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DRIVER ASSISTANCE AND AUTOMATED DRIVING: OPPORTUNITIES, CHALLENGES, SOLUTIONS

Peter Schoeggl

Mario Oswald, Rainer Voegl, Philipp Clement, Michael Stolz, Erich Ramschak
AVL List GmbH

ABSTRACT

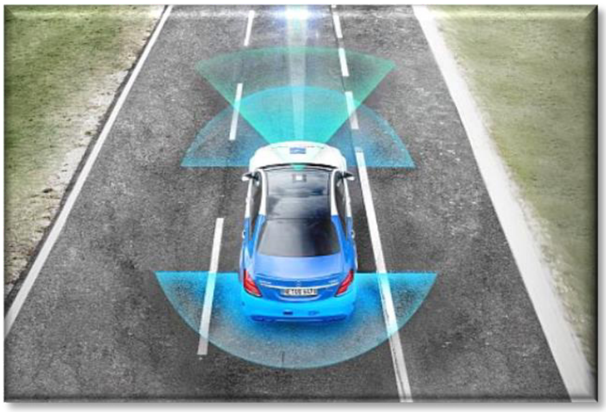
Advanced Driver Assistant Systems (ADAS) are important solutions to increase vehicle safety, comfort, energy efficiency and vehicle operators total cost of ownership. Highly Automated Driving (HAD) will furthermore allow to spend the time in the car in a different way, which can be used to increase profitability. Beside the expected benefits, ADAS and HAD require solving huge challenges in the areas: development time and cost, systems safety, hacker resistance and connectivity.

The paper describes the benefits and challenges of ADAS and HAD and presents a new method to overcome some of the mentioned challenges. The presented method combines real and virtual testing in a very tight way. A unique method for online evaluation of ADAS quality attributes including perceived safety is the basis for efficient transfer of application and validation procedures from road to lab.

The paper describes the method, plus applications on the road and in the virtual world. The combination of the method with actual cloud computing technology with 5000 cores allows to run more than 10 Mio. virtual validated kilometers per week.

1. INTRODUCTION

Advanced driver assistance systems (ADAS), Level 0 – Level 2, have become an integral part of our daily driving routine. Multiple functions for increased safety (e.g. emergency braking, blind spot detection, adaptive cruise control, lane keep assist, etc.) are already increasing our comfort and safety in modern cars. L0-L2 systems require the full concentration of the driver on the traffic.



The introduction of the next L3 function, traffic jam assist (TJA), allows to drive autonomous up to a certain speed, e.g. up to 60 km/h. TJA allows the passenger for the first time to concentrate on other activities, e.g. working, using the smartphone or shopping in the internet. Level 3 systems, expected for 2019, will allow to cover even longer distances without interactions by the driver. Nowadays the development is already focusing on Level 4. L4 systems will allow to concentrate on other activities at all speeds and nearly all traffic situations. L4 can be seen as real revolution in the automotive industry. L5, driverless vehicles, will be introduced some years after L4. Main applications will be Taxis and good transport.

Vehicle manufacturers' vision presents itself stringent to the customer - first ADAS, then highly and finally fully automated driving - the resulting advantages seem to be short within reach.

The potential for drastically improved active safety can be mentioned as first one major benefit ("vision zero accidents"). According to accident statistics, 90% and more of car accidents are caused by driver faults and could potentially be avoided by automated driving. This topic is increasingly important as traffic accidents are now ranked 9th on the ten most frequent causes of fatalities by the WHO (1.3 Mio people killed in road traffic accidents, 50 Mio people are injured each year).

L3 and L4 systems will drastically change our way to use cars and how we spend our time in cars during driving or during being driven. L4 cars can be ergonomic working offices, comfortable living rooms and areas for relaxing and regeneration and much more [1]. This transformation will open a totally new eco-system for emerging business models and markets.

However, these new possibilities are also confronted with major challenges that vehicle manufacturers must face on their way in realizing the vision of highly automated driving. The challenges can be grouped with respect to the vehicle (hardware/software) itself, its development, new legal aspects of automated driving and finally the disruptive potential of new business models [2]. The market for autonomous driving grows to $560 billion by 2035, based on new car revenues, hardware upgrades, apps, and other digital features as stated in [7].

