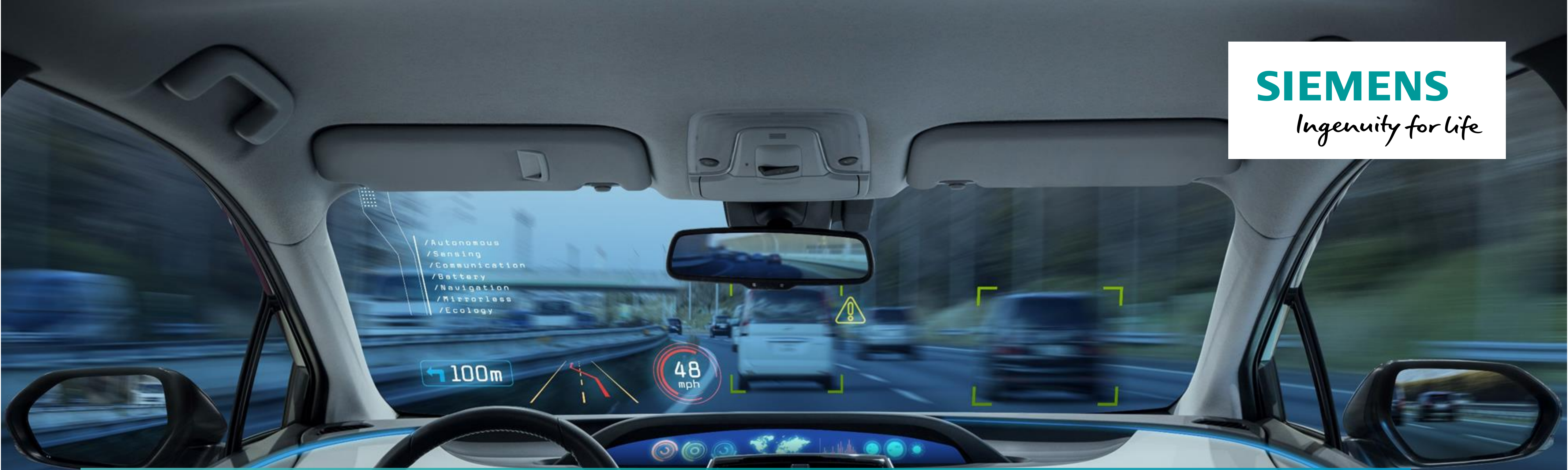

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Autonomous Valet Parking
System definition, development and validation

Where Today Meets Tomorrow

Autonomous Valet Parking
Overview

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- **Context and challenges**
- **Autonomous Valet Parking overview**
- **Requirements and Test cases definition**
- **Perception and controls**
- **Mixed reality testing**
- **Conclusions – Q&A**

Autonomous Valet Parking: context

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30% vehicle accidents are at parking lots

Collision with infrastructure = 85% parking lot accidents

Traffic jams at parking lots of large gatherings

Elderly people poor at driving reverse
Young people poor at parking

Traffic accidents	About 30% of vehicular accidents covered by motor vehicle insurance occur at pa...
	There is a high incidence of accidents where drivers collide with other vehicles, which along with collisions with infrastructure account for 85% of parking lot accidents.
	About 40% of accidents are caused by elderly people aged 60 and up.
	There is a high frequency of accidents involving people in the vicinity of a vehicle when it starts moving.
Traffic jams	Traffic jams take place at the parking lots of shopping malls, theme parks, and other locations ...
Driving stress	Many elderly drivers are poor at driving in reverse, while many young drivers have difficulty parking.
	Accidents caused by drivers aged 75 and above are ... attributed to pressing the wrong pedal.
Security	43.6% of vehicle thefts and accidents occur at monthly parking lots that are outdoors, a ma... often occur between 10 p.m. and 9 a.m. If vehicles are parked in limited managed space, these accidents will be reduc...
Parking spaces	Improvement in effective use of parking space

Marklines.com, "The impact of autonomous parking: Autonomous Vehicle and ADAS Japan 2016 (2)"

Autonomous Valet Parking: benefits

- Fewer accidents, increased safety (also for pedestrians)

  Parking lots are some of the most dangerous places for pedestrians and automobile passengers alike. (*)

- Reduce congestion in/close to Parking lots

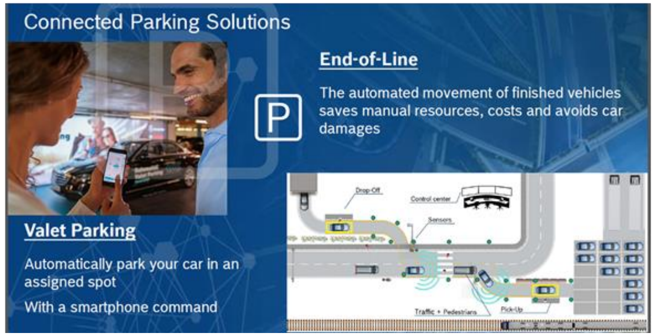
  Currently, an estimated 30 percent of traffic congestion every year comes from drivers simply searching for one of these spots. (**)

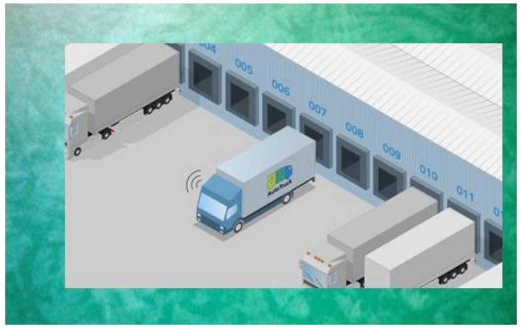
- More optimal use or Parking space

  500 million parking spaces for 326 million citizens spread across 3.5 million square miles of parking infrastructure (**)

(*) (Futurecar, August 18, 2019)

(**) (Curbed, August 6 2018)





Autonomous Valet Parking: challenges

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While parking lots are tricky for human drivers, they're even more of a handful for autonomous vehicle. Unlike roads with well-defined lines, clear road signs, and a regular flow of cars, parking lots aren't as clear cut.

"Each time you turn the dial to increase complexity, the vehicle is beginning to have to assess and predict the behaviors of multiple things at the same time," said Villegas. "That is challenging for sensors.“

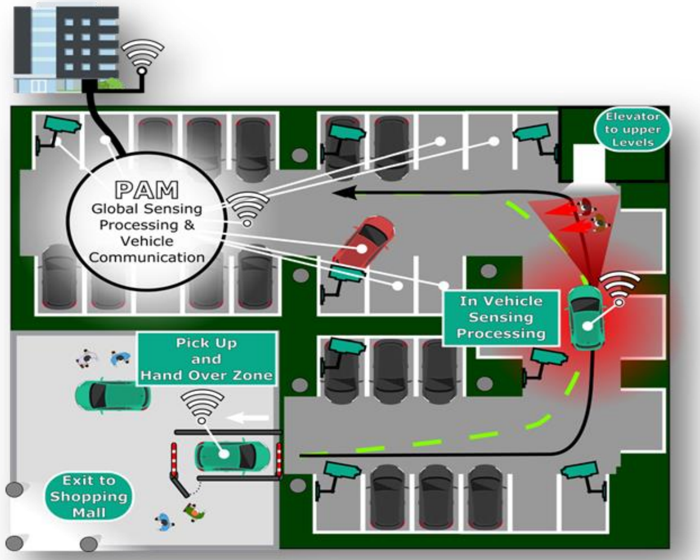
It may sound like a familiar process to getting an autonomous car to drive on a street, but being able to master the intricacies of getting around safely in a parking lot is even harder.

(Futurecar, August 18, 2019)

- Complex environment to perceive (eg compared to highway or even city driving)
- Combine infrastructure and vehicle
- Difficult to define all potential scenarios
- Impossible to test all potential scenarios

EU Enable-S3 Project: 2016 –2019

ES RTD is involved in the Autonomous Valet Parking Use Case



A large project with 74 EU partners

- **Virtual test** of a complete system with realistic environment and sensor models
- **Generation** of synthetic simulation scenarios

- **Siemens** contributes to the industry standards for virtual verification and validation of autonomous systems
- Focus on the optimum fidelity 1D or 3D chassis models combined with environment and sensor simulation
- **Siemens** solutions applied in valet parking, intersection crossing and highway scenarios in close cooperation with industry partners

Steps for development of a Valet Parking solution

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Siemens Industry Software Parking Area in Leuven

Stage 1: Global Planning

- ✓ Define initial and goal position
- ✓ Compute optimal route, avoid static obstacles

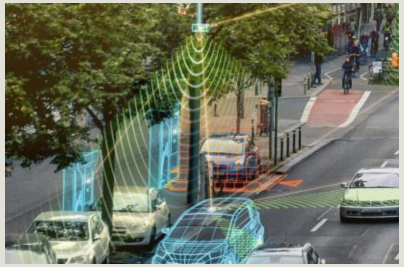
Stage 2: Local Planning and Control

- Avoid dynamic obstacles
- Optimality: time/fuel
- Vehicle constraints (steering, velocity)
- Vehicle, tire dynamics

Stage 3: Maneuvering Planning and Control

- ❑ Different movements
- ❑ Narrow space

Parking Area Management



- Supervise parking environment using infrastructure sensors
- Provide parking map and target parking lot
- Act as an additional safety layer for AV

Steps for development of a Valet Parking solution

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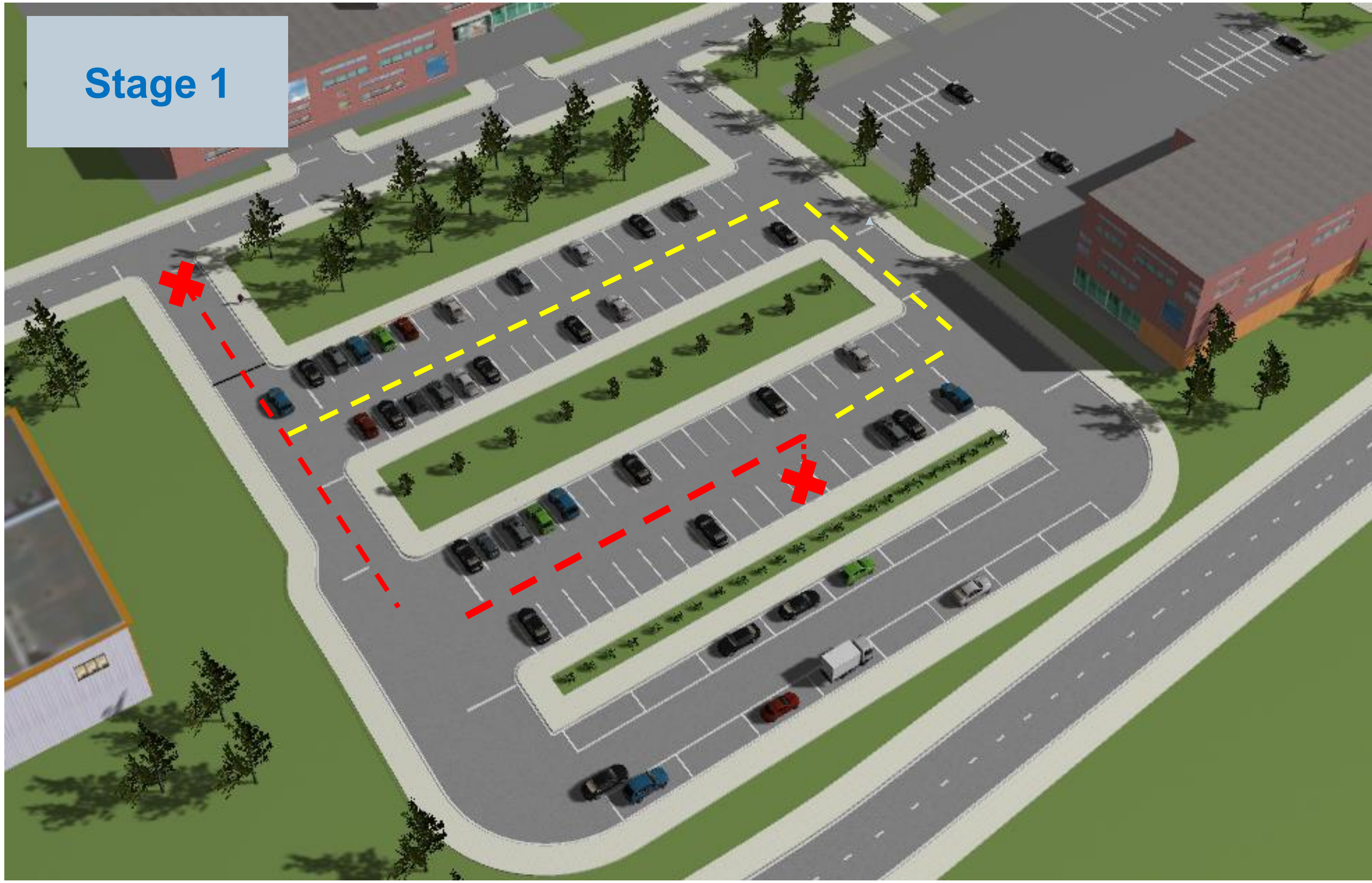

