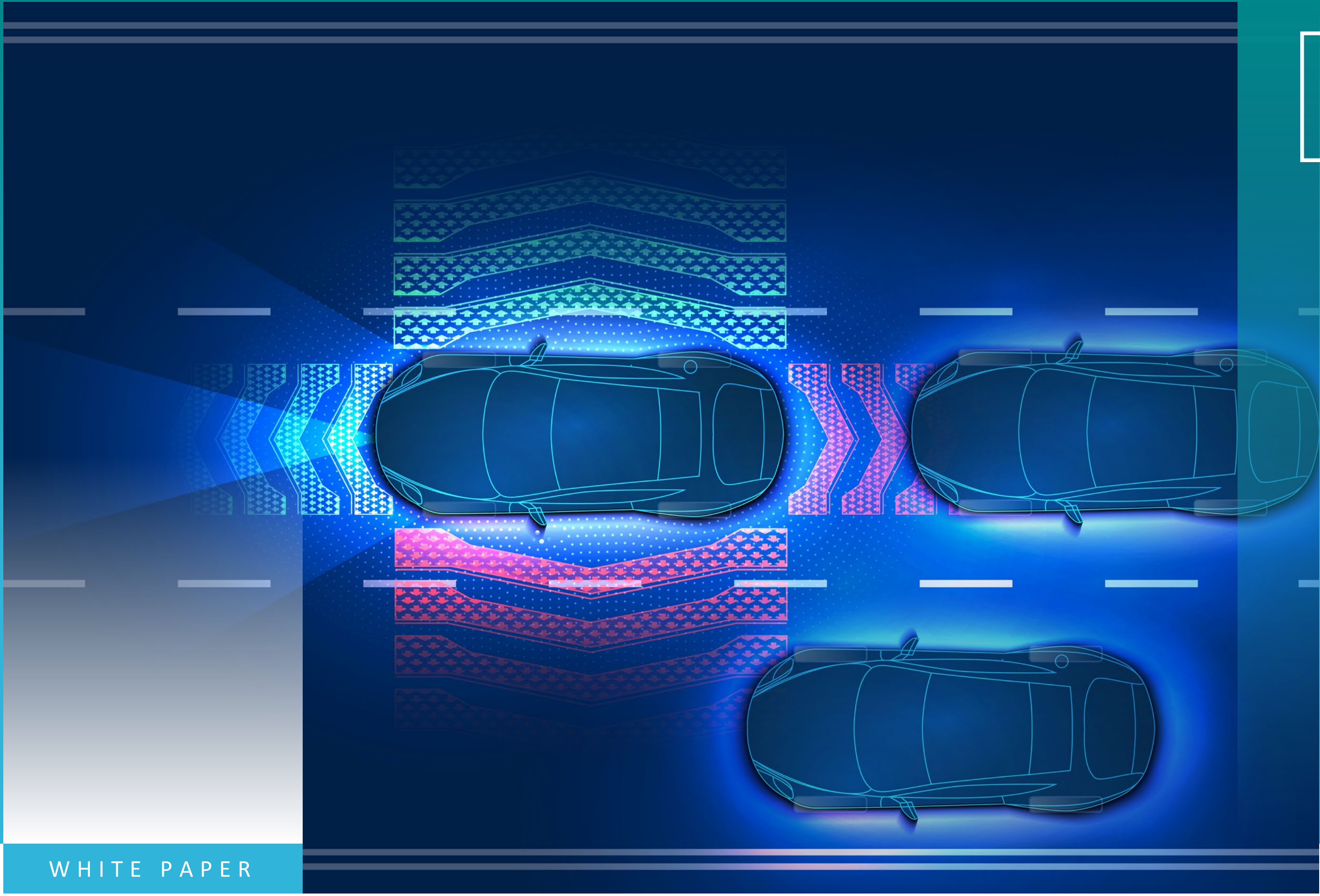


WHITE PAPER

From 200 to 4 Days Simulation to Identify Critical ADAS Scenarios

Scenario based virtual validation of ADAS functions using AVL CAMEO™ Active DoE

THE CHALLENGES IN ADAS VALIDATION

Testing ADAS Functions Is Complex and Expensive

ADAS/AD systems require large numbers of tests to ensure safety, while maintaining comfort metrics.
The increasing complexity of these functional scenarios require increasing number of test cases (concrete scenarios) for validation.

30 vehicle variants — 30 cases

\+

10 assistant systems — 300 cases

\+

10 scenarios per system — 3,000 cases

\+

1000 test cases — 3,000,000 cases

It is infeasible to test all cases.