Important fields of innovation regarding vehicle technology are robust 360° environment perception including divers sensor systems (radar, lidar, camera and ultrasonic) [3], safe and secure high power automotive computing platforms with AI as well as supporting backend services in the cloud. Most of the hardware related challenges are well addressed and the aim is now mostly on efficient mass production: lowering costs, size, and energy consumption of sensors and processing hardware, and meeting automotive standards with respect to robustness. These efforts are important, since lowering the additional costs for ADAS/HAD components and integration is key to ensure future attractiveness of automated cars.

As the vehicle software and its specifically tuned algorithms nowadays are a main attribute to distinguish car-brands, there is a hard competition going on between car manufactures in demonstrating their ability to drive driverless. In August 2013, Mercedes-Benz engineers accomplished a spectacular pioneering work: The S 500 INTELLIGENT DRIVE research vehicle independently drove the 100-kilometer route between Mannheim and Pforzheim, with high traffic density and demanding traffic situations. In 2018 Audi will release the A8 Sedan in the U.S.: the first-ever L3 self-driving car, able to control the car's steering and speed from a total stop up to 60 km/h. Announcements of nearly all OEMs expect L3 and L4 functions in cars of their brands to be released in 202x.

Now, an interesting battleground for autonomous driving is California. In the Golden State key indicators, such as the "autonomous miles driven in average without a driver intervention", are published [4]. Here clearly Waymo, the automated driving arm of Alphabet Inc., leads the game, as can be seen in Fig. 1 and Fig. 2 respectively.
This race about building self-driving cars, not only initiates major changes (reorientation and reorganization) within the competing companies themselves, but also leads to new strategic alliances and joint undertakings being formed [2]. New powerful ecosystems are built and all players will have to conquer new positions in the future value chain [7].

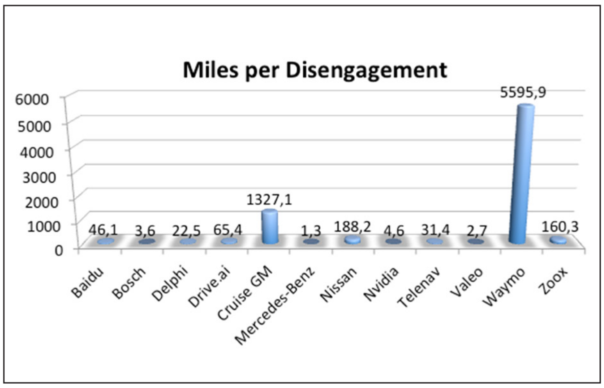


Fig. 1: Miles driven autonomously on average without driver intervention in California in 2017 according to official data published in [4].

Although the total number and the progress of tested miles on road seems impressive on a first look (at least for Waymo), this is only a very small number of miles to drive for validation purposes, even if considering potential additional testing outside California.

In contrast to the strategy of Alphabet Inc., to directly aim driverless cars, most carmakers follow the approach continuously releasing increasing levels of automation. On the way to realize driverless cars, estimated to come true in 2030+ [9], we will therefore see a step-by-step automation of different driving tasks (highway pilot, valet parking, intersection pilot, emergency driver assistant, etc.). It is important to mention, that following this strategy conventional car-manufacturers can take advantage of their leading expertise in car development and catch up on their knowledge in robotics.

There are multiple challenges to be solved. Apart from the vehicle focused challenges there is one big issue left to overcome - vehicle testing & validation. This article is dedicated to new validation approaches and solutions developed by AVL, to proof, that driverless cars meet the demanding expectations with respect to safety and quality.

First the important specific challenges in validation of automated driving are pointed out and a solution based on combining validation steps in virtual and real domain with objective evaluation is given. For the sake of clarity, the procedure is explained and demonstrated exemplarily for a rather simple function – the well-known Adaptive Cruise Control (ACC). The article concludes with a summary of the most important findings and results.

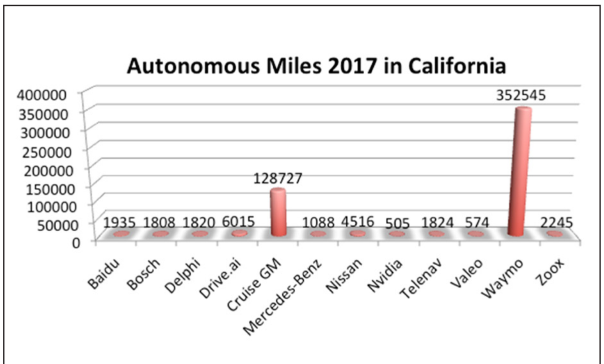


Fig. 2: Total miles driven autonomously in California in 2017 according to official data published in [4].