Steps for development of a Valet Parking solution

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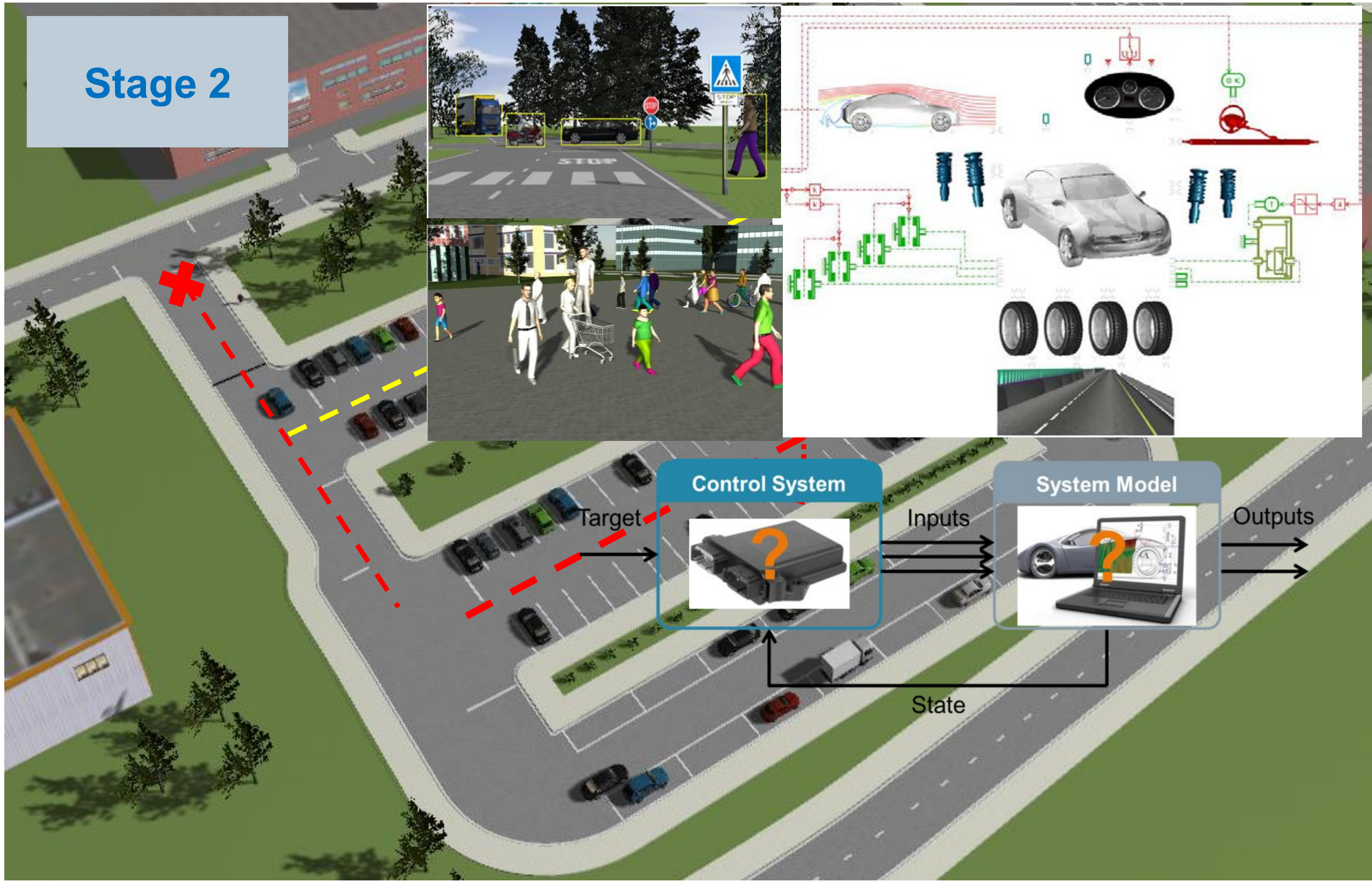

Valet Parking System

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Siemens Industry Software Parking Area in Leuven

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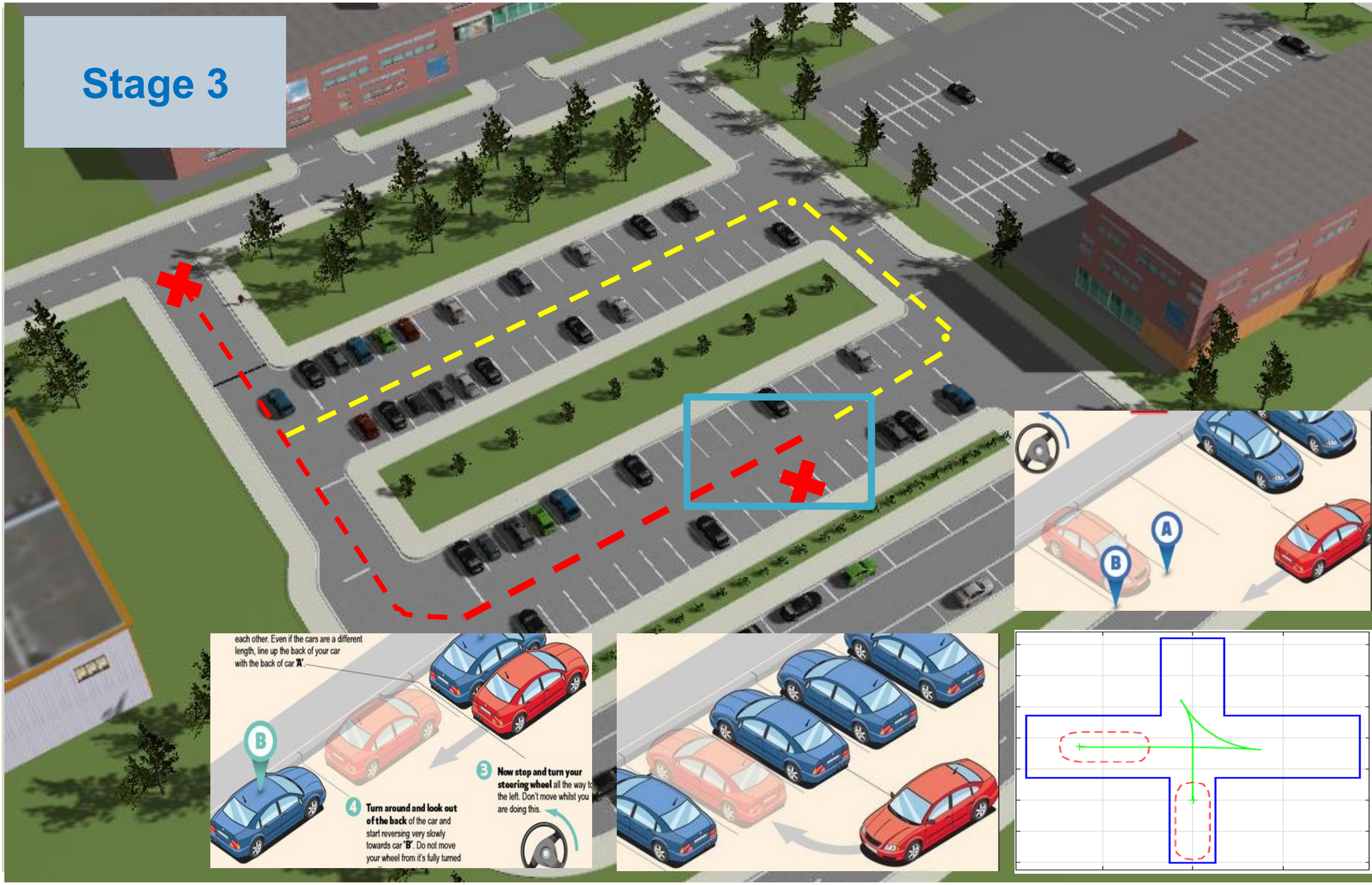
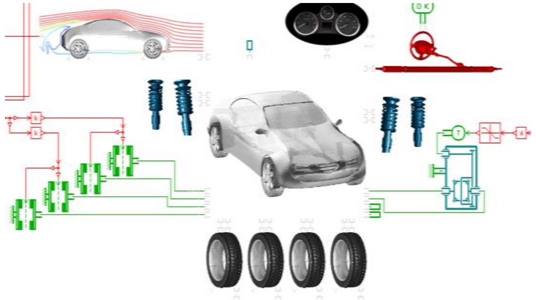
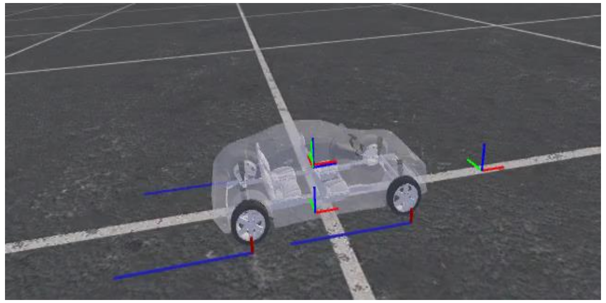


Autonomous Valet Parking (Level 4 – SAE)

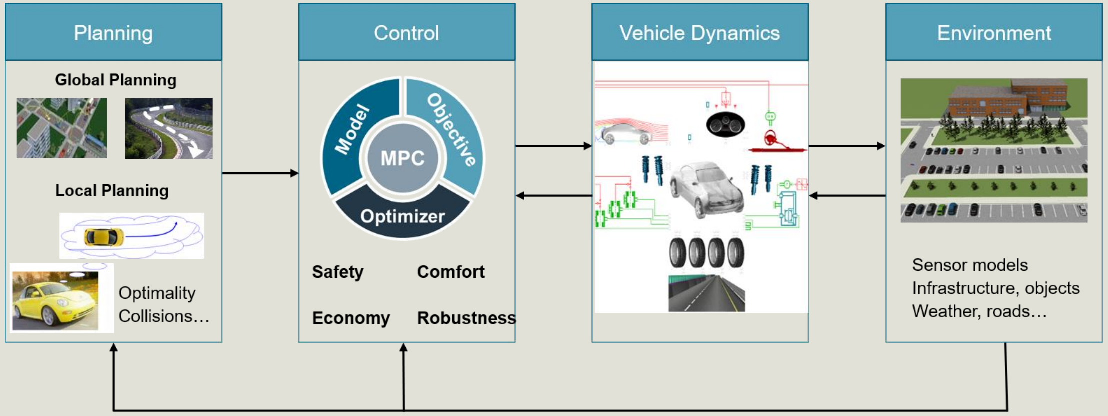
Parking Planning and Control

15DOF Vehicle Model





Co-simulation structure for testing & validation



TECHNOLOGIES

Motion & Path Planning, Tracking Control

Parking Maneuvering (parallel, reserve parking…)

