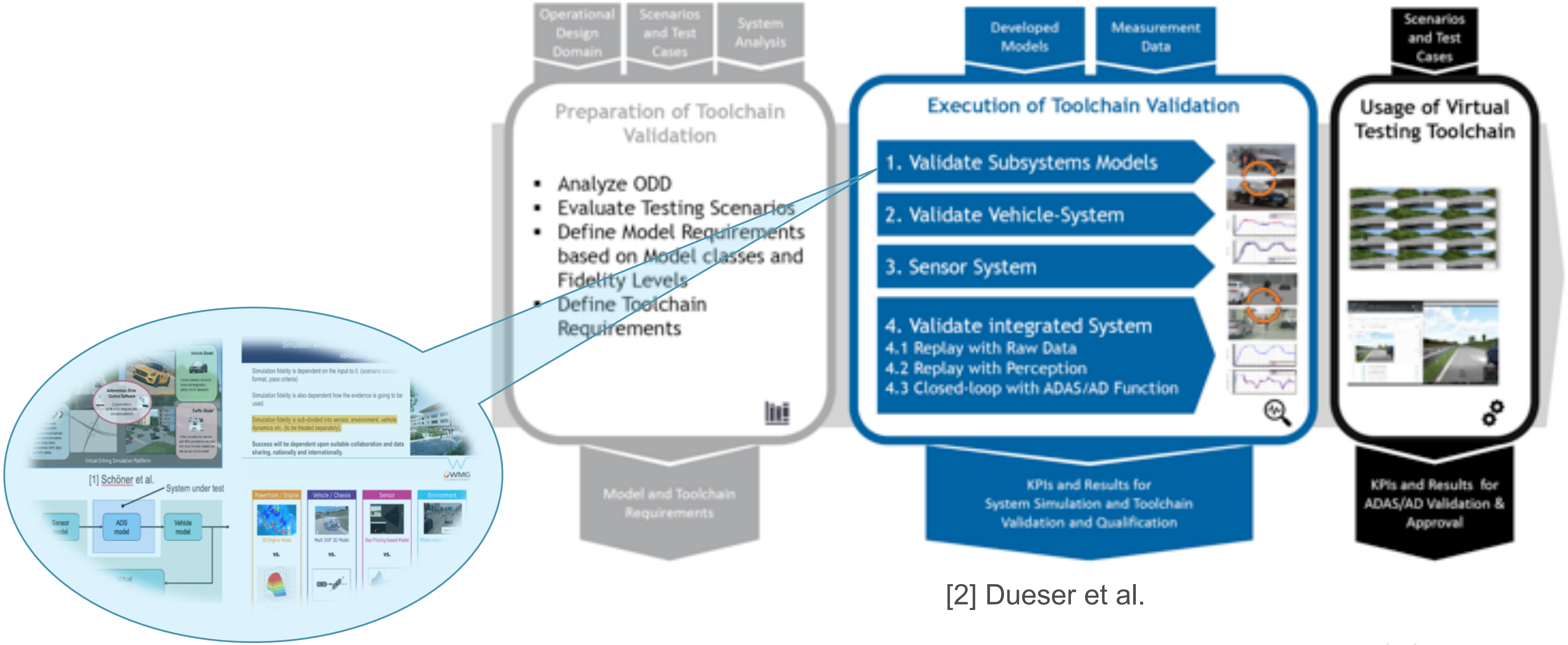
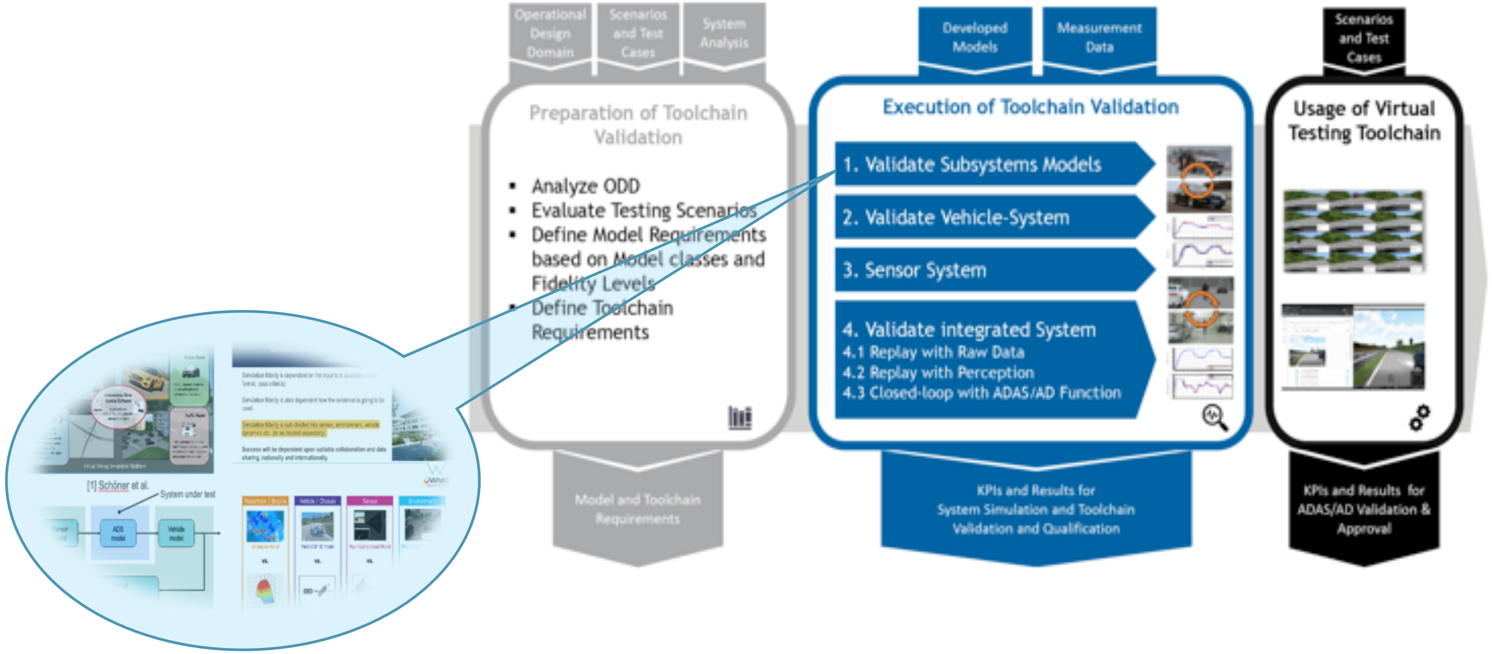
Validation workflow



[2] Dueser et al.