2. VALIDATION – A CHALLENGE

In the following the main differences between conventional and automated cars are analyzed, which are the root cause of the challenges connected with validation.

Cars equipped with ADAS and capable of HAD differ significantly from conventional vehicles in that, a far more complex interaction with the vehicle environment takes place, with the potential of cause-effect circles. For conventional vehicles at the system borders only a limited amount of simple physical quantities (mostly slow changing or constant) had to be considered, such as: air temperature and pressure, road friction and inclination, etc. In conventional validation therefore, different cases of environmental setups are covered with distinct (real) tests.

In contrast to this, automated cars use environment perception, performed by cameras, radar, lidar, sonar sensors, and car to infrastructure communication, leading to far more (and far more complex) physical interfaces between the vehicle and its environment. This has a direct impact on development, tuning, validation and release, of vehicle automation: The impact of the environment on the vehicle - and in some cases additionally its interaction - must also be considered in all these steps. Due to the richness of the interaction with the environment and the resulting multitude of possible situations, however, conventional signal-based testing with distinct test cases and load profiles is no longer sufficient.

Besides the more complex sensor components, automated driving functions base on software, which hierarchically grows with increasing automation levels [13]. Consequently, the functions to be validated increase in number and complexity, since functions of higher automation levels include lower automation features. Both effects increasingly raise the testing and validation effort.

An important trend in sensor data processing (especially in image processing) is the use of artificial intelligence through so called deep neural networks (DNN). This technique in contrast to previously used machine learning approaches, shows to scale far better with the amount of training data. Although DNNs already outperform humans in specific image processing tasks, validation of DNN is cumbersome, since it is still an unsolved question, how to extrapolate one test situation to another similar one. As a result, testing effort for DNNs is still huge. If DNNs are only used in sensor data processing - not for control – the testing effort however can be limited and performed on component level (black-box approach).

Finally, a big challenge in validating automated driving often mentioned is proving, that robot/ software driven cars are at least as safe as cars driven by humans. This is a crucial point for another main challenge connected with selling automated cars – the user acceptance. It seems, that finally for acceptance even higher levels of safety of automated cars compared to human driven ones are requested –practically perfect driving.

The issue with demonstrating quality and safety of software drivers compared with humans, come into play at so called automation level 3 and above according to SAE [5]. These levels of automation allow the driver to be, at least temporally, offline, and therefore the car must accomplish the whole dynamic driving task on its own. The step from level 2 and below to level 3 and above is a dramatic one, since it implies that now the entire task of object and event detection and response is up to the car [5].

State of the art approaches for proving super-human safety, based on statistic considerations of fatalities and travelled distances in public roads are described in [6], [8], [13]. The main point here is, that validation effort in driven distance for vehicle release may rise significantly (see Fig. 3). Following this, on road testing clearly is not feasible, neither from economic point of view nor if development time constraints are considered [8], [11] [12], [13].

Note that Fig. 3 also reveals the potential of using a higher resolution of assessing the quality/safety of an automated vehicle. Moving from 'fatalities' to 'reported crashes' may lower the required distance to drive to prove significant superiority of the automation. Also increasing difference in performance of the vehicle automation and average human beings will reduce the amount of necessary distance to drive to prove superiority.

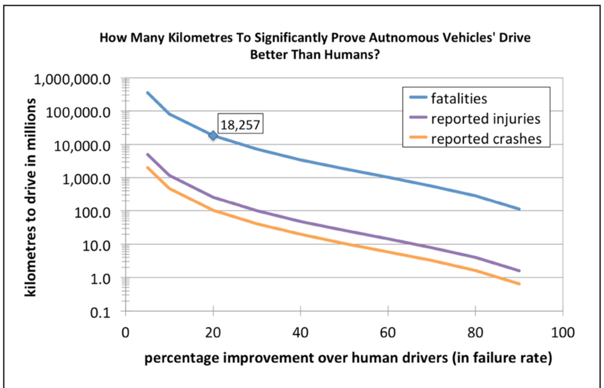


Fig. 3: Kilometers needed to demonstrate with 95% confidence and 80% power, that the autonomous vehicle failure rate is lower than the human driver failure rate according to [8]. E.g. for a system being at 20% lower failure rate 18 bio kilometers would be required. Assuming 100 test-vehicles driving in parallel 24/7 at approx. 40 km/h, this results in over 500 years testing.