Collision Avoidance

Autonomous Valet Parking
Overview

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- Conclusions – Q&A

Control algorithm development process

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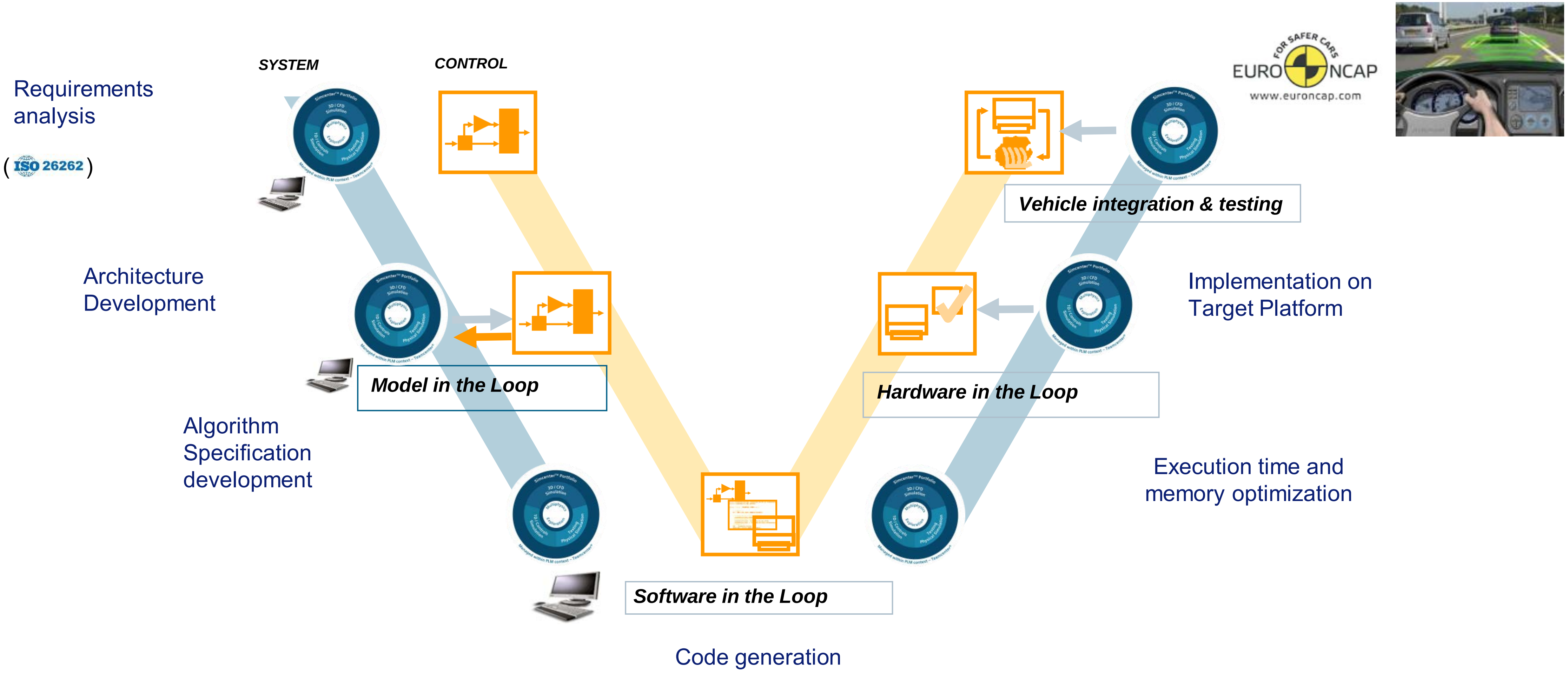
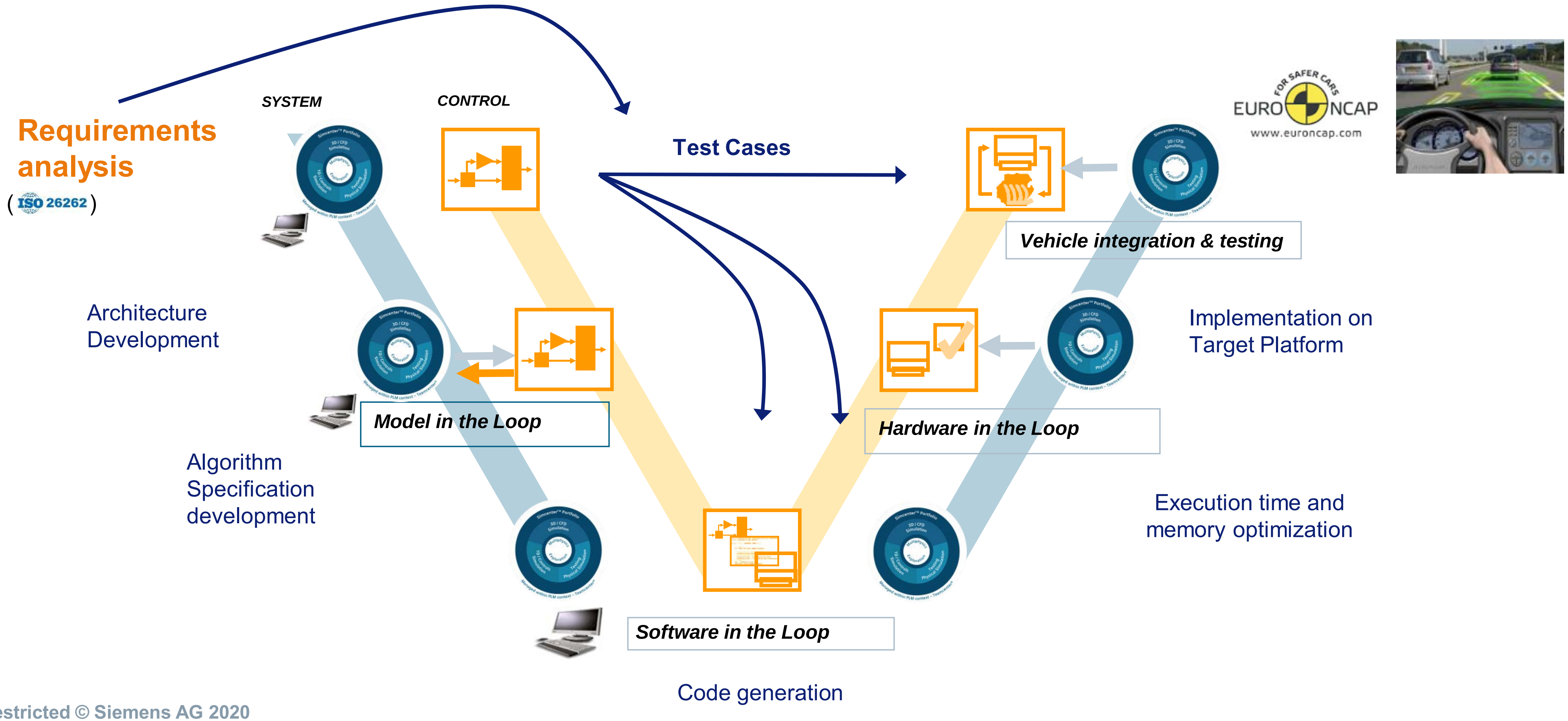


Control algorithm development process
From requirements to Test case definition



Test Scenarios Generation Methodology

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There are several approaches to generate Test Scenarios:

1. Functional Requirements based Test Scenarios
2. Enhance Requirements with STPA and SOTIF analysis
3. Real driving: collect data and then parameterize critical scenarios for further exploration in simulation or real test.
4. Data from accident profiles such as GIDAS and CIDAS
5. Advanced optimizations to identify corner cases through simulation.

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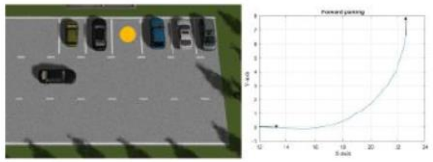

Figure 2.5: Prescan environment and Matlab plot of path from RRT* for forward parking

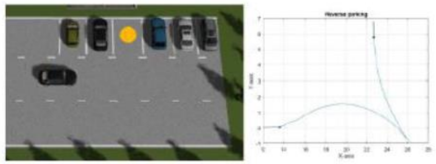

Figure 2.6: Prescan environment and Matlab plot of path from RRT* for reverse parking

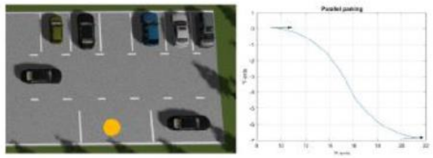

Figure 2.7: Prescan environment and Matlab plot of path from RRT* for parallel parking

Structured Approach to generating Test Cases

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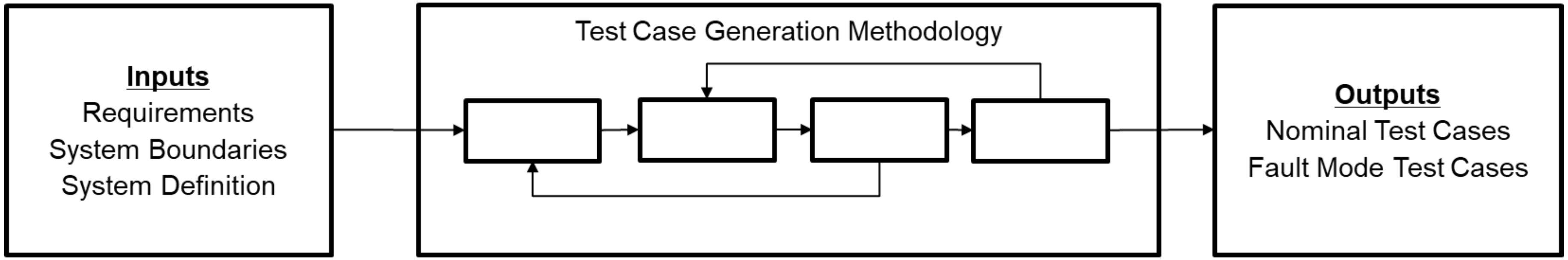

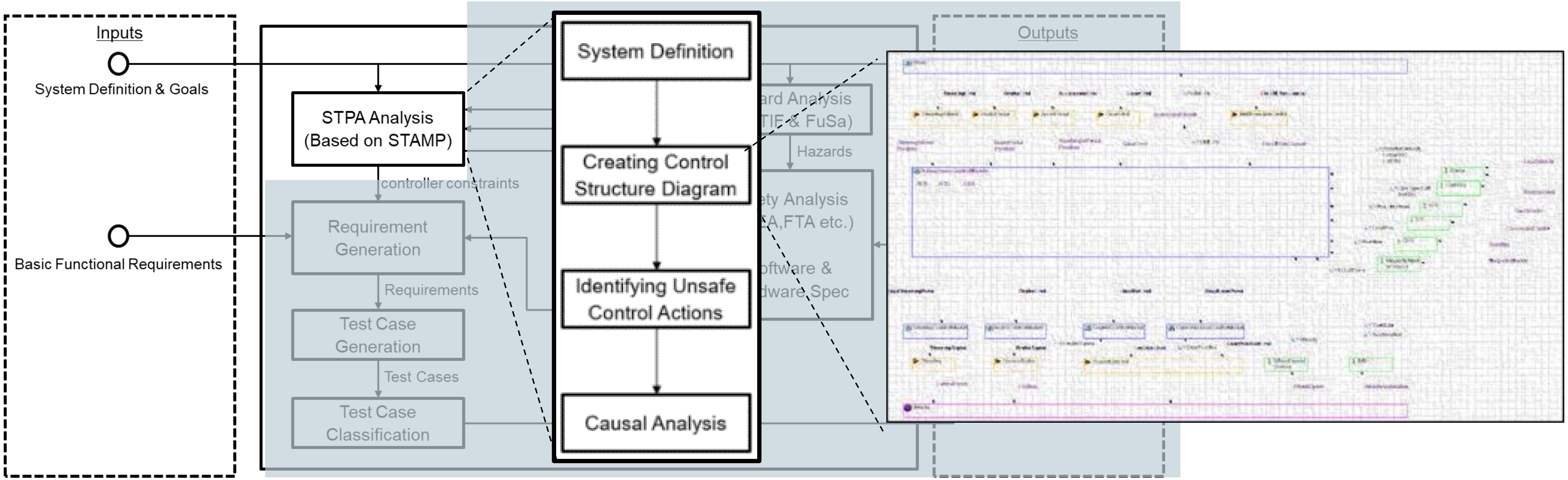

STPA Analysis Sample to derive a single Test Scenario

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LOSS	ACCIDENT	HAZARD	UCA
Injuries	Collision with obstacles	Ego truck does not maintain safe distance from obstacles	Brake is not applied when dynamic obstacle has low TTC
L5	A3	H1	UCA7

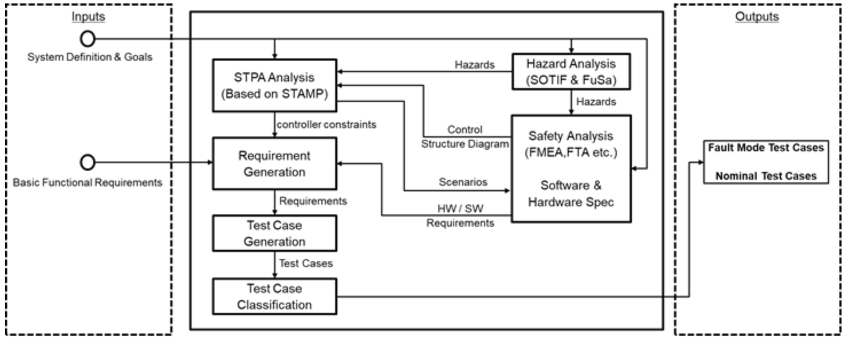
CONSTRAINT	REQUIREMENT
Brake must be applied when dynamic obstacle has low TTC	Ego truck must apply brake signal if the time to collision is less than the specified time (1 sec)
SC11	DR12

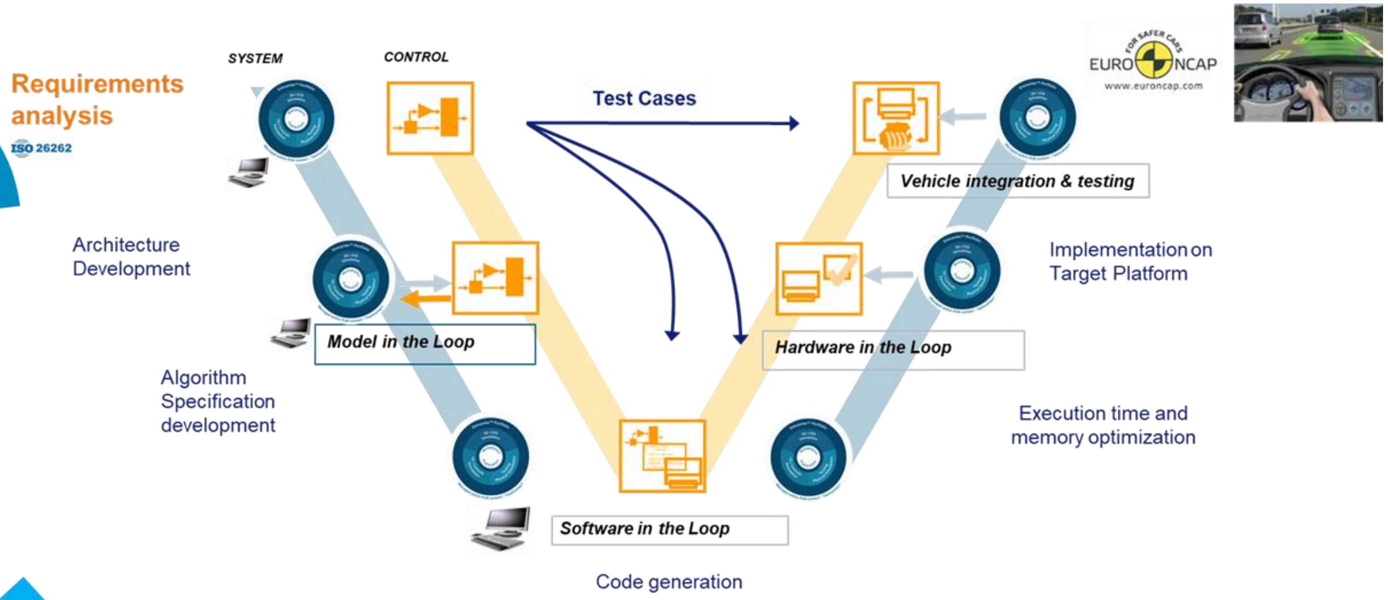
Derive Test Case from this Requirements

Ego truck at rest at (x,y). A pedestrian with trajectory such that the actor will intersect with the ego truck path within 1 sec