Validation pipeline



- KPIs definition
- Correlation method
- Correlation threshold

Subsystem-level validation

1) Sensor models
2) Vehicle dynamics models
3) Environmental models

Subsystem-level validation

- *Non exhaustive* list of sub-models:

Sensor models	**Vehicle Dynamics models**	**Environment models**
Camera	Steering system	Road layout
LiDAR	Braking system	Tarmac specification
RADAR	Powertrain	Traffic objects
GPS	Tyres	Weather condition
…	…	…

Vehicle-system validation

1) Chassis models
2) Multibody models

Vehicle-system validation

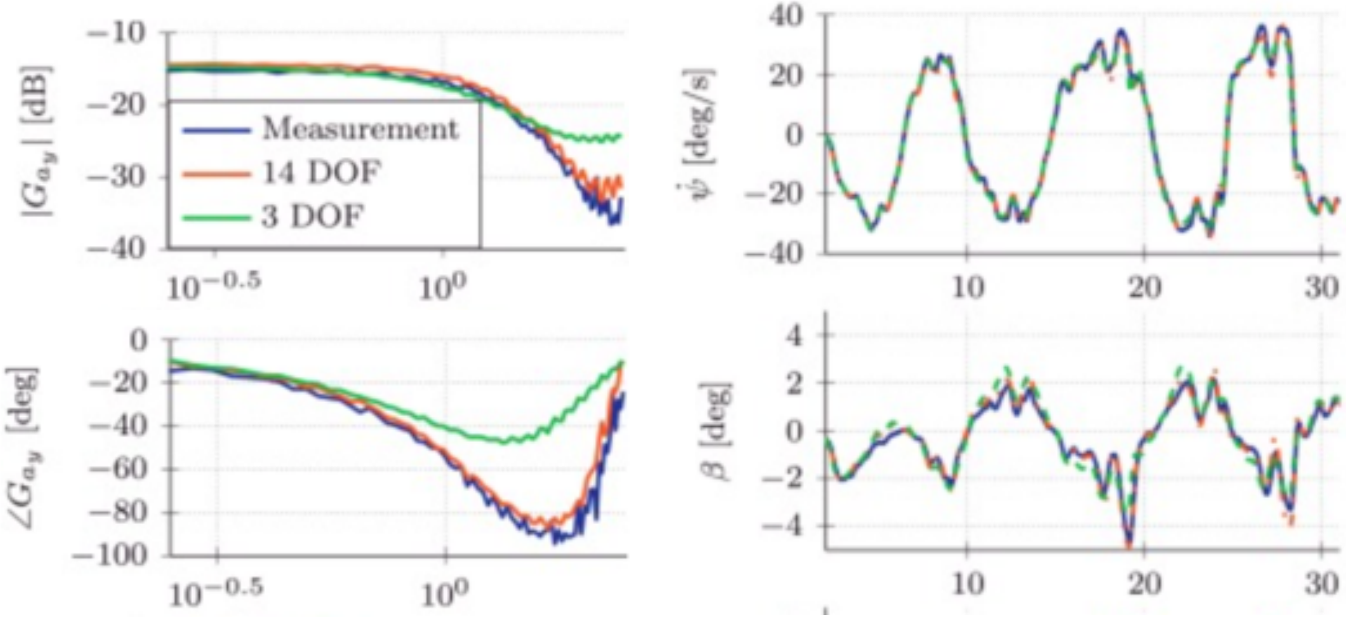
- Survey work in Kutlay et al. [3]
- Models for vehicle dynamics characterized by wide range of options:
  - Sub-models for specific applications (e.g. suspension model for ride/comfort analysis)
  - Chassis models for medium fidelity simulation (e.g. single track + Pacejka tyre)
  - Multibody models for high fidelity simulation
- Importance of data collection:
  - (Quasi-) steady state
  - Step response
  - Pulse response
  - Real-world manoeuvres

Vehicle-system validation

- Tyres and suspensions are (typically) the main sources of uncertainties
- Establish **consistency** between **model parameters** and **validation metrics**: any quantity which plays fundamental role for the application shall be accounted for in the metrics
- Validation should enforce time + frequency domain approaches.
- Formulate domain validity in terms of group of inputs and outputs (e.g. a lateral acceleration range or a steering angle input frequency interval)

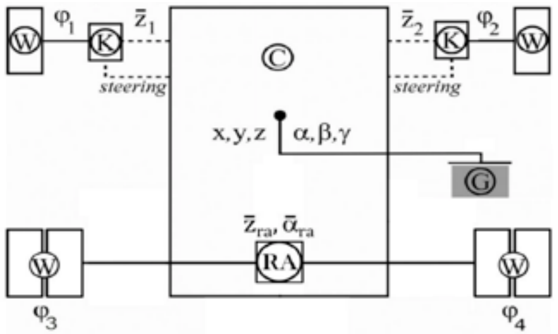
Vehicle-system validation

- Relevant KPIs for metrics computation
  - $v_x, a_y, \beta, \dot{\psi}$
- Relevant methods
  - Steady-state $\dot{\psi}$ gain
  - a_y build-up time
  - $a_y/\dot{\psi}$ peak values
  - …