Another important trend in the development of automated driving, is a paradigm-shift regarding development time and development cycles. Short update cycles (approx. bi-weekly to bi-annual) and agile development known from software-products enter the automotive domain, which was traditionally used to longer vehicle development cycles (e.g. 2-3 years). Consequently, release testing efforts will dramatically increase with the introduction of agile development paradigm.

To conclude, the challenges due to the nature of highly automated/autonomous cars are:

- Complexity of the automated systems still rises with automation levels, due to increasing amount of software.
- The dynamic behavior of the environment must be considered in testing.
- DNNs will play an increasing role in sensor data processing, and require high testing efforts.
- Statistically significant statements regarding safety, based on road traffic fatalities, require huge distances to be driven in tests.
- Agile development paradigms demand significantly more release-testing.
- The huge number of tests must be evaluated safely.

3. VALIDATION

To overcome the discussed challenges, the well-known V-process is still applicable, but specific measures must be met to apply to highly automated vehicles [11]. First system components (sensors, actuators, software, vehicle hardware, etc.) must successfully be tested, e.g. based on conventional signal-based methods. In a second step, early scenario-based virtual tests of the entire automated system must be performed using simulation. Additionally, different techniques for combining real and virtual testing can be applied [12].

For conventional development and release, digitalization and simulation, which in this context often are referred to, as 'virtualization' or 'front-loading', is beneficial - for HAD, virtualization of development and testing is mandatory.

As suggested in [10], [13] future validation will, additionally to synthetically generated driving scenarios, consider real driving scenarios, recorded not only in specific test-vehicles, but also reported from already released cars in operation. As premium cars will be equipped with all necessary sensors soon, relevant data for testing the next generation autonomous systems can be extracted easily.

As virtual validation is most promising to be the answer to the challenges in the assessment of HAD, in Fig. 4, steps of the proposed approach for virtual optimization/validation, based on objective assessment, are sketched. Details are explained in in the following using an ACC example.

3.1 OBJECTIFICATION

Checking development results against requirements is key in all modern development approaches. The faster and more accurate the check is done, the faster and more effective the development can be performed. In this context objectification is the base technology to address complex measuring tasks to check product maturity.

We use the term objectification, since it enables direct objective measuring of complex and mostly abstract behavior attributes of a vehicle. These attributes are defined usually from a subjective point of view – from the drivers view. To be independent from one specific subjective judgement and to be able to make reproducible statements, objectification is used to rate driving performance on an objective scale.

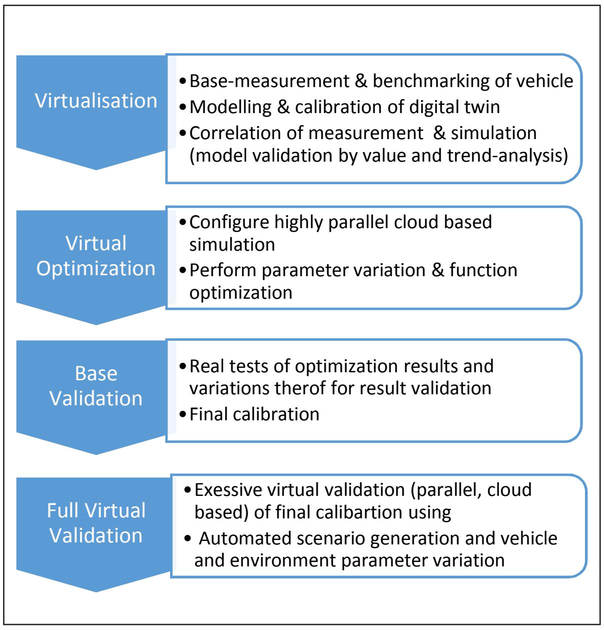


Fig. 4: Development and validation approach for automated driving based on objectification and aligned tests on road and in virtual domain.

This objectification can either be reached by statistical approaches (lots of drivers rating the vehicle), or by software-based evaluation, derived from expert knowledge condensed in specific KPI-values.