It is almost impossible to execute all of the test cases on the road, a HiL, or even in simulation. Nevertheless, the penalties for accidents are severe.

Road
15 min per road test
→ 85 years on the road

Simulation
Standard simulation assumes 10x parallelization and 60 seconds per simulation run
→ 200 days of simulation

What are now the most critical questions?

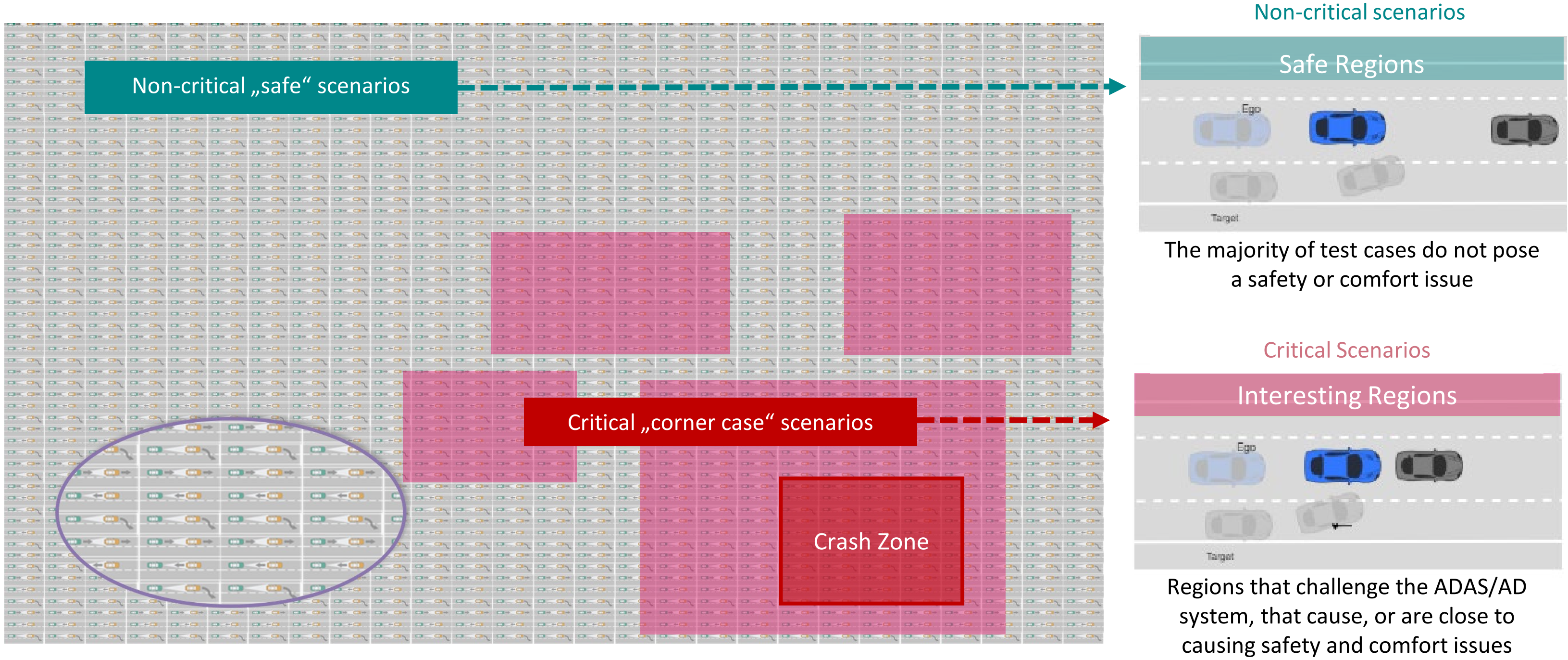
How do you

1. ensure scenario space **coverage**?
2. ensure the **safety** of the assistant system?
3. intelligently **reduce** the number of test cases?

FEATURES

WHAT ARE CRITICAL SCENARIOS / CORNER CASES?

A critical scenario, also known as a corner case, is a special category of test case, residing in the interesting regions of a functional scenario space. Running all the test cases is expensive and time consuming and arguably not necessary, since a large proportion of test cases are non-critical and do not pose a safety or comfort issue.