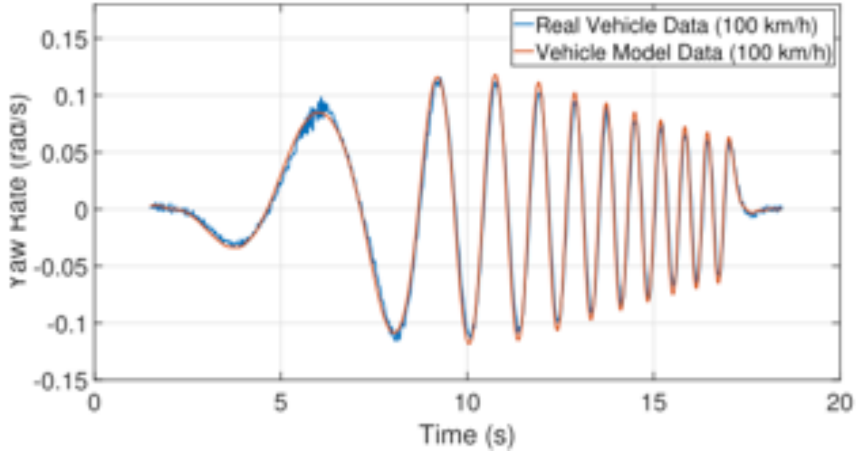


Effect of model reduction, adapted from [9]

Vehicle-system validation [17]

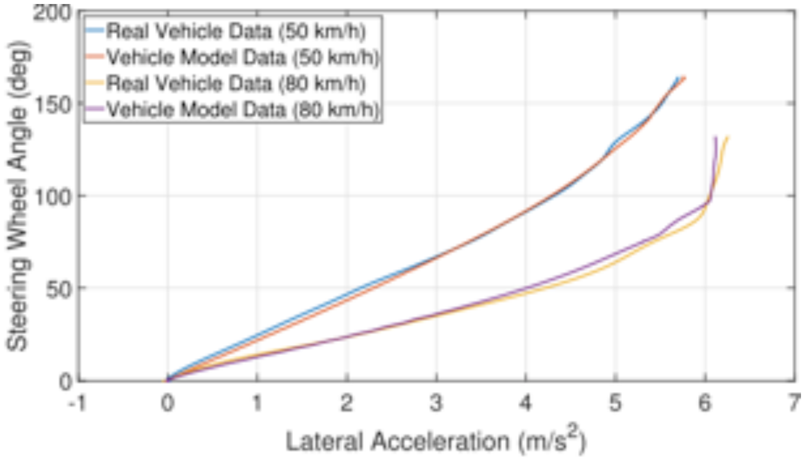


- Highly detailed multibody model (14 DoF)
- KPIs: $v_x, a_y, \dot{\psi}$
- Validation: RMSE(V)



	Steering Angle degrees		
80 km/h	12	22	32
Lat. Acc. RMSE [m/s^2]	0.0827	0.1575	0.2221
Yaw Rate RMSE [rad/s]	0.0019	0.0020	0.0024

	Steering Angle degrees		
100 km/h	15	23	35
Lat. Acc. RMSE [m/s^2]	0.1332	0.2059	0.3052
Yaw Rate RMSE [rad/s]	0.0025	0.0042	0.0040



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Vehicle-system validation

- Advanced concepts in validation Viehof et al. [8]
- Introduce statistics via testing the model against multiple configurations of the real vehicle(s) ⇨ increase trust in the model
  - Try to decouple *model validity* to *parametrization accuracy*
- Correlation threshold mostly left subjective
- 95% confidence interval typically adopted

Sensor-system validation

- RADAR
- LiDAR
- Camera

Fidelity levels [14]

- "Low" fidelity:
  - object positions retrieved from object status in the virtual environment
  - sensor models are based on geometrical aspects (FOV,…)
- "Medium" fidelity:
  - object positions retrieved from object status in the virtual environment
  - Introduce the detection probability/physical aspects
- "High" fidelity:
  - Take advantage of rendering techniques (e.g. ray tracing, rasterization)

Despite different sensors' working principles, common modelling approach

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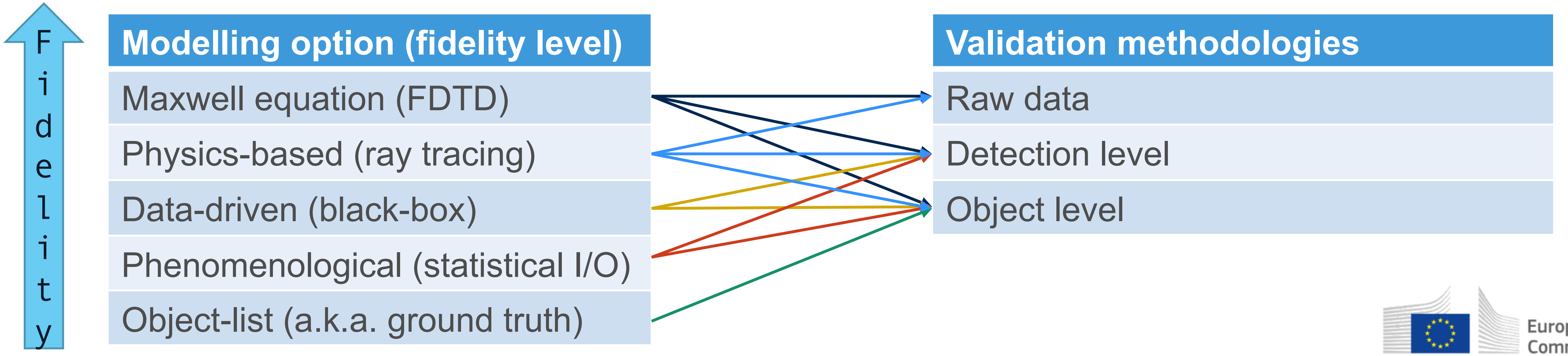
RADAR-system validation