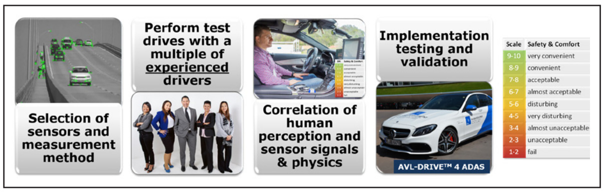


Fig. 5: Objective assessment of ADAS on feature level through standardized KPIs and automated evaluation.

AVL's tool-based objectification (AVL-DRIVE™) is used to evaluate quality, safety and perceived safety of different maneuvers using absolute rating values in a range of 0-10. This software based rating approach speeds up the evaluation of calibration and by this is the key enabler for efficient and fast optimization, and finally reproducible validation of AD-functions as depicted in Fig. 6 and discussed in [14].

Fig. 6: High quality fulfilment & development efficiency from target setting to validation through measurable parameters & highly automated processing. Objective assessment creates benefits along the entire development process from requirements engineering to release testing leading to a high level of quality and speed in development.

For the selected example of the adaptive cruise control objective assessment is done for specific features such as:

- Quality of speed control in different driving conditions at different speeds (no preceding vehicle).
- Quality of distance/time-gap control when following a preceding vehicle.
- Dynamic of approaching a target vehicle.
- Quality of sudden cut-in/cut-out scenarios.
- …

The rating is executed automatically, if a corresponding scenario is detected by permanently monitoring the vehicles states, its sensors, and additional sensors of the test equipment during driving tests in the operational design domain. Weighted combination of the rated sub-features leads to an over-all rating of a driving automation system.

The objective assessment also enables to benchmark existing solutions and define distinct design targets to position new applications compared to existing ones as shown in Fig. 7.

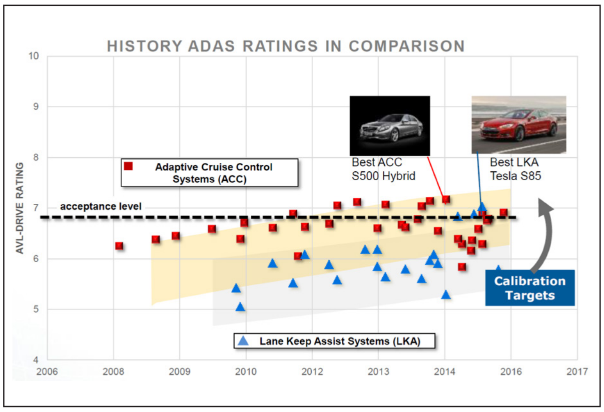


Fig. 7: History of combined rating of various adaptive cruise control and lane keeping assistant systems over the past enables positioning and target value design for future applications.

3.2 VIRTUALIZATION

Virtualization of the subject under test consists of transforming the vehicle, its sensors and software, and the surrounding environment into simulation models and execute test-scenarios in simulation tools, as summarized in Fig. 8.

Attention must be paid here that results from virtual domain can successfully be transferred back to the real vehicle. First detailed physical modelling of the

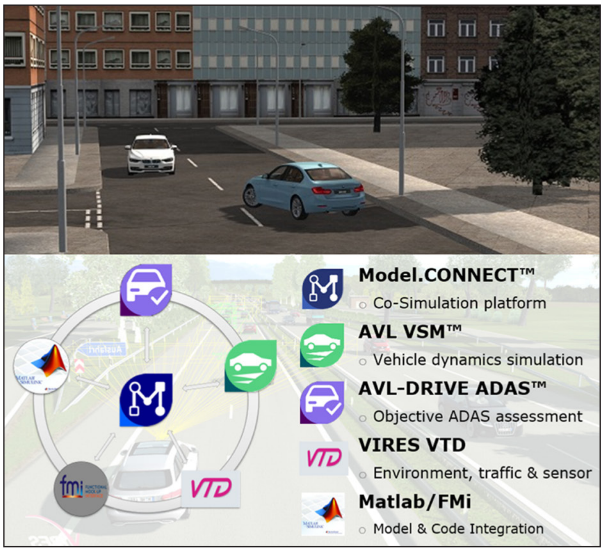


Fig. 8: AVL ADAS/AD tool-chain for virtual development, testing and validation

vehicle and direct transfer of the ADAS-software is mandatory. In addition to that validation of the digital twin is achieved by correlating KPI-values between virtual domain and reality, of the overall closed loop behavior of the entire system (automated vehicle plus environment).