Functional scenario space

The main challenges

1. Define criteria for the interesting region, such as safety and comfort
2. Identify all the interesting regions in the scenario space
3. Generate a manageable number of critical scenarios in those areas, to take forward into the various validation environments

A NOVEL APPROACH TO ADAS SCENARIO VALIDATION

The output of untested scenarios can not usually be known without simulating them first. This creates a serious problem when looking for critical scenarios. With traditional methods, the whole scenario space has to be covered to ensure nothing critical is missed. While this seems to be an insurmountable problem, AVL has developed a novel approach called KPI model-based validation, using machine learning technology from AVL CAMEO™ Active DoE.

What is a KPI?

A KPI (Key Performance Indicator) is a safety, comfort or method relevant system output metric that is of interest, such as minimum inter-vehicle distance, or maximum deceleration.

What is a mode-based validation?

No system is completely random, and there are trends in the outputs of any system, relative to the inputs. This allows us to model the trends in the output behaviour of the ADAS scenarios quite accurately, even with relatively low coverage of the scenario input space (compared to full factorial). We call this a behavioural model. Model-based validation relies on the ability to predict the behaviour of untested input combinations, without needing to run the full, time-consuming simulation.

How does KPI based model-based validation work?

This method takes advantage of three properties of the system, that help us to solve the issue.

1 SYSTEM TRENDS CAN BE MODELLED

Using a behavior model, we can quickly predict with sufficient accuracy, the output of scenarios we have not yet tested, as long as similar scenarios are tested and the trends are correctly captured by the model.

Behavior model can be created and queried very fast

2 AREAS OF INTEREST ARE KNOWN

This allows separation of the scenario space into 2 areas that have different data gathering requirements.

“OUTSIDE” interesting areas
lower data density

- Make sure no interesting areas have been missed

“INSIDE” interesting areas
higher data density

- Good model quality
- Find boundary of interesting area

3 AREAS OF INTEREST ARE SMALL

As long as the area of interest is small relative to the whole functional scenario space, the area where data gathering requirements is lower, becomes the majority of the scenario space.

High data density only required in a small part of the scenario space

HOW DO WE KNOW WHEN WE HAVE ENOUGH DATA?

Now that we have determined that the

- scenario space can be split into two areas: critical and non-critical
- data density needs to be higher inside the critical area, than outside

the remaining major question is: What should the data density be in those two areas? This is required to decide when we have enough data and we can stop the simulations. CAMEO Active DoE has in-built algorithms to answer this critical question with

- objective non-scenario specific KPI's for the model quality “inside” and “outside” the interesting areas, for each target safety and comfort KPI
- exploratory algorithms to put points where they are needed in the design space to ensure good coverage
- objective criteria for what model quality is satisfactory, both “inside” and “outside”

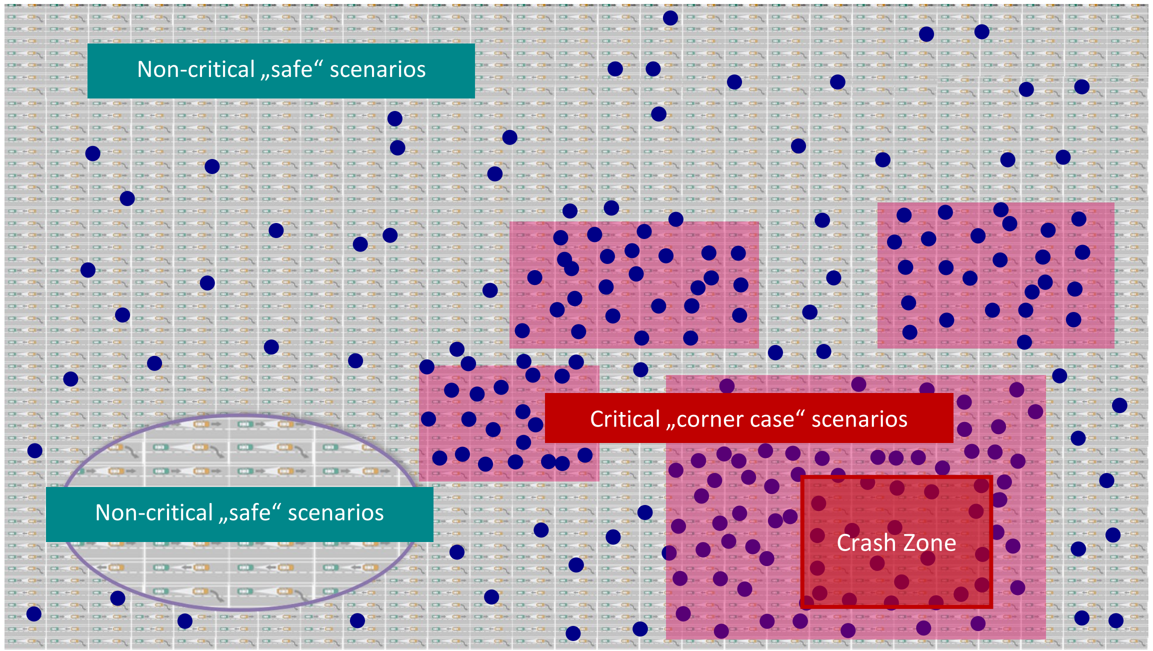
CAMEO then intelligently combines these metrics to keep the number of simulations required to the absolute minimum to accomplish your task.