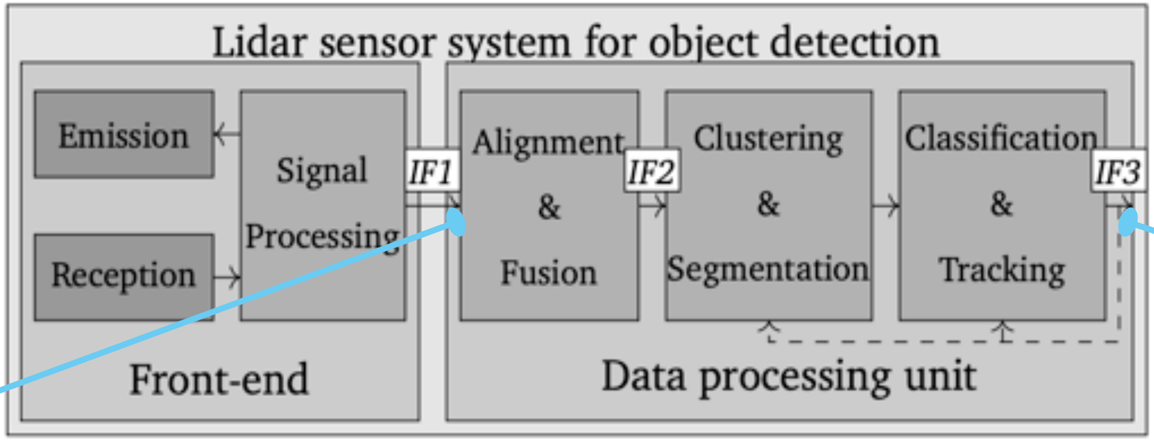
- Rosenberg et al. [4]:
  - Ultimate standard for modelling & validating RADAR does not exists
  - Strong coupling between modelling fidelity level & simulation environment rendering capabilities (hard to decouple RADAR's model from environment)
  - Challenges hard to reproduce: multipath-propagation, separability of targets, consistency of RCS (Radar Cross Section)



RADAR/LiDAR-system validation

- Due to similar modelling paradigms (ray-tracing) physics-based RADARs/LiDARs models have similar validation methodologies
- Strong connection between simulation engine & physics-based sensor models

“Explicit testing”



“Implicit testing”

Interfaces specification [5]

RADAR/LiDAR-system validation

Adapted from [5]

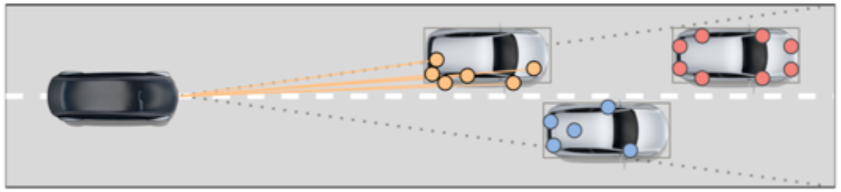
- Metrics & values for physics-based models:
  - **Occupancy-grid** pixel loss: $\sum_{x=0}^{\text{width}} \sum_{y=0}^{\text{height}} |sim_{grid}(x,y) - real_{grid}(x,y)|$
  - **Occupancy-grid** Pearson correlation (0.57-0.76 [5,18]): $\frac{\left|\sum_{i=1}^{m} (x_{i,j}-\bar{x}_j)(y_i-\bar{y})\right|}{\sqrt{\sum_{i=1}^{m} (x_{i,j}-\bar{x}_j)^2 \sum_{i=1}^{m} (y_i-\bar{y})^2}}$
  - **Occupancy-grid** ratio (0.2-0.5 [6]): $\frac{\sum_{i}^{N\,cell\,sim} c_i}{\sum_{j}^{N\,cell\,real} c_j}$
  - **Average minimal euclidean distance** points in cloud (0.1-0-7 m [6]):

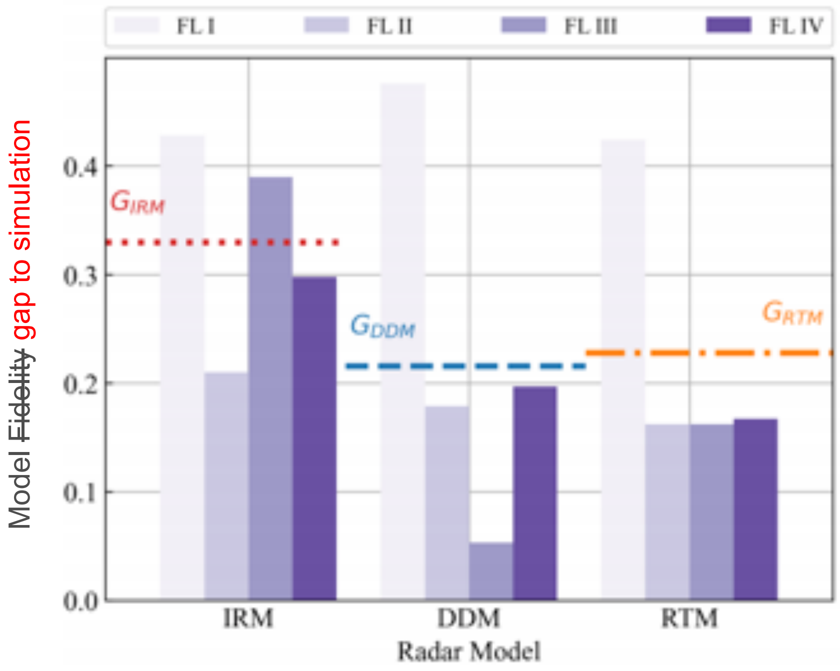
$$D'_{pp}(P_{sim}, P_{real}) := \frac{1}{M} \sum_{m=1}^{M} \min_{1 \le n \le N} \|p_{sim} - p_{real}\|$$

RADAR-system validation

- Models' comparison work in Ngo et al. [12]
  - High-level Evaluation: point clouds/objects tracking
  - Low-level Evaluation: Doppler effect/object position
  - IRM: lowest fidelity RADAR's model (●)
  - DDM: medium fidelity RADAR's model (●)
  - RTM: highest fidelity RADAR's model(●)

	High Level Evaluation	Low Level Evaluation
Implicit Sensor Model Evaluation	Fidelity Level I	Fidelity Level II
Explicit Sensor Model Evaluation	Fidelity Level III	Fidelity Level IV