Test Cases Generation

1. *Test Cases are updated at every stage of the development in an iterative fashion as and when more details of the controller are realized in the V-Process.*





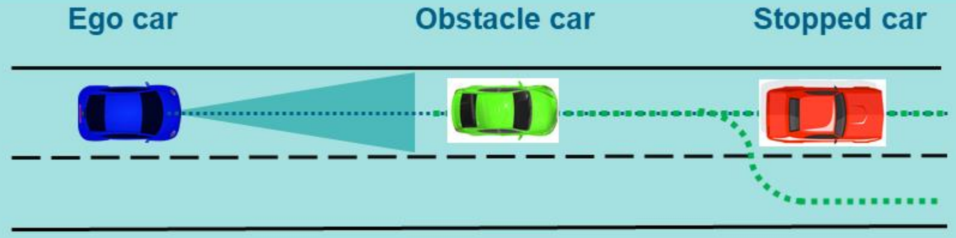
2. *Test Cases are further expanded by performing coverage of the influencing factors such as time of day, sunlight conditions, traffic conditions, road lane conditions, etc.*

3. *In addition, the system is further tested with range of traffic conditions using an auto-traffic generator. This can be used for identification of special cases to be tested in simulation and in vehicle.*

Scenario Generation example:

Cut-out scenario verification of ACC algorithms

Scenario Generation

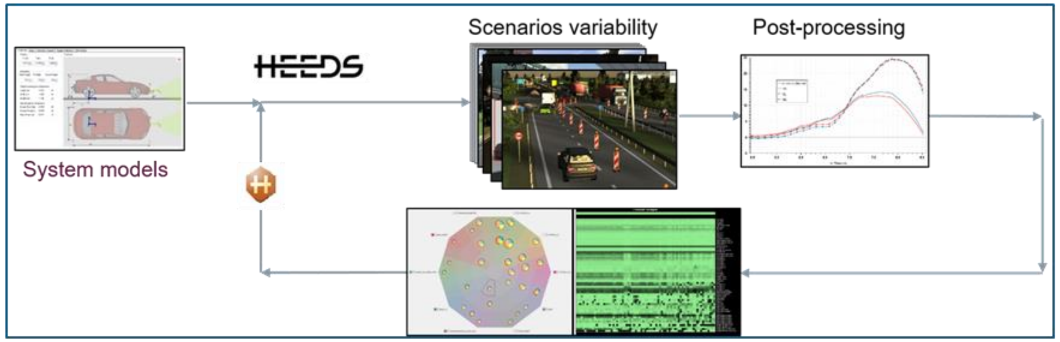


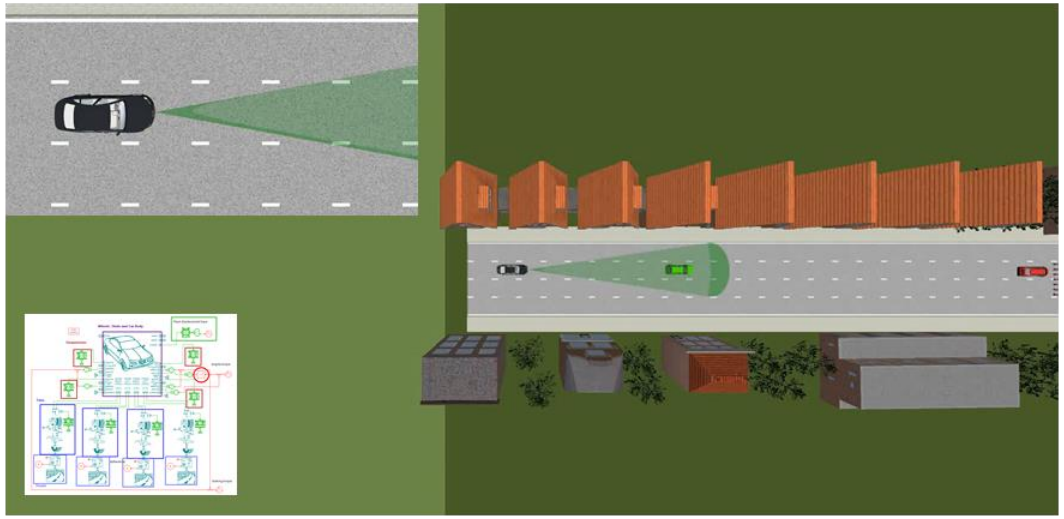
Scenario Generation Objective
Find obstacle car initial position, velocity and acceleration signals that make the brake control fails the requirements (these are called critical scenarios)

Requirements

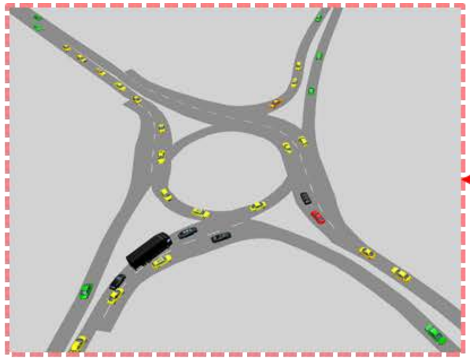
- If a moving car is detected, time to collision must be greater than 2s (adaptive cruise control)
- If a stopped car is detected, time to collision must be greater than 0 (emergency braking control)
- Using temporal logic requirement and optimization solvers, our development algorithm can obtain critical scenarios

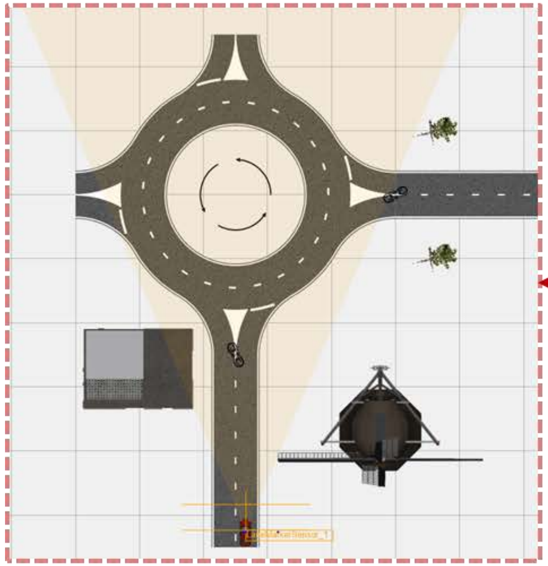
Assessed system performance mapping

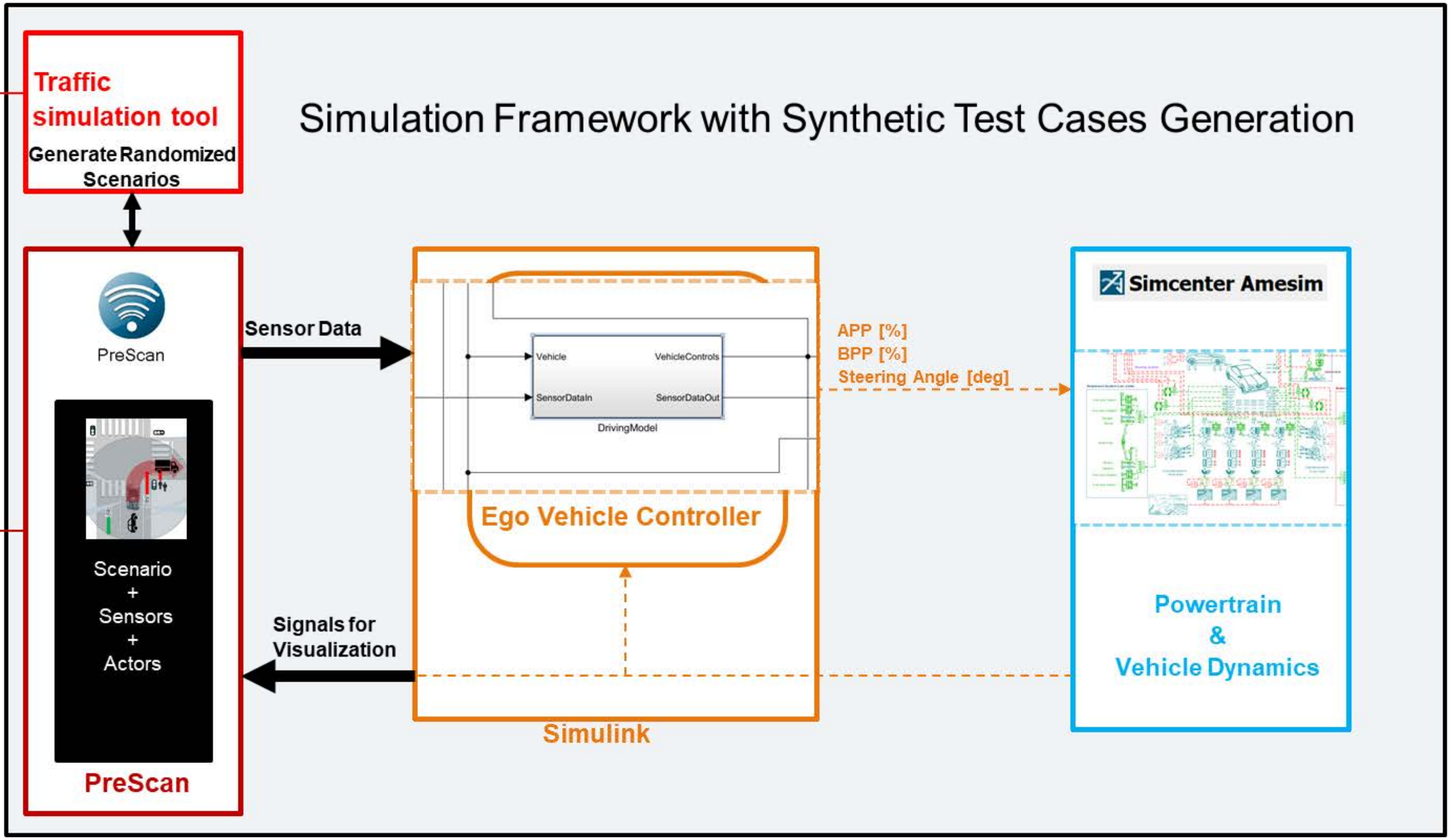




Synthetic Test Cases generation through synthetic data sweep to identify critical parameters for Testing







Consistent organization of test cases for Controls Development

Bidirectional Traceability between Requirements, Models, and Test Cases

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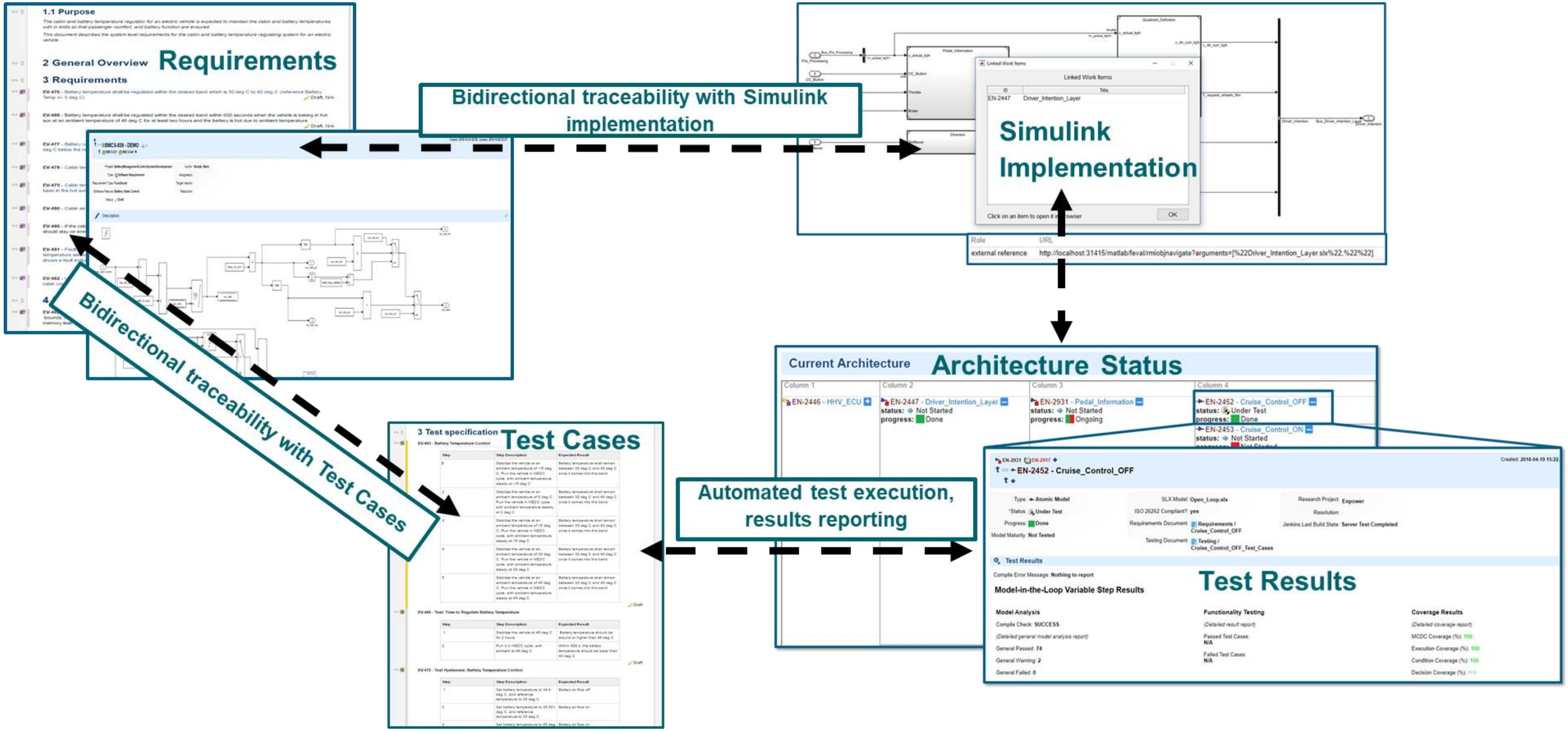