For the example of the mentioned ACC-function in practice virtualization involved:

- Tuning a detailed first principle vehicle model in a vehicle simulation software (AVL VSM™) to match recorded vehicle dynamic behavior in a predefined maneuver catalogue.
- Modelling the required radar-sensor in the environment simulation to generate required inputs to the ACC-software. This was done using an abstract geometric sensor model considering mounting location, and a simplified sensor range and detection area approach.
- Transferring the ACC-software to run as part of the system simulation. In the example, this was accomplished by an export of the software to a functional mock-up unit (FMU).
- Defining a scenario-catalogue and use an automated execution and evaluation tool-chain.

The discussed example was realized using AVL's integrated open development platform Model.CONNECT™ to coordinate and link all involved simulation and evaluation tools as shown in Fig. 8.

The validation of the digital twin was done based on correlation of KPI-vales of vehicle measurement and simulation results (matched AVL-DRIVE™

ratings). This correlation step may also include parameter variations to additionally prove, that also trends (sensitivity of parameters) are mapped properly as depicted in Fig. 9 and Fig. 10.

Fig. 9: Digital twin: Matched scenarios in vehicle road test (left) and vehicle simulation (right) to check correlation of real and virtual domain, based on matching physical signals and objective assessment.

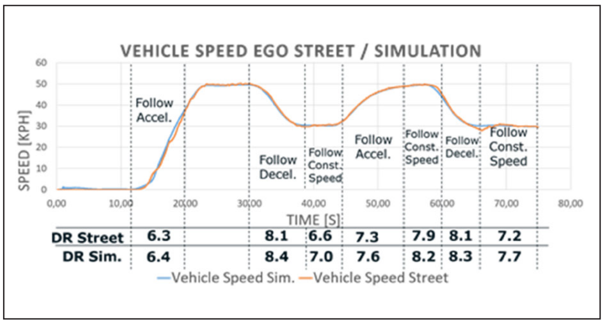


Fig. 10: Exemplary time plots of velocity of ego-vehicle to validate closed-loop longitudinal vehicle behavior (correlation of real and virtual domain for ACC-Validation) also based on matched AVL-DRIVE™ ratings (DR).

3.3 VIRTUAL OPTIMIZATION

Tuning driving functions to satisfy a targeted brand specific customer impression involves extensive testing, as the entire vehicle system may need to be involved. To keep short time-to-market development cycles, automated tuning in the virtual domain plays a key role in developing high quality driving functions fast.

As the virtualization step is successfully done, the digital twin can be used for optimization and function tuning in virtual domain.

The advantage is clear: an extended range of tests can be performed compared to real-road tests. Even potentially dangerous driving situations can be included safely. Reproducible results are guaranteed and automated objective test evaluation ensures a fast and effective calibration process of the AD-function at any time considering the complex interaction with the environment.

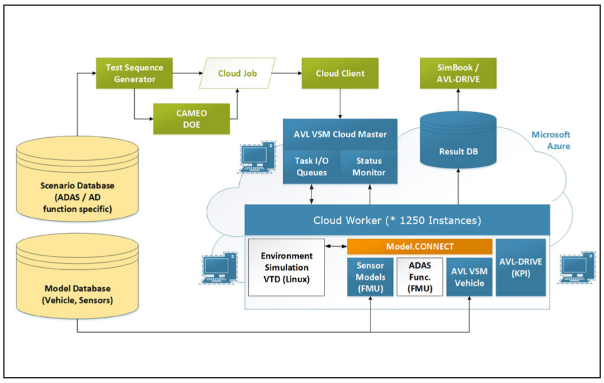


Fig. 11: Cluster/Cloud simulation process

Executing detailed parameter variations for optimizing the tuning parameters in simulation is limited by the computational resources of standard office computers. To successfully tackle more demanding tuning tasks, aligned cluster/cloud execution of simulation is required for scaling the approach to the specific needs as shown in [15]. Cluster/Cloud execution of multiple simulation instances as depicted in Fig. 11 will clearly lead to faster execution of the optimization task compared to office computer usage, but will create additional overhead for coordinating execution in the cluster/cloud. For the example case of the ACC optimization this tradeoff has been analyzed and results are summarized in Fig. 12. The take-home-massage is that using AVL's tool chain the breakeven is reached very soon, i.e. mainly after the cloud setup-time is compensated by the first results.