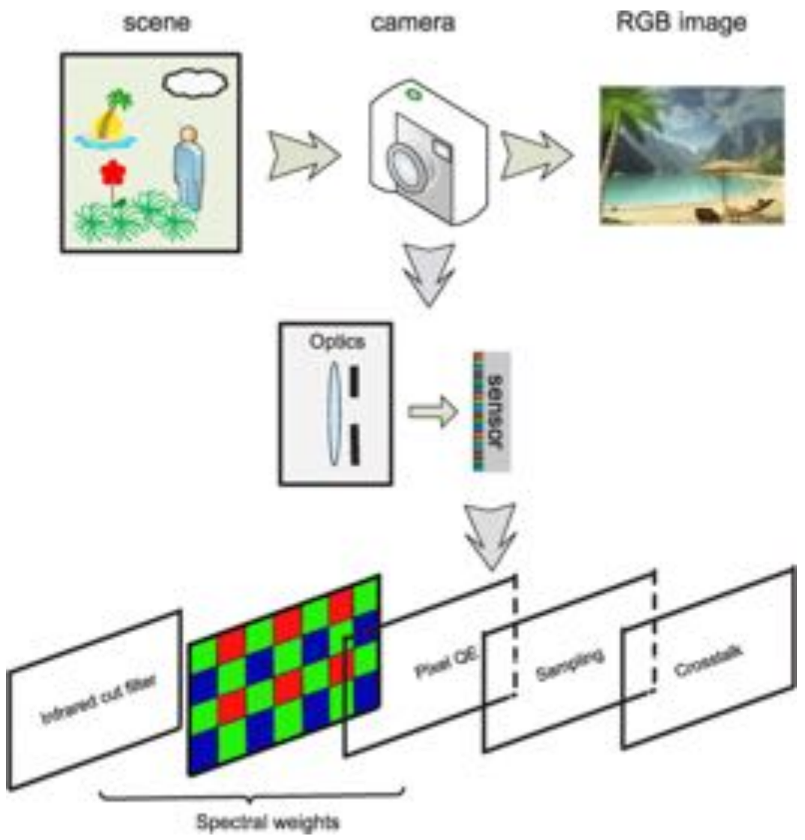


Camera-model validation

- Camera share similar working principle to human eyes:
  - Their modelling might seem easier wrt RADARs/LiDARs
- Typically cameras’ output fed into AI modules (CNNs):
  - Black-box software stack: hard to predict the effect of modelling artifacts to the final output of the AI algorithm
  - Need to create sensor-grade and AI-grade realism

Camera-model validation

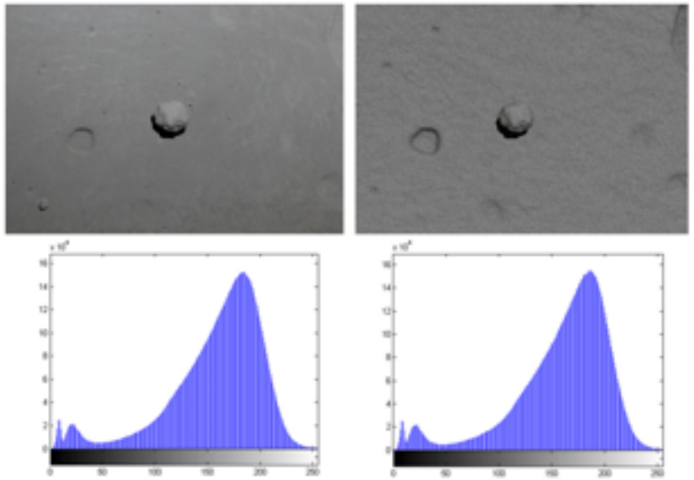
- Camera-related phenomena:
  - **Lens distortion:** optical aberration due to projection
  - **Vignette:** darkening of the screen border.
  - **Grain jitter:** white noise injection.
  - **Bloom:** presence of fringes around bright areas
  - **Auto exposure:** image gamma adaption to darker or brighter areas.
  - **Lens flares:** reflection of bright objects on the lens.
  - **Depth of field:** blurring of objects near or very far away of the camera.
  - **Exposure time:** shutter opening duration.



Camera model [10]

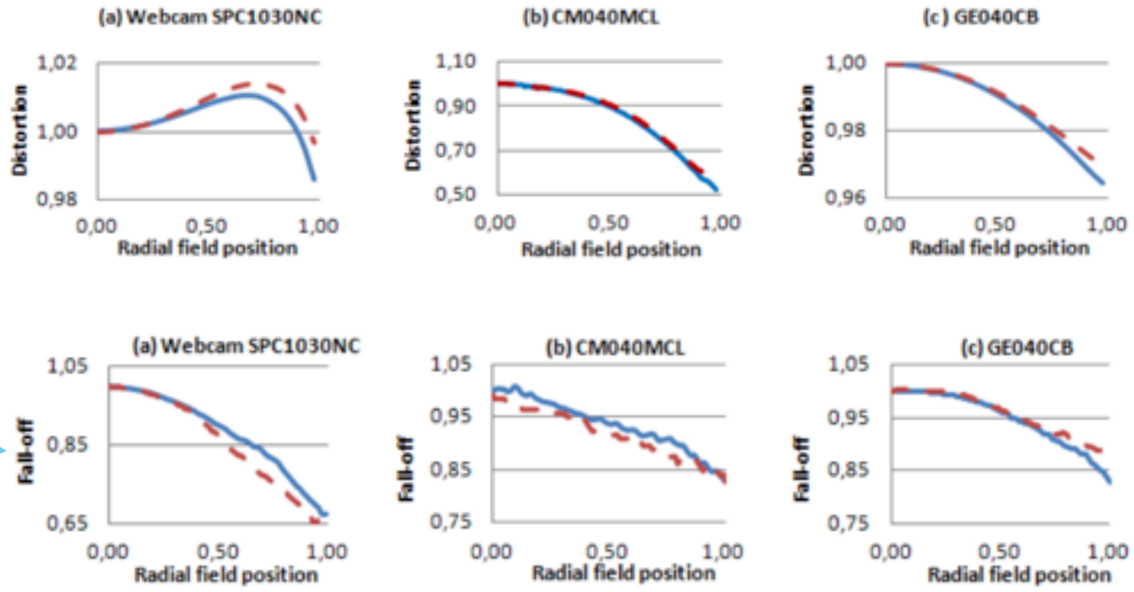
Camera-model validation [15]