Autonomous Valet Parking Overview

- Context and challenges
- Autonomous Valet Parking overview
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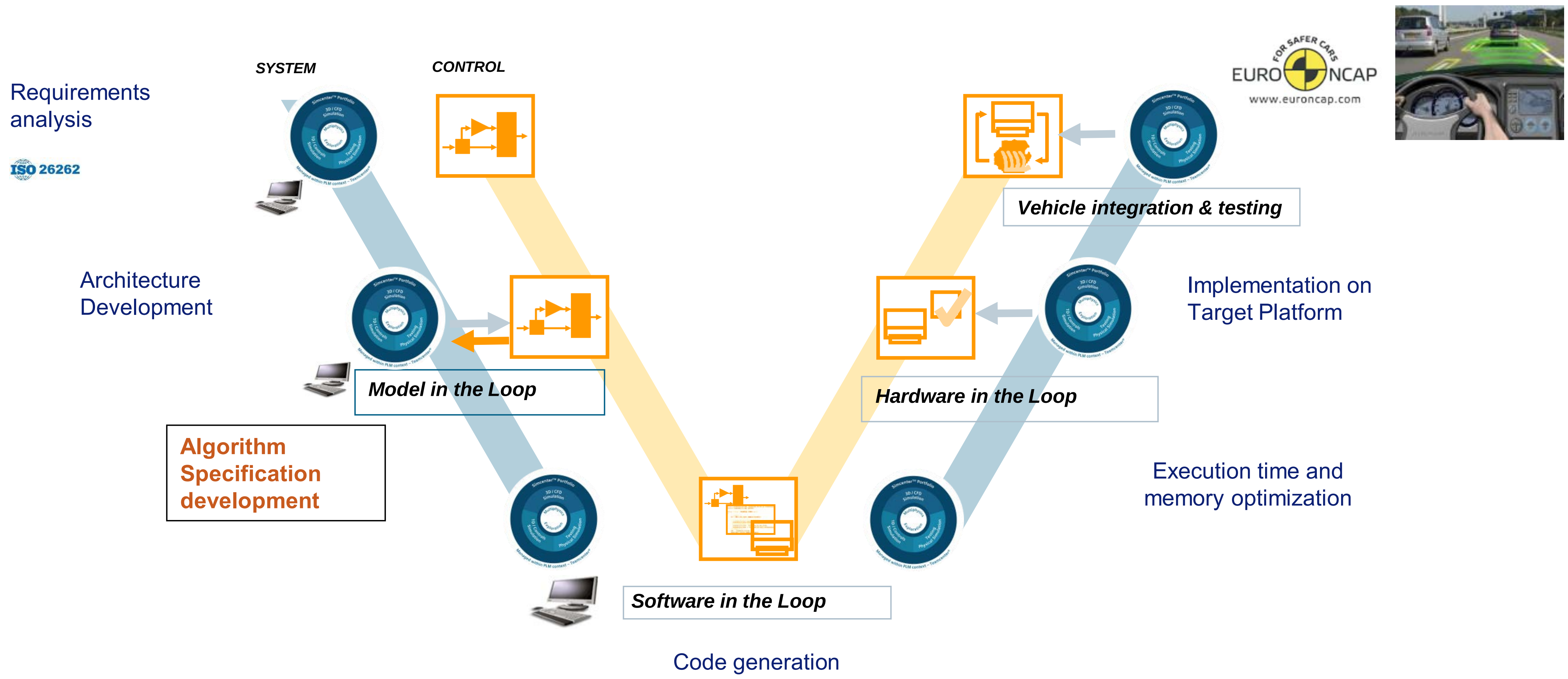
- **Perception and controls**
- Mixed reality testing
- Conclusions – Q&A

Control algorithm development process



Mazda

Driving scene recognition for optimized HEV controls

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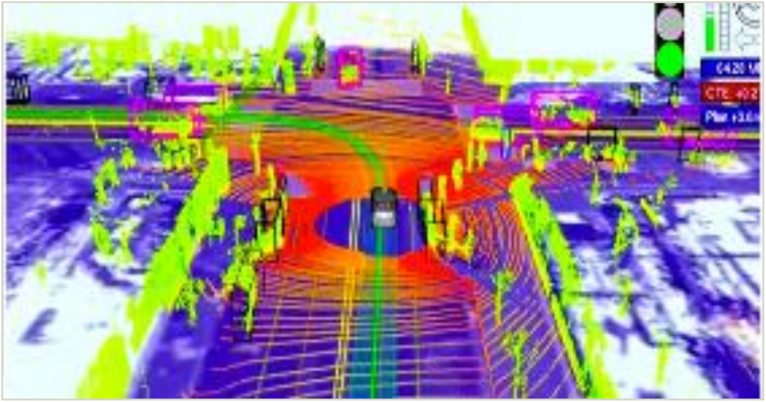
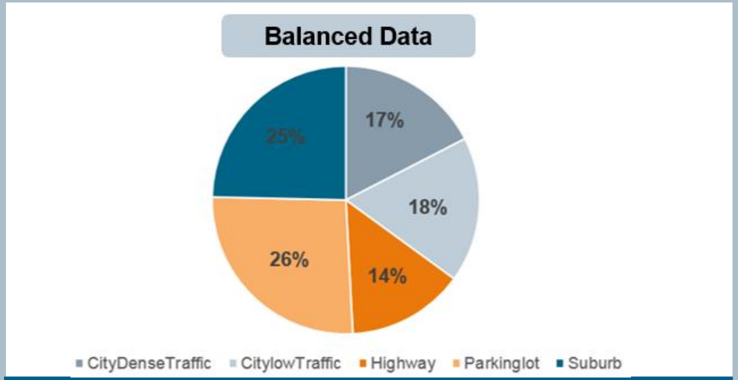
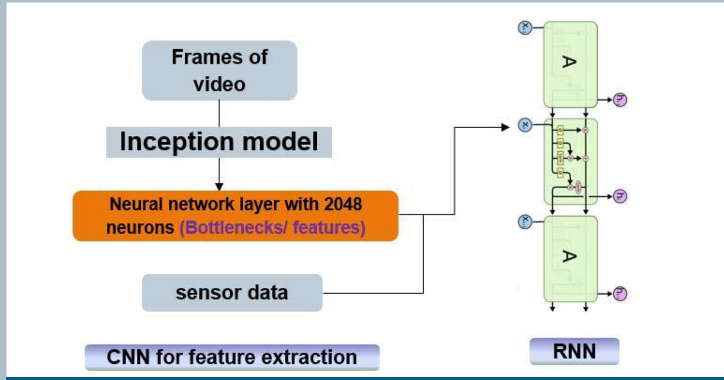


- Improve HEV Controls using recognition of driving scene based on Deep Learning algorithms
- Obtain better switching strategies for the supervisory HEV controller, leading to better performance and lower fuel consumption

Recognition of driving scene using Deep Learning algorithms



Balanced training dataset combining OEM and open-source data



Tuning of network architecture and parameters towards maximal predictability

- Combine convolutional neural networks with recurrent neural networks
- Use of camera data with traditional vehicle sensors to improve algorithm performance

“Simcenter Engineering experts developed Driving Scene Recognition algorithms to improve HEV controls based on real-time scenario identification with heterogeneous sensors. We are now able to optimally adapt our HEV controls to the exact required driving conditions such as stop-go traffic, urban/highway, …”

Paper at ITEC 2017, Pune, India

Embedded perception algorithms

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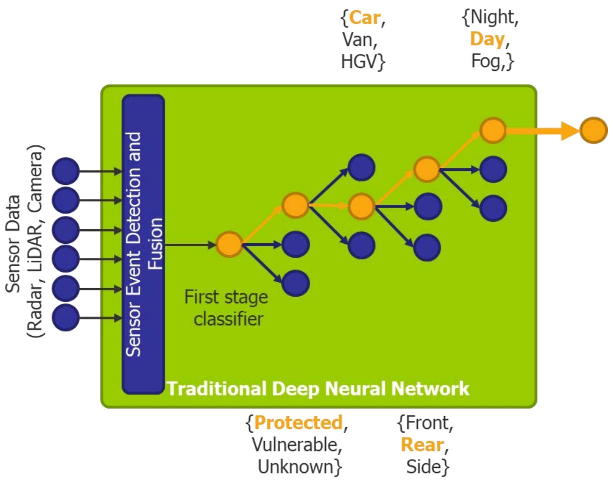
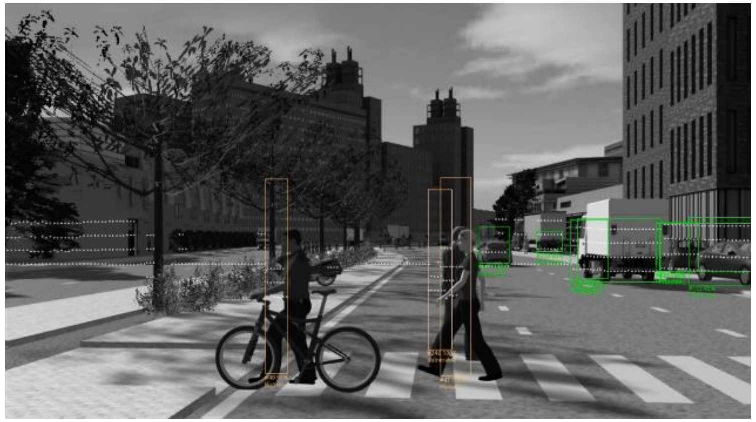
Multistage Classifier



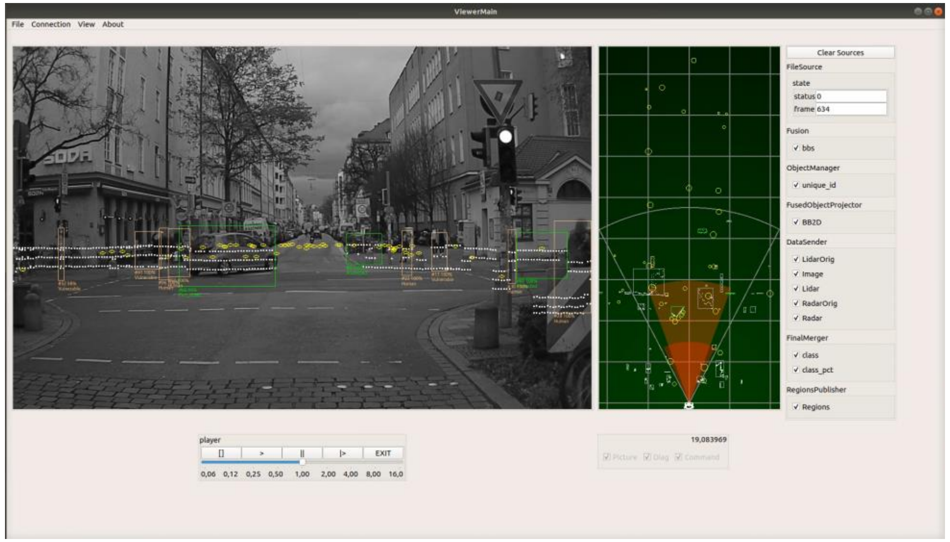


Prescan Simulation

Simulated Data

Real World Data

Target e.g. Xilinx ZynQ



Parking Maneuvering Path Planning

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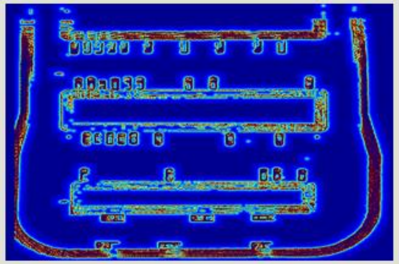
Mapping

Cost map generated from

Prescan virtual lidar sensor

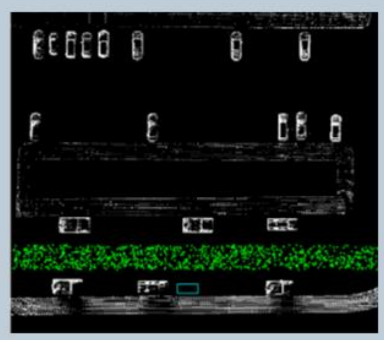


Occupancy map

Forward and Parallel Parking

Human-like driving, collision avoidance

Cost	Description
Distance to goal	drives the car toward the location and orientation of the goal
Reverse	reverse cost more than forward
Steering	change of steering angle cost more
Previous cost	cost of the previous node



Validation:

99.3% success in 1000 scenarios

Path planning example

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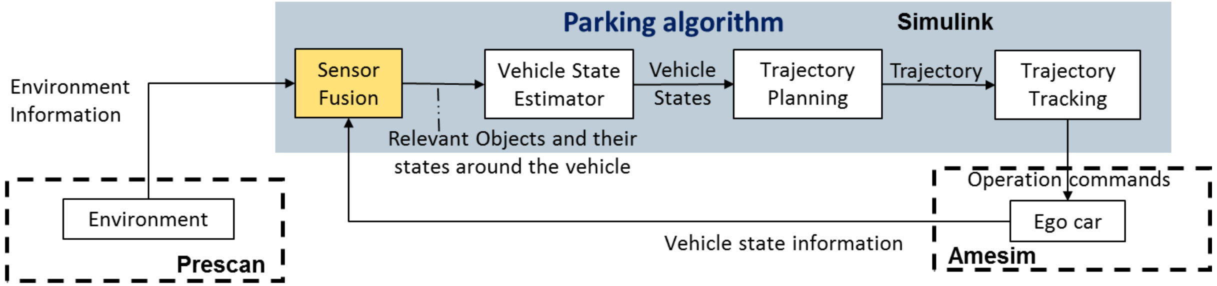
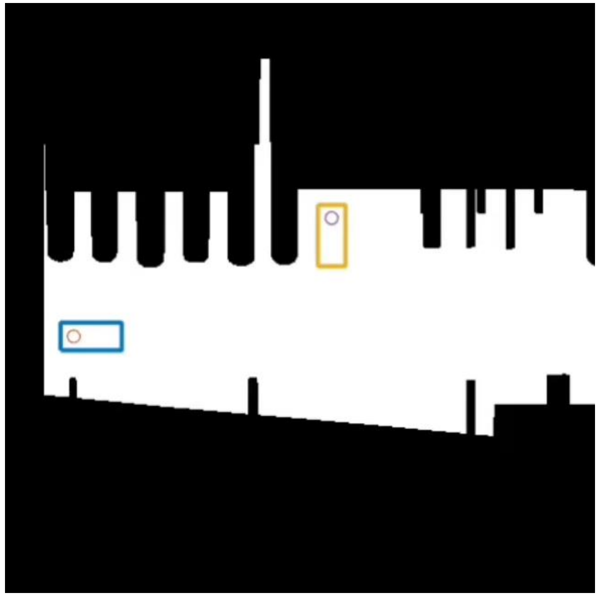




Current state of the vehicle

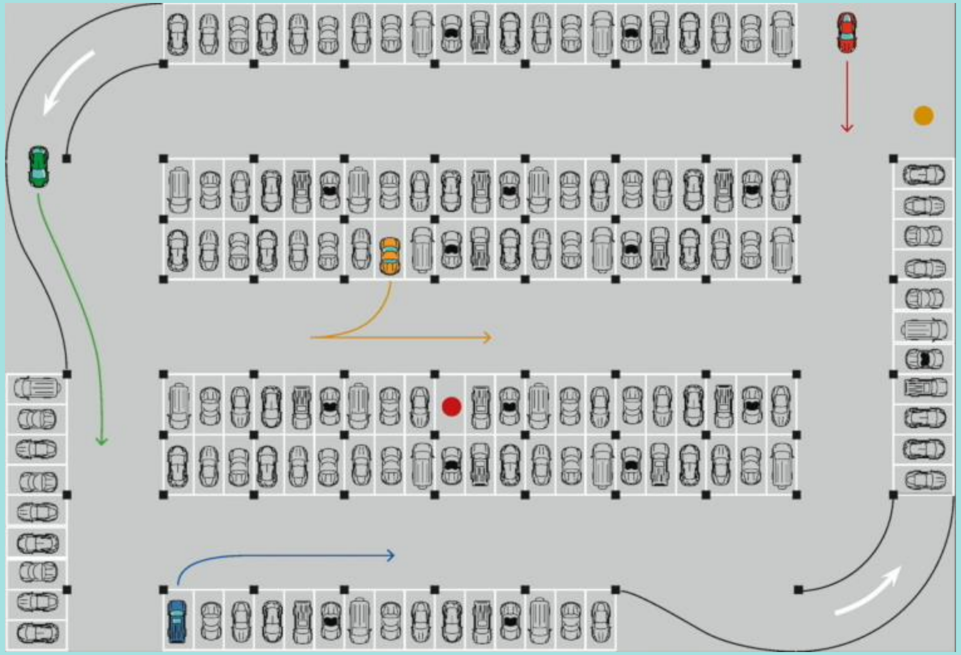
Desired state of the vehicle

Hybrid A-Star search tree

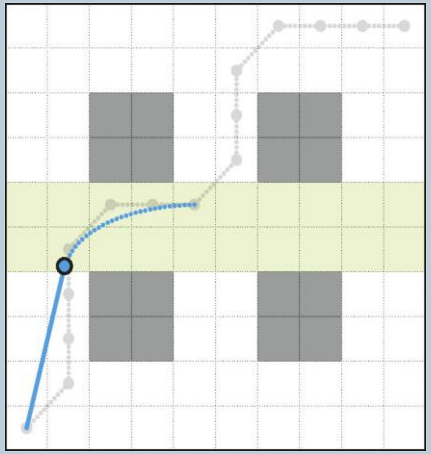
Final planned path

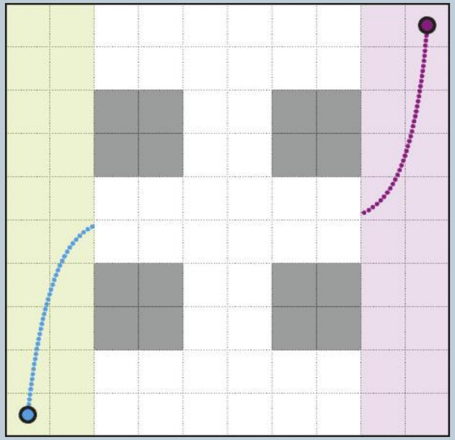
Distributed Motion Planning in Autonomous Valet Parking

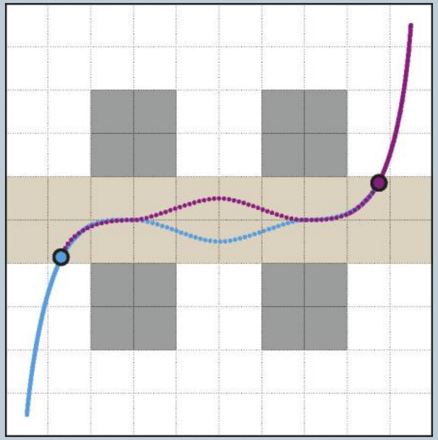
Time-optimal motion planning for multiple vehicles in a parking garage



- Global Planning using frames or grids based
- Local Planning in each frame
- Avoid collision active when vehicles are in the same or intersected frame

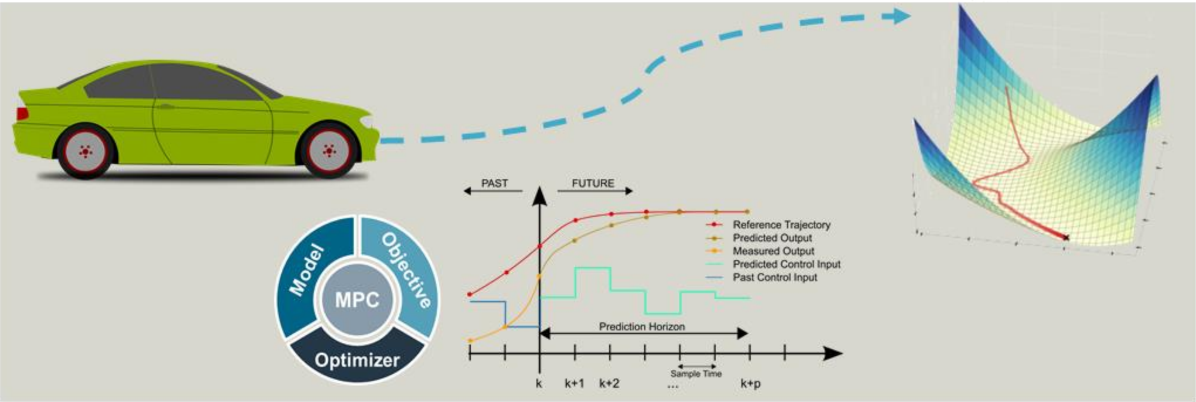


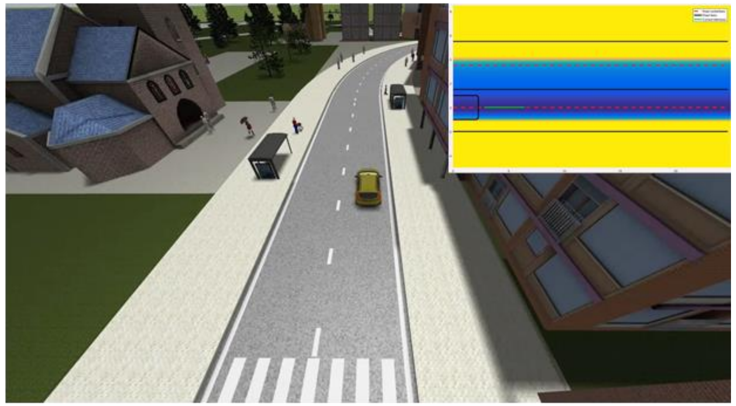


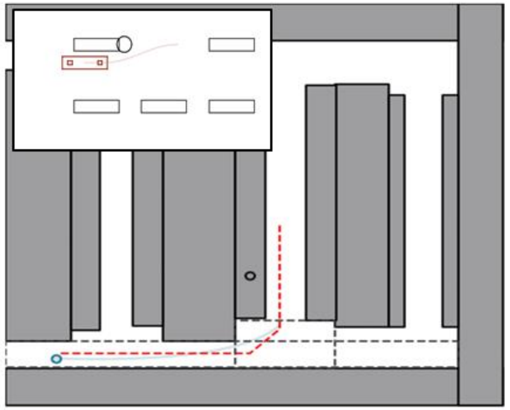


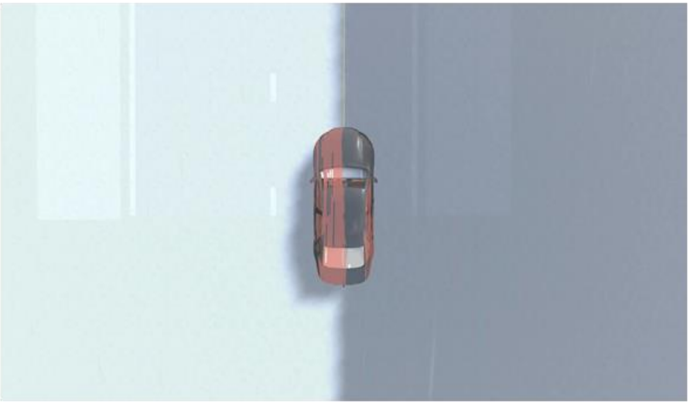
Collision Avoidance Technologies with Dynamic Obstacles

and testing with MiL, SiL, HiL



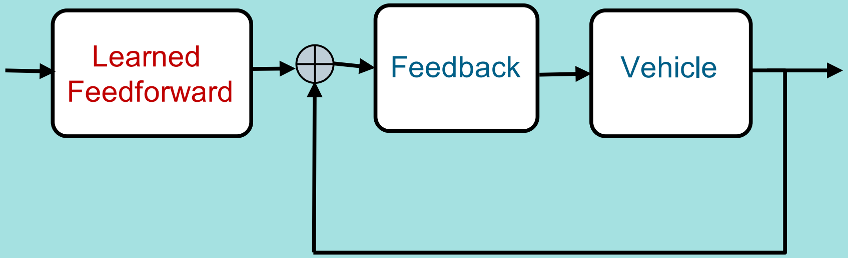






- Optimal control, real-time MPC for collision avoidance (i.e. dSpace, NI)
- Combined model-based and AI

Autonomous Vehicle Control



Patent filed

- **Data from previous similar executions can be exploited to improve feedforward control, hence system performance (tracking, time, fuel economy,…)**
- **Safety guaranteed formally**

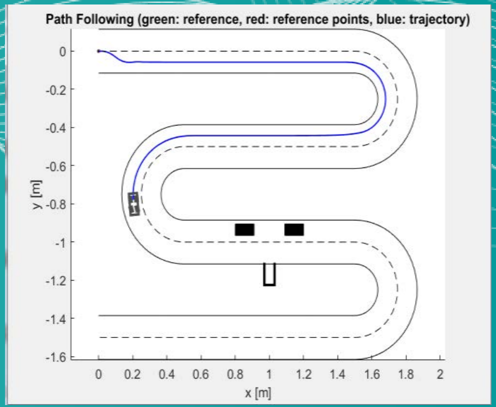
Autonomous Home or Apartment Parking

- Repetitive similar trajectories, i.e. 10 times per week driving the same route
- Sometimes long distance, narrow spaces, not easy to drive (i.e. late afternoon, raining, snowing, multi floor parking garage…), time consuming
- Human drives on the first time to let the car learns about desired parking trajectory. In the following times, the car will learn to drive like that.