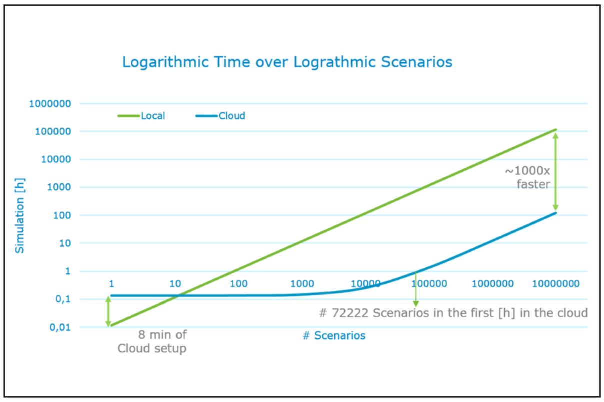


Fig. 12: Cluster/Cloud execution (1250 instances, 4 cores each) vs. local office computer (16 cores).

AVL's unique tool-chain fully covers the crucial step of scaling and offers simulation, evaluation and optimization executed on cluster/cloud computing. Convenient configuration abilities take care of specific user's needs. as shown in Fig. 13.

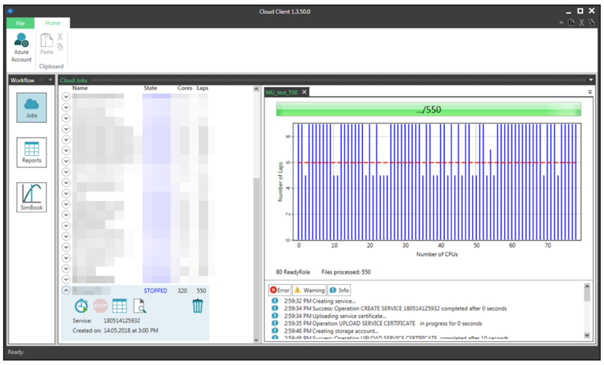


Fig. 13: Cluster/ Cloud based simulation, evaluation, optimization customized in tool frontend.

In the example of the ACC, control parameters of the speed and distance control have been optimized with respect to KPIs defined in the requirements of the function as depicted in Fig. 14. Note that this approach inherently supports agile development methodologies, as they are state of the art within the calibration process.

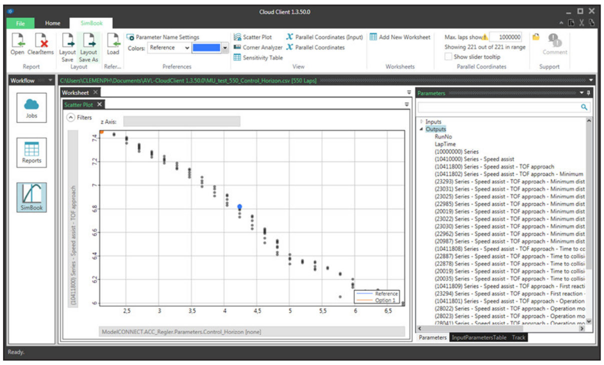


Fig. 14: Analysis of cloud based optimization. The plot shows exemplarily the objective rating of the ACC over a variation of the control horizon. As can be seen additional variation of another control parameter leads to minor dispersion, but main influence on over all drive-rating is the control horizon in this example.

As shown in Fig. 15 also robustness analysis can be performed within the optimization step using the proposed setup.

The result of the cloud based optimization step is a set of optimal tuning parameters for the driving function. Note that, only if the optimization criteria considers both, standard and driving performance KPI's objectifying subjective impression of the driver, a safe and brand specific tuning can be achieved.

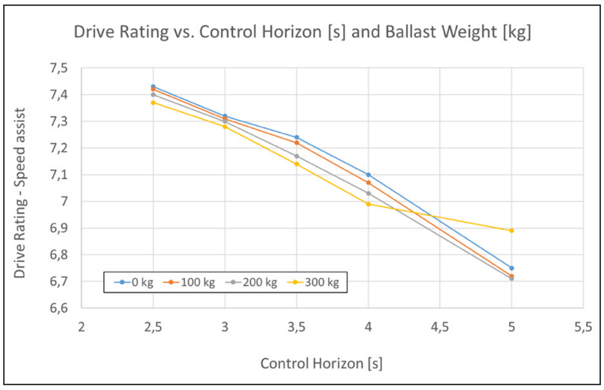


Fig. 15: Analysis of robustness of the ACC-rating, against disturbances depending on the control horizon.