- Comparison of camera stimulation vs MiL simulation
- Specific camera simulation software
  - Pixel-level loss (error 3/255)
  - Colour spectrum



Camera-model validation [16]

- Physics-inspired camera model
- Validated against 3 real cameras
  - Focal length
  - Distortion
  - Vignetting
  - Linearity



Virtual-world validation

- Roads
- Traffic Agents
- …

Virtual-world validation

- Widely recognized modelling standards
  - Virtual road network: ASAM OpenDrive® + ASAM OpenCRG®
  - Virtual traffic agents: ASAM OpenScenario®
    - No requirements on traffic agent modelling, e.g. how to reproduce **traffic dynamics**?
  - Virtual 3D reconstruction of the driving environment:
    - Obstruction of view, weather conditions…
    - Move beyond visual realism, need to provide *sensors grade* realism

Virtual-world validation

- No sufficiently established discussion on validation approaches
- Large variety of modelling approaches for traffic agents makes it almost impossible to compare performances
- Validation mainly defined “a posteriori” once integrated tests are carried out with validated sub-modes
- Validation might *not even be necessary* in case of *scenario-based* assessment

Integrated-system validation

1) Replay with raw-data
2) Replay with perception in-the-loop
3) Closed-loop with ADS

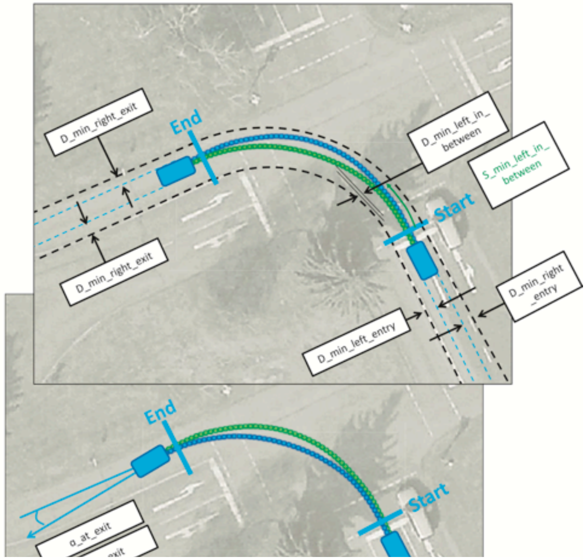
Integrated-system validation

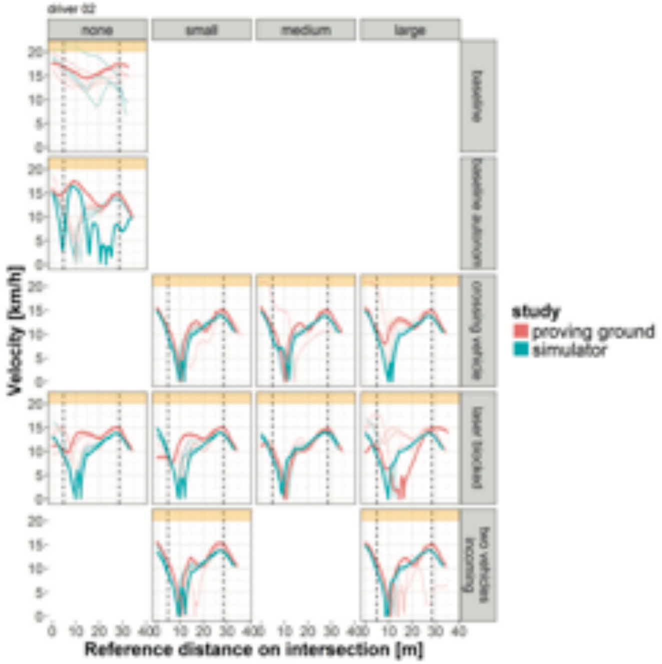
- Aims at creating a “Virtual Proving Ground”
- Direct comparison between each sub-module and its physical counterpart is *necessary* but *not sufficient*
- Need to investigate overall closed-loop behaviour of the M&S
- Examples (Closed-loop with ADS):
  - Enable S3 (VeHIL)
  - UTAC Ceram AEBS proposal (discussed on March, 31st 2021)
  - Riedmaier et al. [13], car-following scenario (MIL/VeHIL)
  - Riedmaier et al. [11], LKS (R79-like) validation (HIL)

Integrated-system validation

- Enable-S3 results
  - Left turn unprotected junction scenario
  - Overarching list of KPIs
  - Only qualitative assessment of velocity presented

KPI	EXPLANATION
Stops	number of times the car stopped in intersection
Time Stops	cumulative time of critical stops
Maximum Lateral Acceleration	Maximum lateral acceleration
Maximum Longitudinal Acceleration	Maximum longitudinal acceleration
Maximum Lateral Jerk	Maximum lateral jerk
Maximum Longitudinal Jerk	Maximum longitudinal jerk
Travel Time	time spent on intersection
V At Entry	velocity when entering the intersection
V At Exit	velocity when exiting the intersection
g_at_exit	distance to lane center at exiting intersection
d_min_left(right)_entry	Minimal distance to lane marking at entry arm
d_min_left(right)_exit	Minimal distance to lane marking at exit arm
d_min_virtual_lane	Minimal distance to virtual lane marking within intersection
RMS normal distance to ideal track	Root mean squared distance between position and ideal trajectory
RMS_of_longitudinal_jerk	Root mean squared of longitudinal jerk
RMS_of_lateral_jerk	Root mean squared of lateral jerk