“Outside” the interesting areas

Low scenario space coverage, lower than usual full factorial

“Inside” the interesting areas

High coverage, as high or higher than usual full factorial



FEATURES

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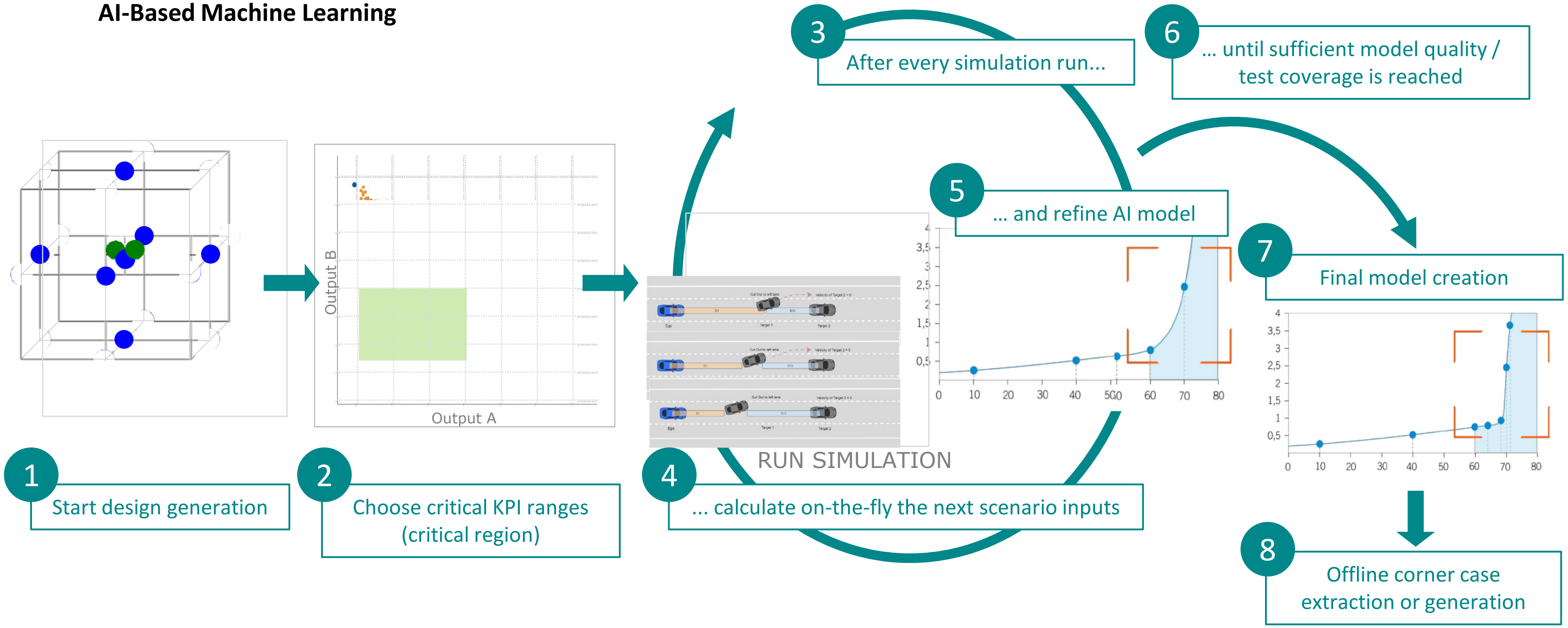
The AVL Solution
Workflow
Architecture
Case Study
Conclusion

THE CAMEO ACTIVE DOE WORKFLOW

AI-Based Machine Learning



Using patented machine learning algorithms, Active DoE learns where the areas of interest are and actively steers the generated scenarios on-the-fly towards:

- Interesting / critical regions
- Regions of the scenario space lacking coverage
- Regions of the scenario space with very non-linear behaviour

And reducing coverage of:

- Known safe areas
- Regions where crash is unavoidable

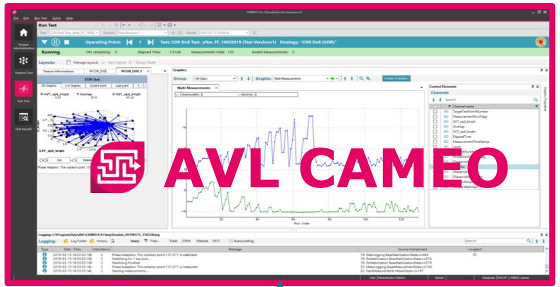
Simulations will automatically stop, once sufficient model quality and coverage “outside” and “inside” are achieved. This keeps simulation time to the absolute minimum to identify critical scenarios for further validation activities. CAMEO also has the ability to generate a user-definable number of corner cases to uniformly fill the identified critical region.

ARCHITECTURE : CAMEO IN THE ADAS TOOLCHAIN

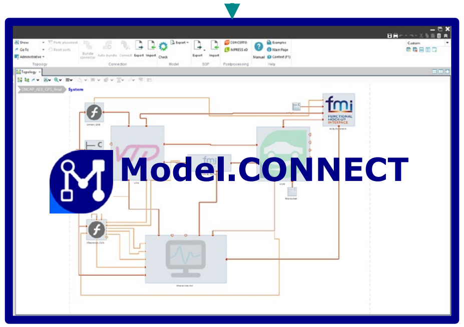
The CAMEO windows client provides a flexible local solution where CAMEO is the master tool, driving and coordinating simulation, automation and optimization, all from the same tool.

CAMEO can be connected to Model.CONNECT™ but also 3rd party tools via various possible interface solutions.