Home/Valet Parking

Racing Car

Shuttle & School Bus



Drift parking control is obtained after only 5 running samples

Vehicle Dynamics Model for ADAS (example of reverse engineering)

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Operational scenarios

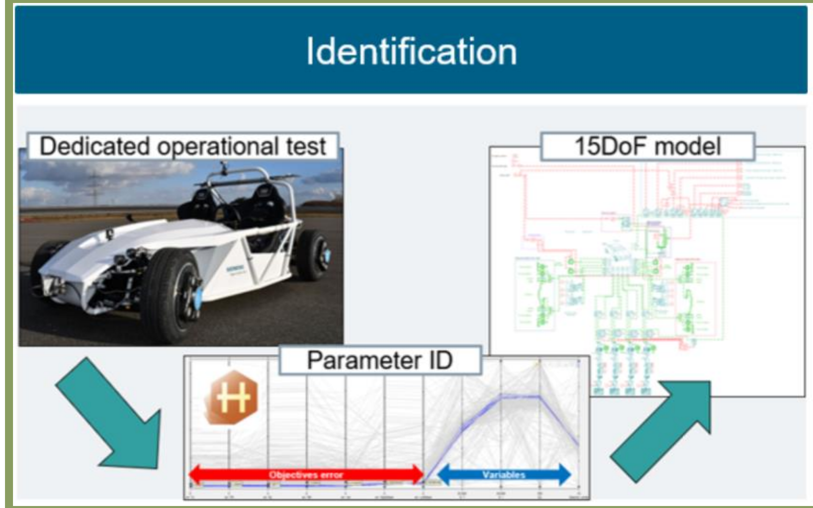
Testing scenarios:

- Slow ramp steer
- Frequency sweep
- Step steer
- Cleat impact

Tire testing

- MF-Swift identification (upgraded to include turn-slip performance)

Analysis and parameter identification



Vehicle Dynamics Model for ADAS (example of reverse engineering)

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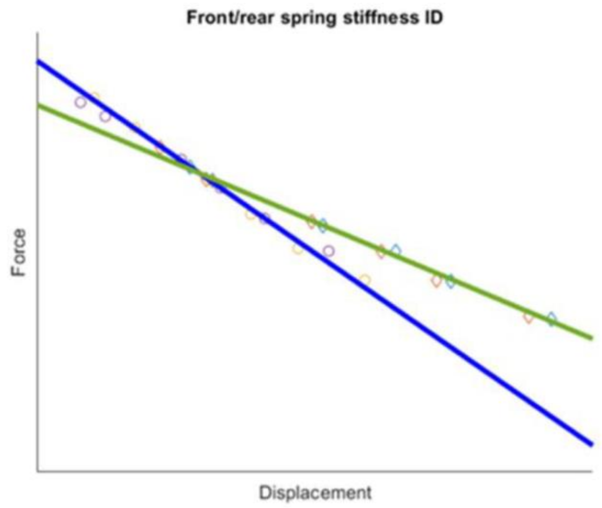
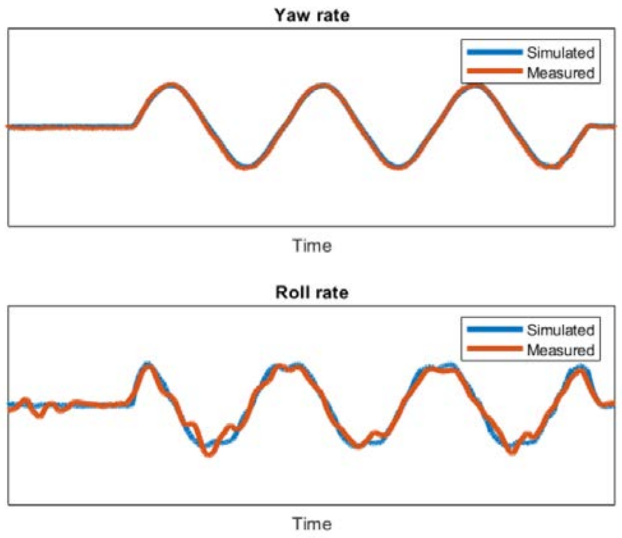
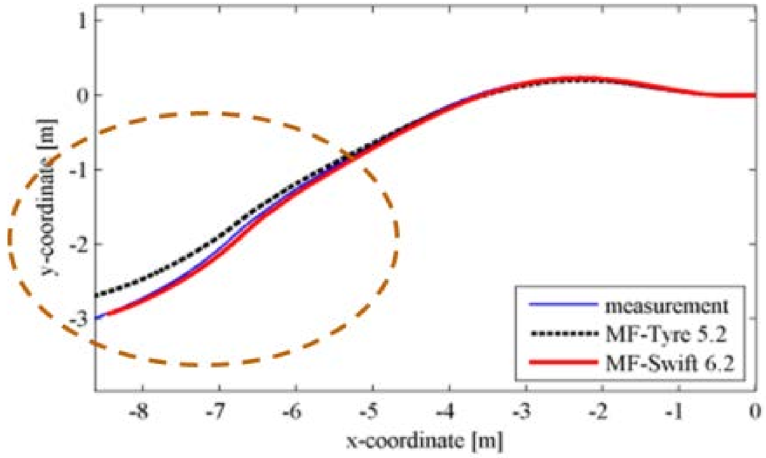


Separation of front/rear suspension stiffness by means of dedicated tests



Identification of lateral and roll dynamics



improved Tire behavior in low-speed parking with MF-Swift 6.2 including with turn slip functionality

Autonomous Valet Parking Overview

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- Context and challenges
- Autonomous Valet Parking overview
- Requirements and Test cases definition
- Perception and controls
- **Mixed reality testing**
- Conclusions – Q&A

Valet parking system development process
Interest of Mixed-reality testing

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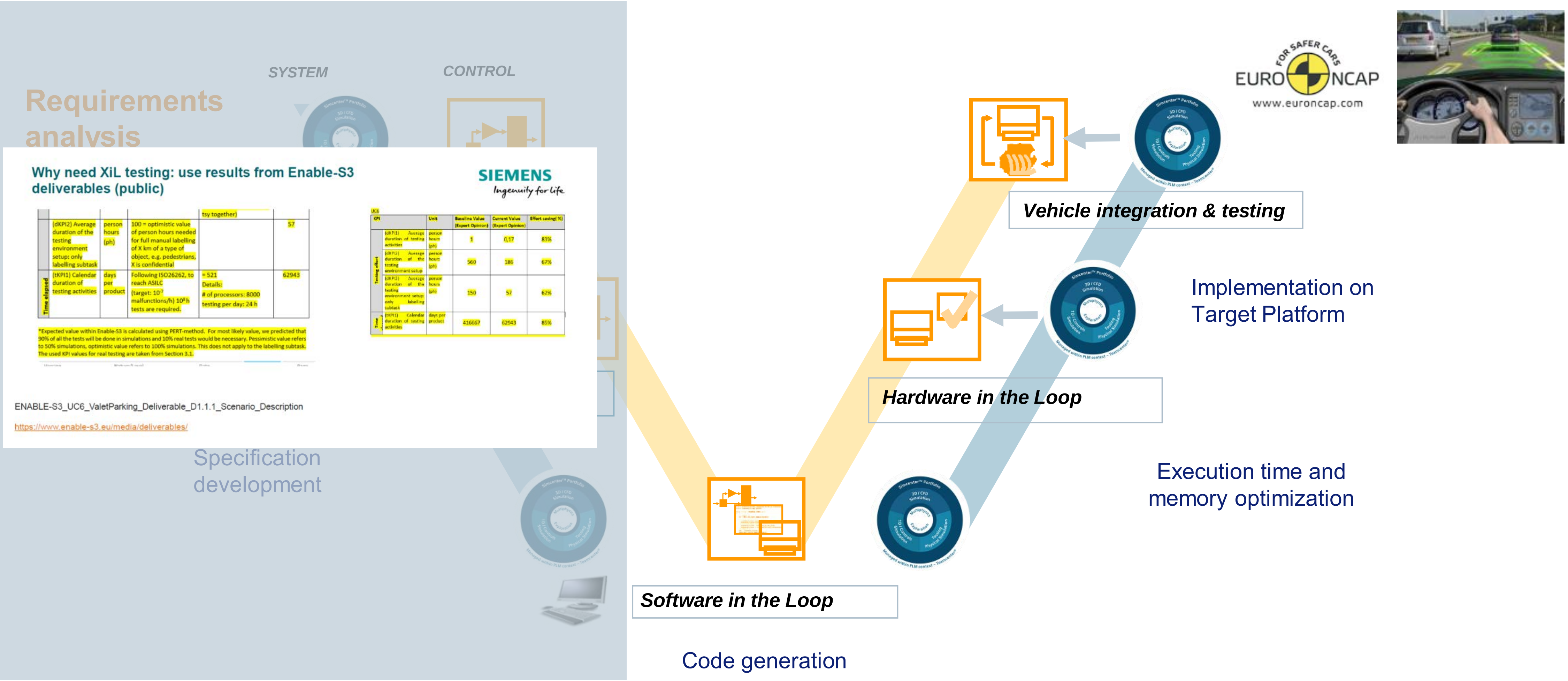

Why need XiL testing: use results from Enable-S3 deliverables (public)

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				tsy together)	
	(dKPI2) Average duration of the testing environment setup: only labelling subtask	person hours (ph)	100 = optimistic value of person hours needed for full manual labelling of X km of a type of object, e.g. pedestrians, X is confidential		57
Time elapsed	(tKPI1) Calendar duration of testing activities	days per product	Following ISO26262, to reach ASILC (target: 10^{-7} malfunctions/h) 10^{8} h tests are required.	= 521 Details: # of processors: 8000 testing per day: 24 h	62943

*Expected value within Enable-S3 is calculated using PERT-method. For most likely value, we predicted that 90% of all the tests will be done in simulations and 10% real tests would be necessary. Pessimistic value refers to 50% simulations, optimistic value refers to 100% simulations. This does not apply to the labelling subtask. The used KPI values for real testing are taken from Section 3.1.

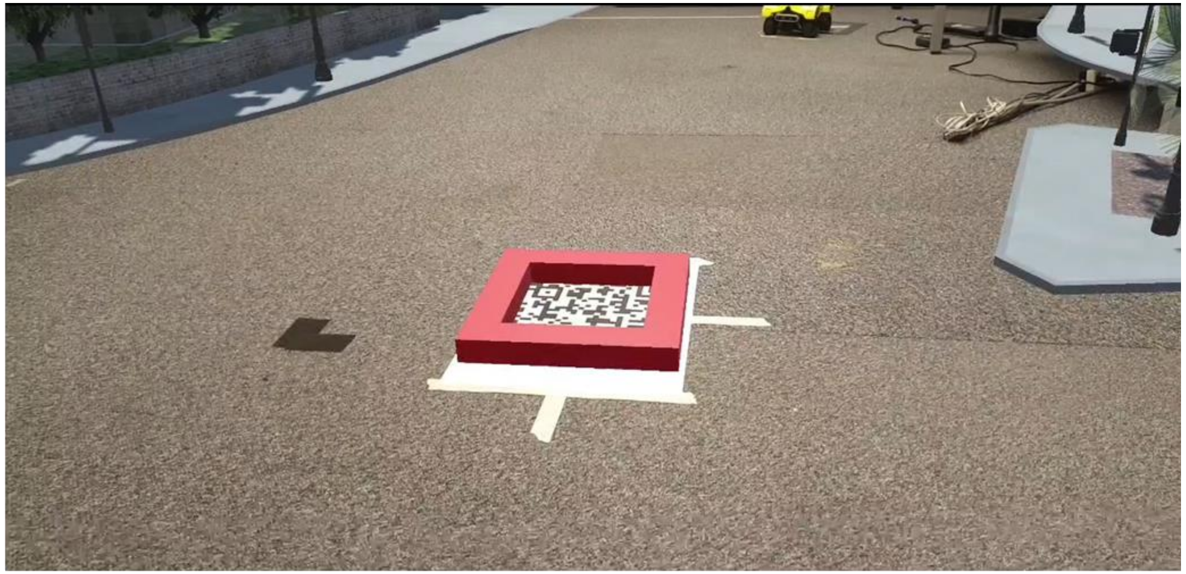
UC6

KPI		Unit	Baseline Value (Expert Opinion)	Current Value (Expert Opinion)	Effort saving(%)
Testing effort	(dKPI1) Average duration of testing activities	person hours (ph)	1	0,17	83%
Testing effort	(dKPI2) Average duration of the testing environment setup	person hours (ph)	560	186	67%
Testing effort	(dKPI2) Average duration of the testing environment setup: only labelling subtask	person hours (ph)	150	57	62%
Time elapsed	(tKPI1) Calendar duration of testing activities	days per product	416667	62943	85%