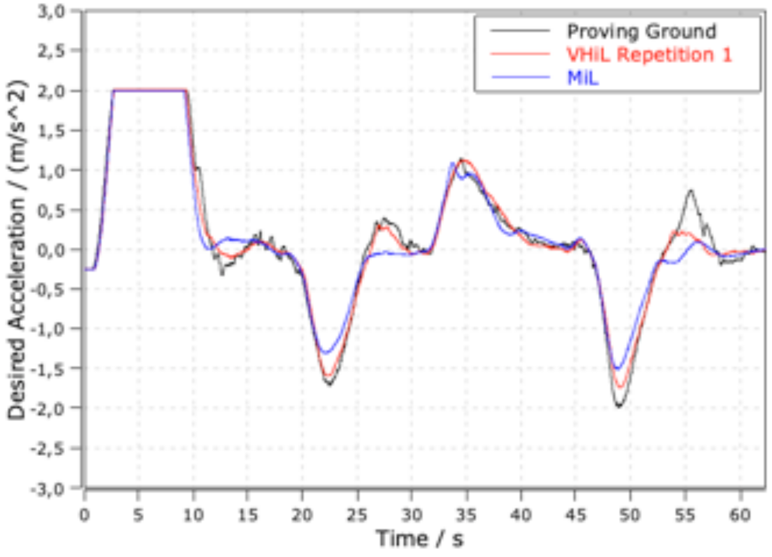


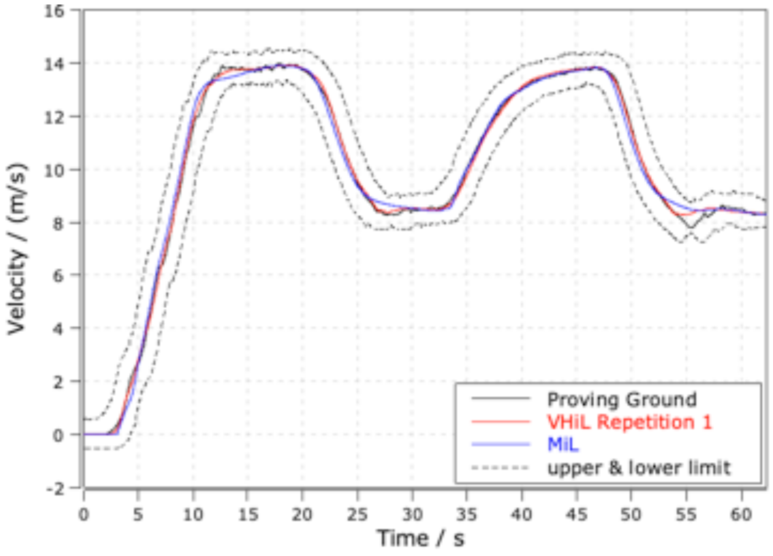
Integrated-system validation

- Car-following application [13]
  - Study *repetitiveness* of VeHIL (signal injection) setup
  - Check consistency of initial conditions
  - KPIs: Δs, v_x, a_x
  - Computational tools: correlation, graphical

	v_{TSV}/ (m/s)	Δv/ (m/s)	Δs_{act}/ m	a_{des}/ (m/s^2)	v/ (m/s)
$\bar{\sigma}_{VP}$	0,0035	0,0668	0,2413	0,0592	0,0716
$\hat{\sigma}_{VP}$	0,0253	0,4097	0,8058	0,4190	0,4174
$\bar{\sigma}_{MP}$	0,0035	0,1301	0,5938	0,1040	0,1365
$\hat{\sigma}_{MP}$	0,0253	0,5292	1,4623	0,5554	0,5683

	PG	VHiL/DC	MiL
PG	1	0,9994	0,9974
VHiL/DC	0,9994	1	0,9980
MiL	0,9974	0,9980	1



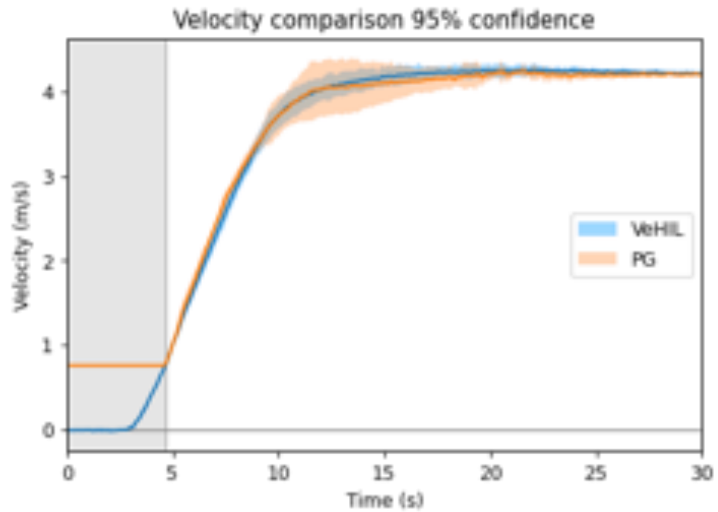


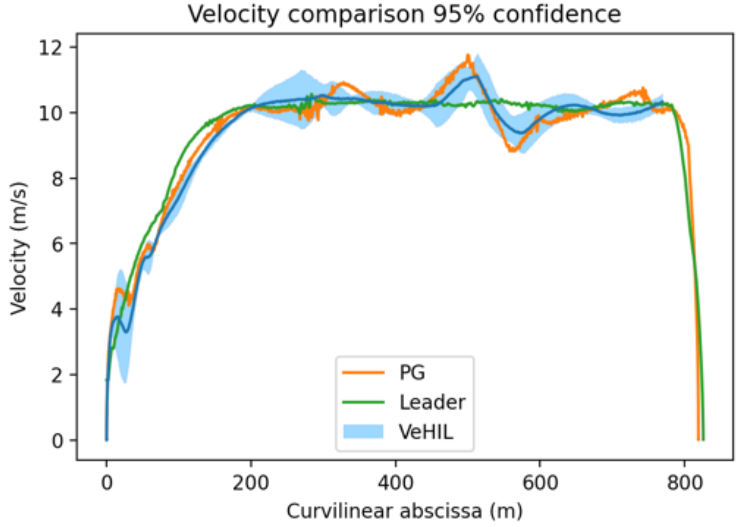
Integrated-system validation JRC

- Car following application
  - Study *repetitiveness* of VeHIL (camera *stimulation*) setup
  - KPIs: v_x, a_x
  - Importance of the ADS in “stimulating” the testing environment