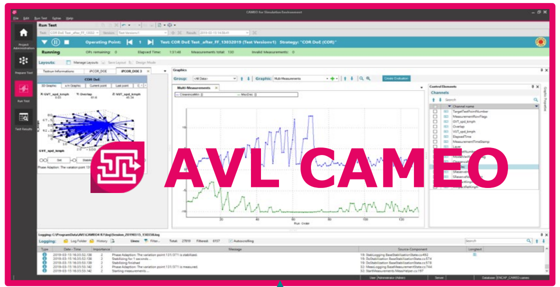
Local solution with Model.CONNECT



- DVI2 Interface



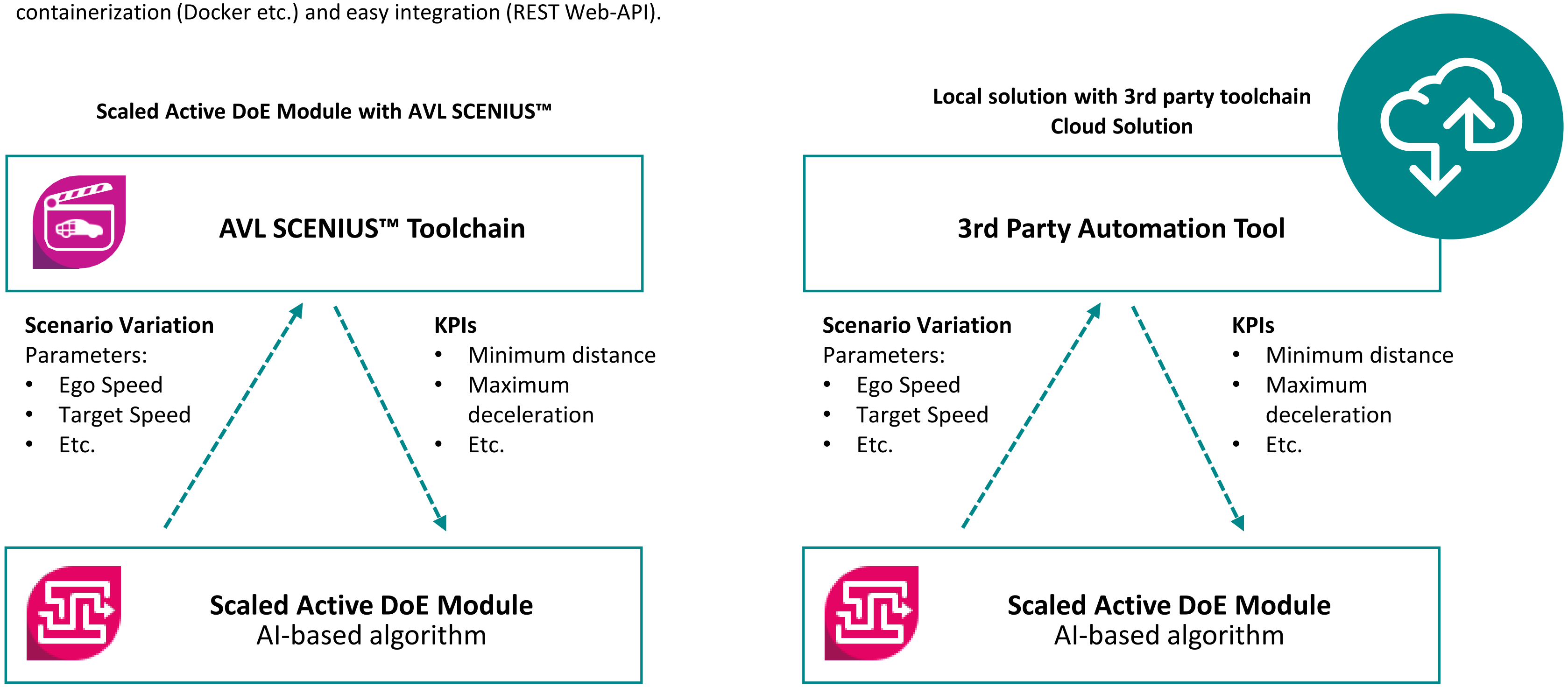
Local solution with 3rd party toolchain



- Standard interface
- Scripting interface
- Web-API
- Etc.

ARCHITECTURE : SCALED ACTIVE DOE MODULE IN THE ADAS TOOLCHAIN

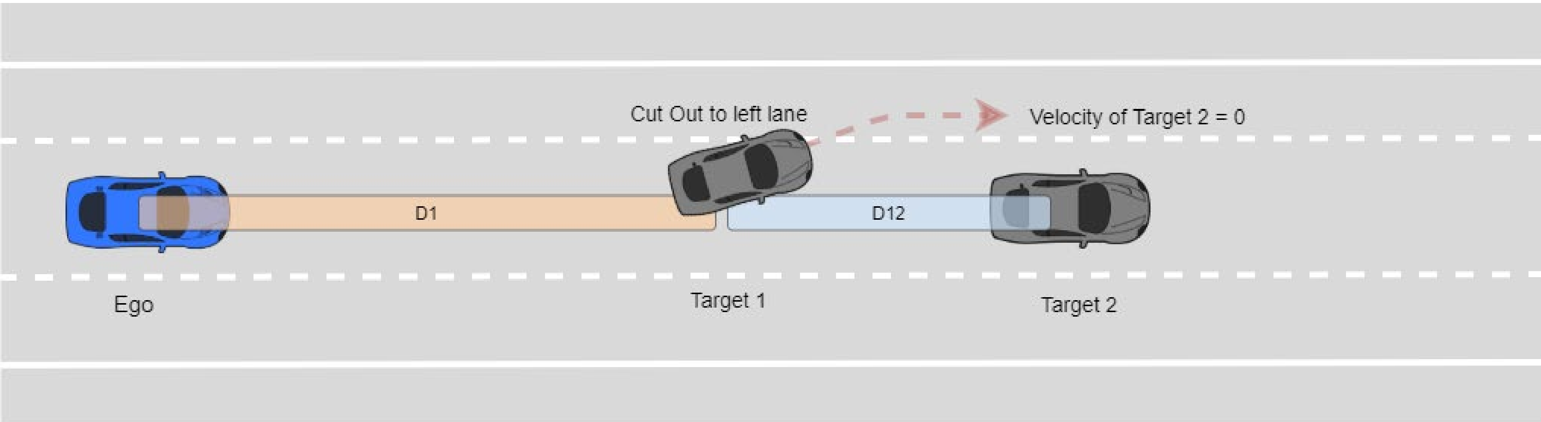
The CAMEO Scaled Active DoE Module provides ultimate flexibility to integrate the power of AI-based Machine Learning Active DoE into a ADAS simulation workflow. No CAMEO Windows Client is needed, and the Scaled Active DoE Module is prepared for parallelization, cloud deployment, containerization (Docker etc.) and easy integration (REST Web-API).