ENABLE-S3_UC6_ValetParking_Deliverable_D1.1.1_Scenario_Description

https://www.enable-s3.eu/media/deliverables/

Toolchain for mixed virtual – real testing: efficient time and cost



Toolchain for mixed virtual – real testing: efficient time and cost

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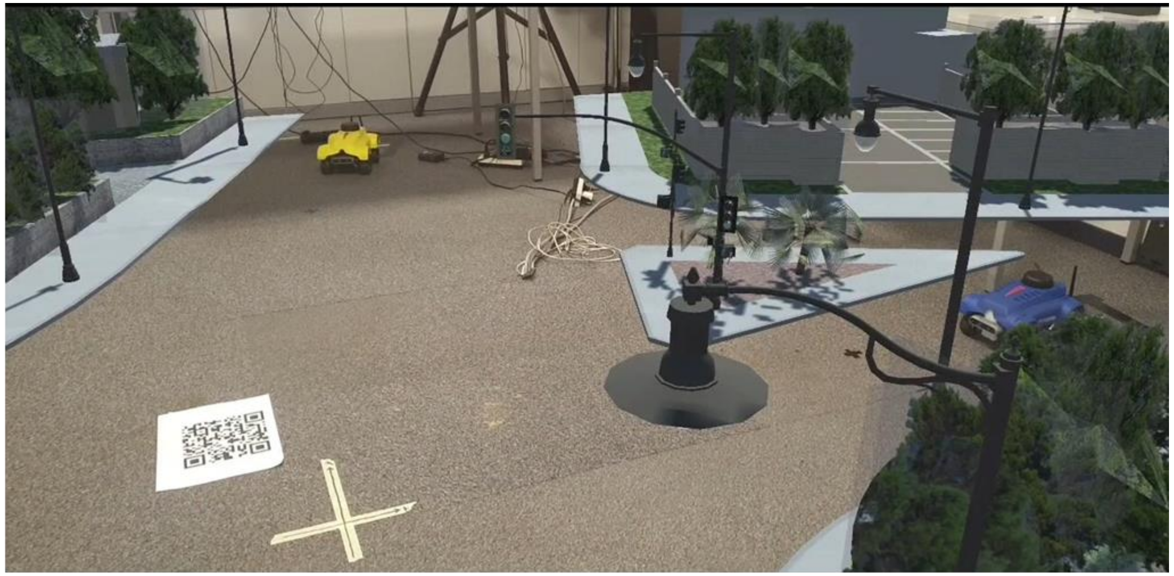
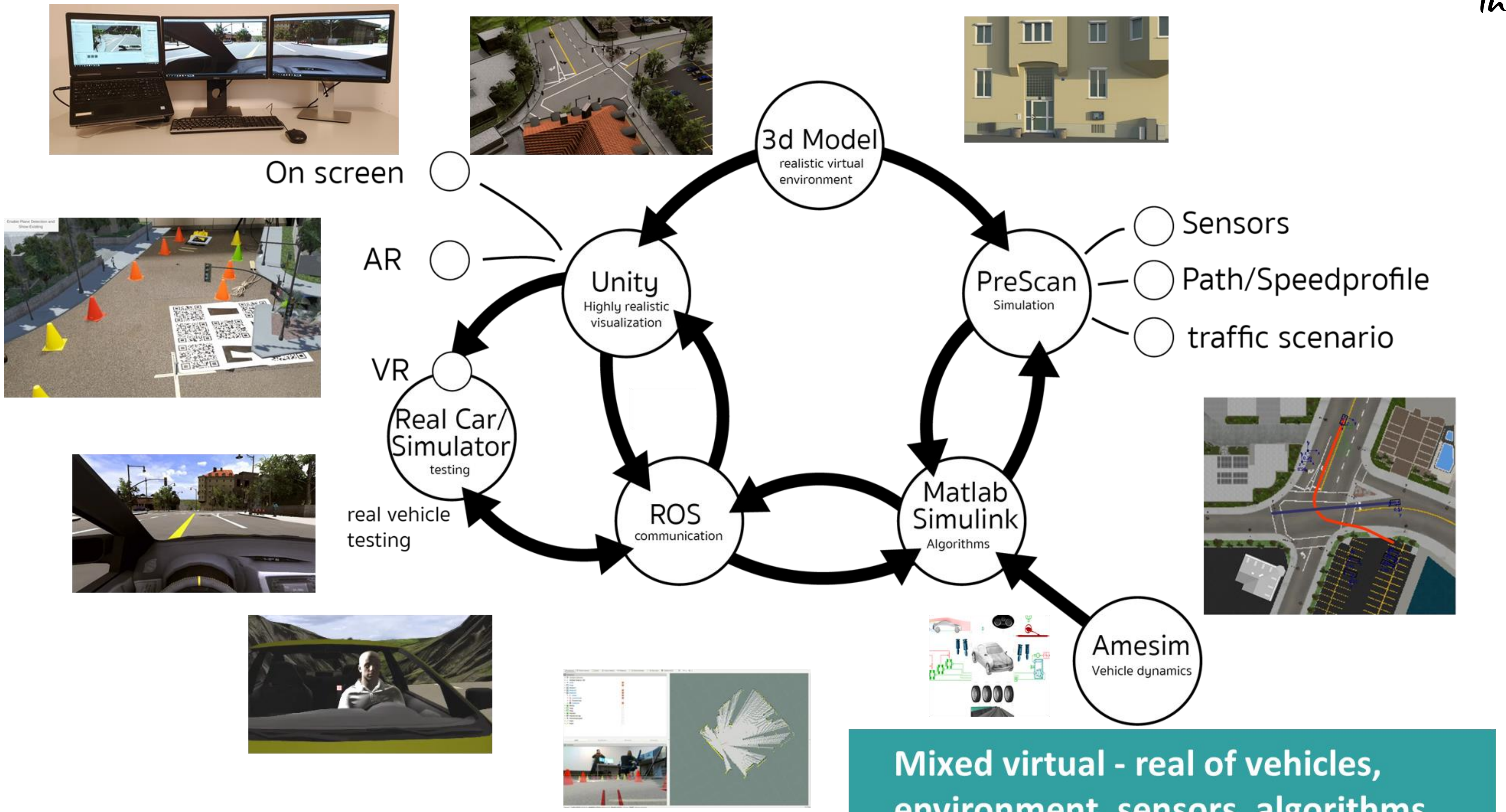


Toolchain for mixed virtual – real testing: efficient time and cost



Mixed virtual - real of vehicles, environment, sensors, algorithms

Mixed Reality Testing of Multi-vehicle Coordination
- collaboration with Denso DE in Enable-S3

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Accepted to the 21st IFAC – (International Federation of Automatic Control) World Congress in Berlin, Germany, July 12-17, 2020

Mixed Reality Testing of Multi-vehicle Coordination in an Automated Valet Parking Environment

Maximilian Kneissl *,*** Sebastian vom Dorff * Adam Molin *
Maxime Denniel ** Tong Duy Son ** Nicolas Ochoa Lleras *
Hasan Esen * Sandra Hirche ***

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** *Siemens PLM Software, 3001 Leuven, Belgium (e-mail: son.tong@siemens.com)*
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Automated Valet Parking joint demonstration with Denso Germany and other Enable-S3 partners in the AVP Use Case

Mixed Reality Testing

System under test
- Multi-vehicle planning and interactive control

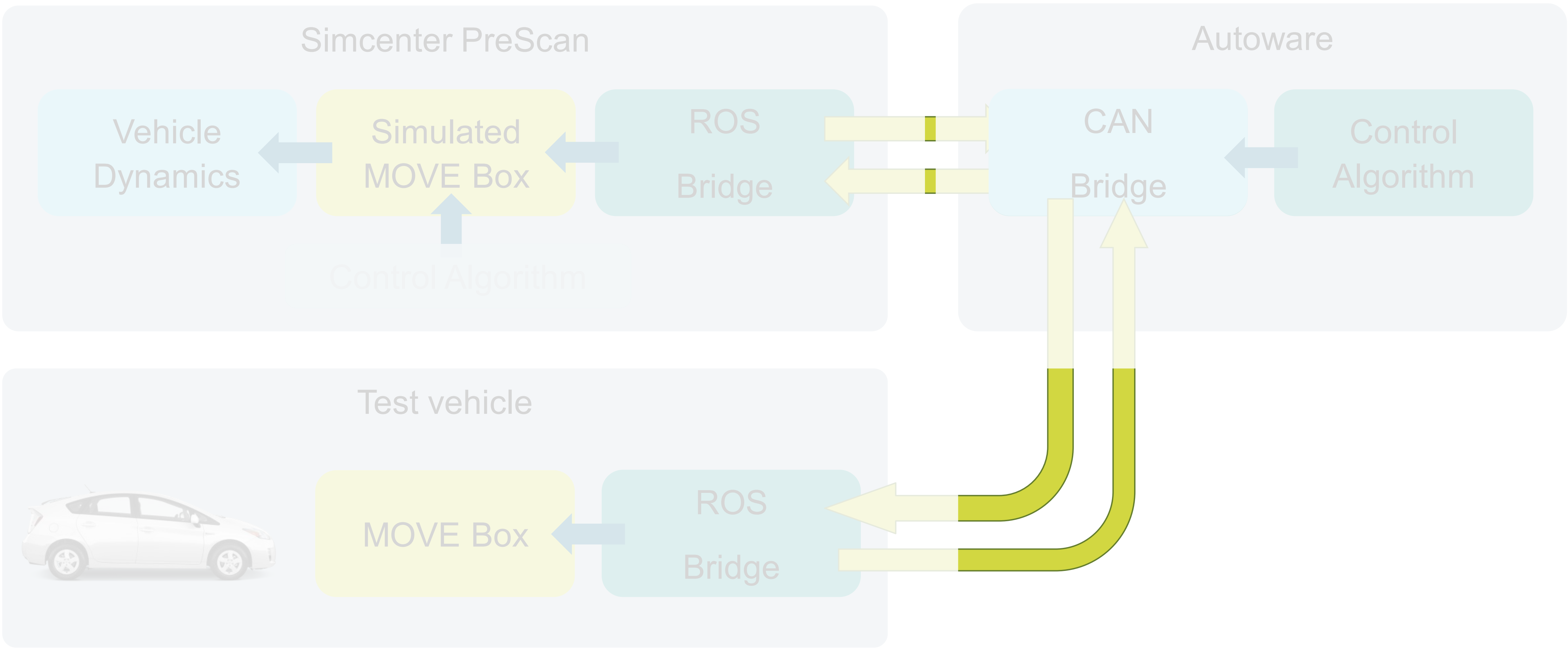
Simulated environment
- Auto-populated car park environment

Real environment
- Operation on an empty test ground
- Projection of test car behavior into virtual environment

DENSO
Crafting the Core

Controller testing capabilities

From Virtual vehicle to Physical vehicle



Algorithm verification on test vehicles

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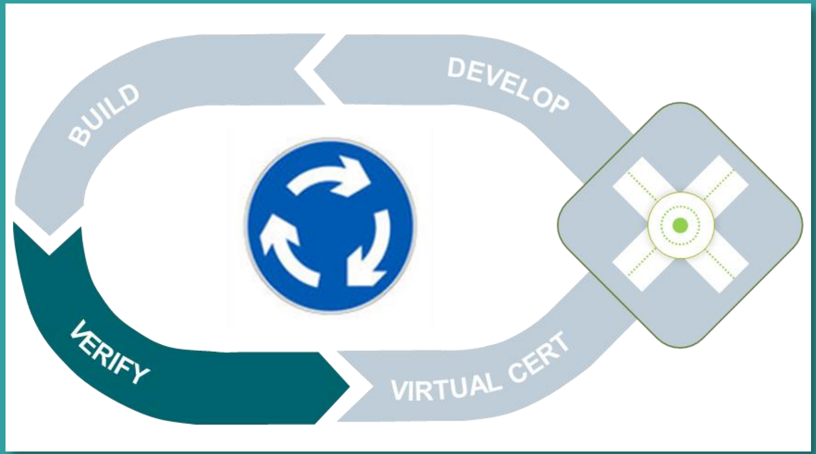

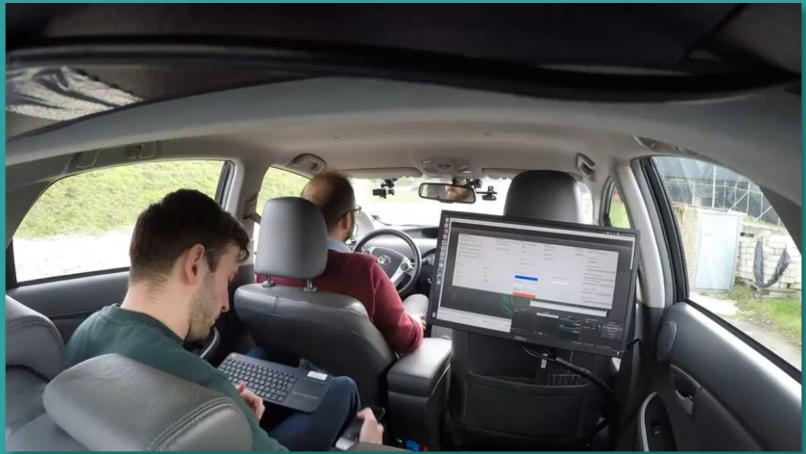

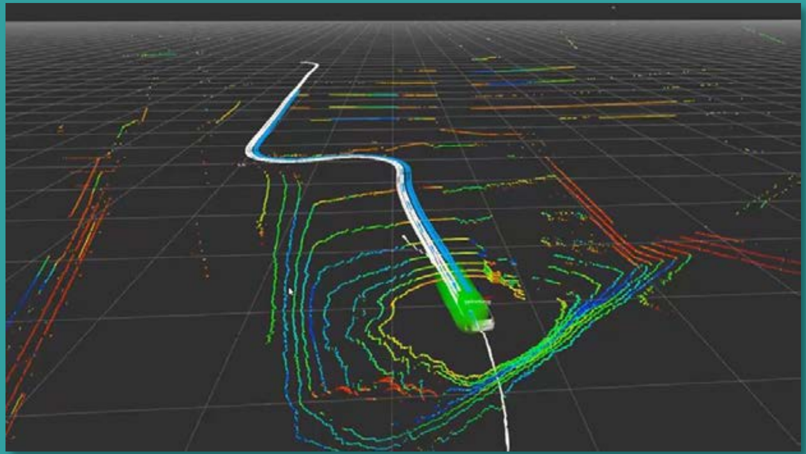

Verification of algorithms on test vehicles

- Assess algorithm performance on real vehicle
- Switch easily between vehicle and lab environment with identical software stacks
- Results flow directly back into the development process

Autonomous Valet Parking Overview

- Context and challenges
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- **Conclusions – Q&A**

Autonomous Valet Parking Overview

Complex environment	Numerous scenarios	Corner cases
Accurate Virtual Framework	Engineering expertise	From pure Virtual to Mixed-reality

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Thank you