FREE-FLOW	RMSE	$\overline{\sigma}$	PEARSON
VELOCITY	0.041	0.0403	0.9974
ACCELERATION	0.088	0.0656	0.9764

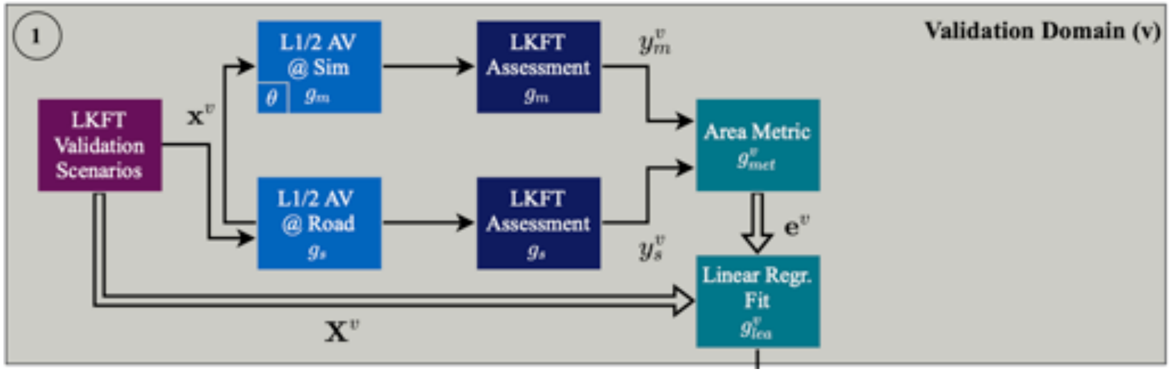
CAR-FOLLOW	RMSE	$\overline{\sigma}$	PEARSON
VELOCITY	0.376	0.3612	0.9898
ACCELERATION	0.166	0.1657	0.7384

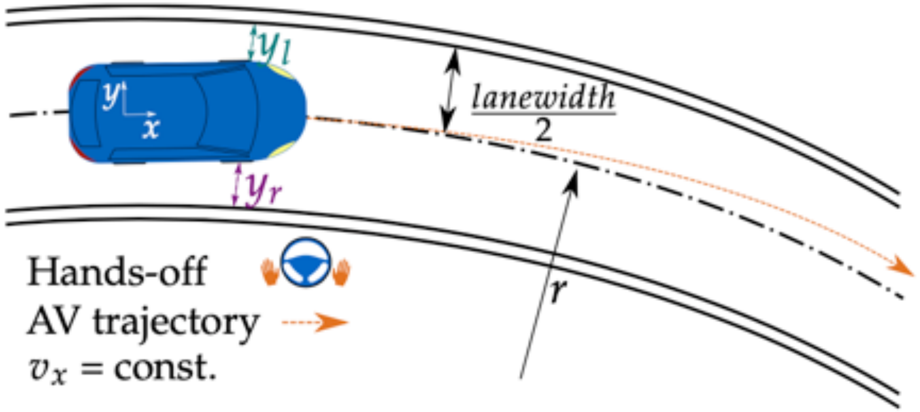




Integrated-system validation

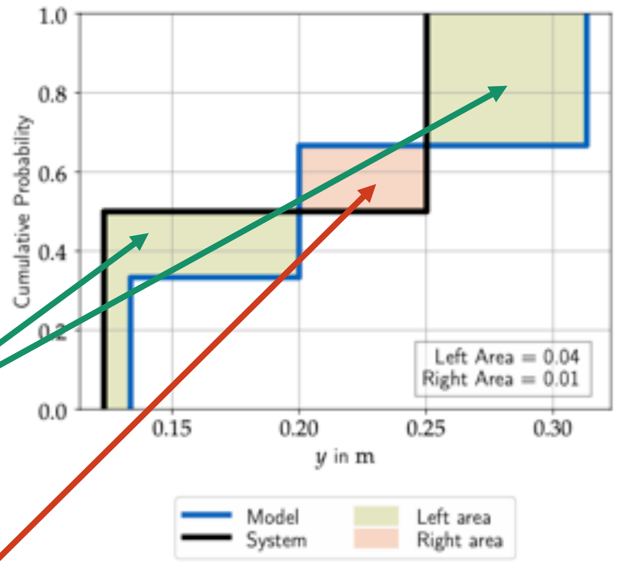
- LKS application [11]
  - Complete validation pipeline
  - Scenario allocation
  - Signal processing
  - Event finder
  - KPIs selection (coverage & acceptance)
  - Statistical analysis





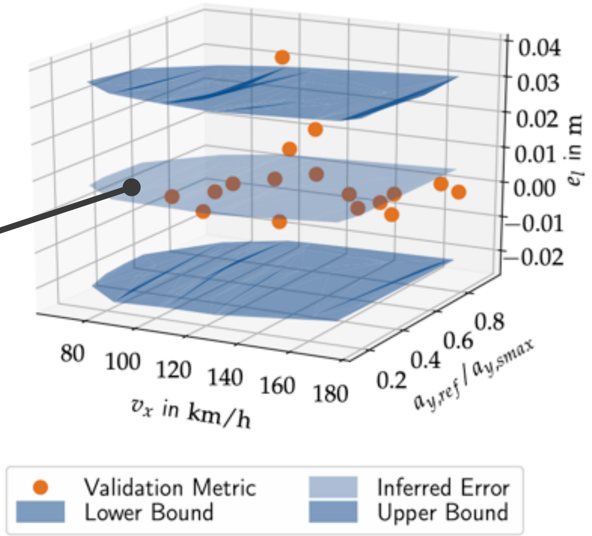
Integrated-system validation

- LKS application [11] in HiL
  - Metric: distance areas between CDFs
  - Move beyond tolerances by considering CDF
  - Prediction interval characterization
  - Investigation over domain (v_x, a_y) of unsafe error
  - Regression model to estimate unsafe error and prediction intervals (95% confidence)



Unsafe area

Safe area



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