CASE STUDY

Validation of a 'Highway Pilot Function' for a 'Cut-Out With Approach' Scenario

A 'highway pilot function' has to be validated in various scenarios. For this example we use a `cut-out with approach` scenario. The interesting area in this case is a critical deceleration request of the ego vehicle after the target 1 vehicle does a cut-out. In the picture below the scenario is graphically described. In order to find the interesting region in this case, we vary 6 parameters.



6 Variation Parameters

1. Distance to target 1 vehicle [m] *(D1 [1- 5])*
2. Distance between target 1 and target 2 vehicle [m] *(D12 [8 -15])*
3. Ego vehicle speed [m/s] *(V_ego [22.22- 36.11])*
4. Target 1 vehicle speed [m/s] *(V_Target1 [22.22- 36.11])*
5. Lane Change Controller_factor1 [no unit] *[0.1 - 1]*
6. Lane Change Controller_factor2 [no unit] *[0 -1]*

Target KPIs

- Identify the critical output KPI for the system under test *(deceleration request)*
- Define the interesting region of the output KPI, deceleration request *[-10, -6]m/s2*

CASE STUDY

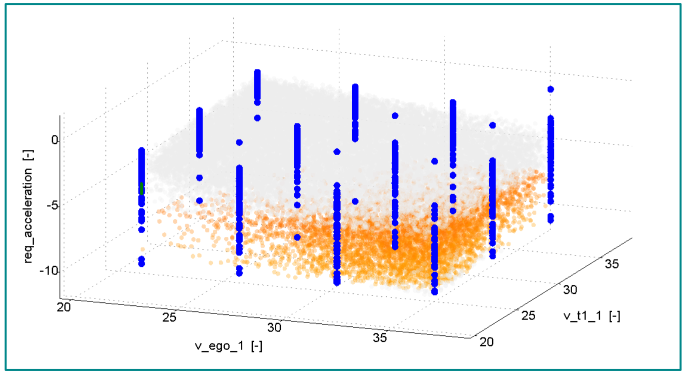
CAMEO Active DoE vs Conventional Method

For the `highway pilot function` and the `cut-out with approach` scenario point distribution between the conventional method and CAMEO Active DoE is shown below. On the axes the ego vehicle speed and the target vehicle speed versus the requested deceleration are shown. With the CAMEO Active DoE method and the same number of total simulations, Active DoE puts many more simulations are in the critical area. This results in a much better model quality in the interesting region, while ensuring no critical regions are missed, and it enables reduction in the number of scenario simulations.

CAMEO Active DoE highlights

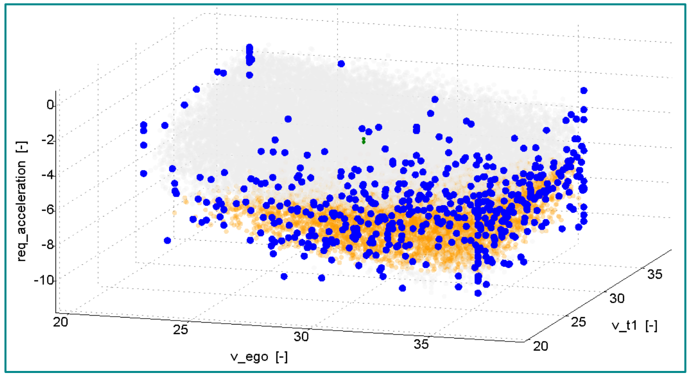
- 160% increase in points in the critical region (481 vs 186 in 1000 simulation run)
- 95% model quality in the critical region, in less than 1/4 of the time (227 vs 1000)
- 1/3 of the scenarios fall in the critical region during those first 227 simulations (76 out of 227)

CONVENTIONAL METHODS - FULL FACTORIAL



- 1000 simulation points
- 186 points in the critical region

CAMEO ACTIVE DOE



- 1000 simulation points
- 481 points in the critical region
- 95% model quality in 227 simulations with 76 (33%) of the points inside the interesting region

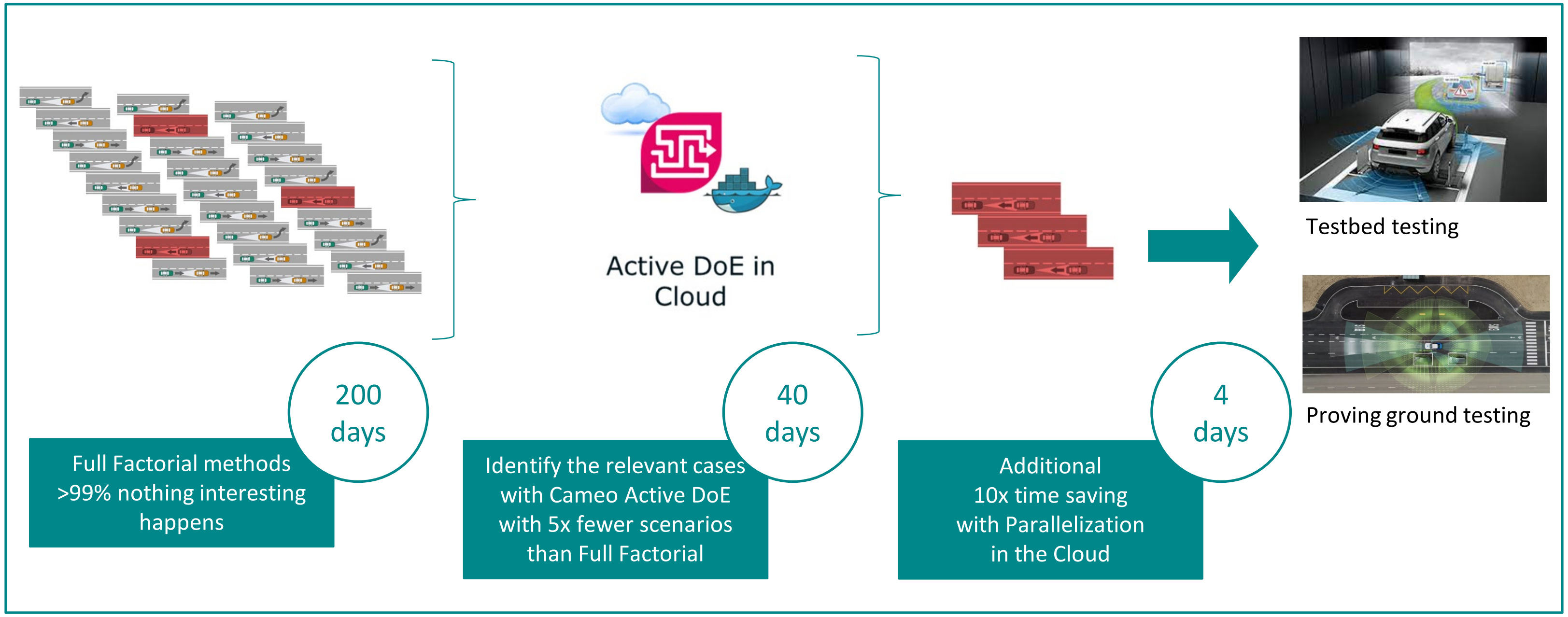
Active DoE ensures model quality in the interesting region is high and no critical regions are missed

FEATURES

CASE STUDY

The Benefits

The CAMEO Active DoE method has demonstrated 5 times fewer simulations, to achieve the same goal. Compared to conventional methods, we have also demonstrated similar or better model quality, if behaviour models were to be created from the simulation data. By combining this method with cloud or cluster parallelization, a reduction in simulation time from 200 to only 4 days has been realized. An additional advantage is the significant reduction in simulation of unrealistic and uninteresting scenarios that will not enrich the dataset, or give any meaningful feedback to the engineers. A reduced set of corner cases for downstream physical or semi-physical test environments (e.g. HiL, Driving Cube, proving ground) can be easily extracted. The strong mathematical basis supporting this reduction, also gives confidence that nothing critical has been missed, and simulation time and resources were efficiently used. Finally, offline CAMEO tools can ensure that when transitioning out of simulation, the scenarios are safe to execute in the real world. This is achieved by taking the input uncertainties in the real world and calculating crash probabilities. This allows scenarios that appeared safe in simulation, but would potentially cause a crash on the road, to be automatically excluded from the scenario generation process.



* Standard Simulation assumes 10 x parallelization and 60 seconds per simulation run

** Further 10 x parallelization assumed when transitioning from local to cloud computing

CONCLUSION

From 200 to 4 Days Simulation to Identify Critical ADAS Scenarios

5x time saving compared to conventional methods.

40 instead of 200 days simulation with further saving potential using parallelization

Optimum and relevant test cases for road/test track testing are generated, including robust scenario generation that ensures driver safety when transitioning scenarios from simulation to the road

Better understanding of the scenario space and functional weaknesses

AVL is the world's largest independent technology partner for the development, simulation and testing of powertrain systems as well as innovative automotive solution concepts.

FIND OUT MORE

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