3.4 BASE VALIDATION

The optimized final calibration set from virtual domain in this step is now to be validated and cross-checked on the real vehicle in core scenarios, forming a so called base validation. Again, this may include checking variation of scenario parameters to also cover sensitivity mapping. This process is like the model-validation step during virtualization, which is done using correlation of closed-loop simulation results and evaluation of KPI's thereof.

3.5 VIRTUAL VALIDATION

For the last step - the virtual validation - finally the tool-setup from optimization can be re-used, but instead of function parameter optimization the target is now to execute the full validation plan. This comprises a wide range of variation in parameters of selected test-scenarios. The validation plan includes an extended scenario-catalogue required for proving quality, safety and perceived safety of the vehicle. Again, cloud execution offers benefits in scalability by massive parallelization and customizability. The online evaluation of the tests enables direct visualization of the test-coverage with respect to user-defined KPI's (Fig. 16).

In comparison to the calibration approach, which uses the variation of controller parameters to improve the performance overall, the validation uses the validation plan, an abstract form of environment variation. Both are using the same methods of scalability of the cluster/cloud enabled virtual co-simulation environment.

In contrast to simple (fail/pass) evaluation the rating-based approach offers quantitative insight

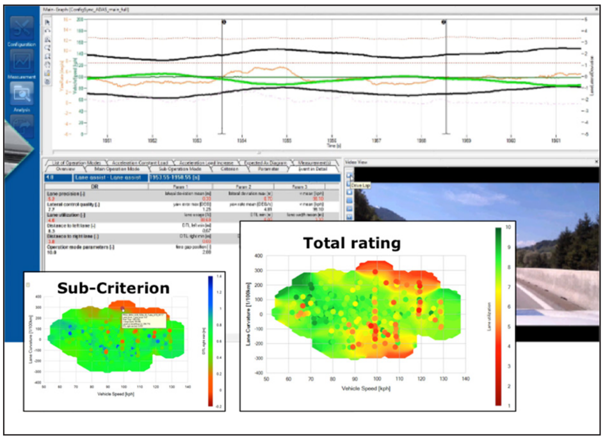


Fig. 16: Dynamic test result and test coverage reports.

into overall quality and safety. This enables effective improvement and finally results in a consistent customer impression. Additional to final reports, all virtual tests results are collected and are available for detailed analysis.

4. CONCLUSION

After clearly stating the challenges in validating highly automated and autonomous vehicles, a combined real/virtual optimization and validation process was proposed and explained using an example.

The proposed process closely coordinates real and virtual optimization/validation steps. The used objective assessment within this method turns out to be the central key, enabling a high level of test-automation, consistent quality and finally a safe validation. Through this the required savings in time and effort for the discussed example could be reached (testing time reduced by 80-90%).
High quality fulfilment and development efficiency, from target setting to validation, is guaranteed through measurable parameters and highly automated processing. The objective evaluation of driver feeling paves the way to best in class driving quality and perceived safety, which has already been proven in series production solutions SAE L0 to L2 and successfully been implemented at several premium OEMs. As an added value, the objective assessment is open to multiple suppliers and enables flexibility to be adapted for future cost- effective solutions.

LITERATURE

[1] Klaus Mittermair, Yann-Georg Hansa, "KPMG's Global Automotive Executive Survey 2017," 2017, KPMG International,

[2] Paul Gao, Hans-Werner Kaas, Detlev Mohr, Dominik Wee, „Automotive revolution – perspective towards 2030 How the convergence of disruptive technology-driven trends could transform the auto industry," Report, 2016, McKinsey&Company,

[3] A. Cacilo et al., "Hochautomatisiertes Fahren Auf Autobahnen – Industriepolitische Schluss-folgerungen", 2015

[4] State of California, Department of Motor Vehicles, „Autonomous Vehicle Disengagement Reports 2017", 2017

[5] SAE International, On-Road Automated Driving (Orad) Committee On-Road Automated Driving (Orad) Committee , Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems (International standard J3016), 2016

[6] Winner, Hermann & Hakuli, S & Lotz, F & Singer, C. (2015). Handbook of driver assistance systems: Basic information, components and systems for active safety and comfort. 10.1007/978-3-319-12352-3.

[7] M. Römer, S. Gaenzle, and C. Weiss, "How Automakers Can Survive the Self-Driving Era", 2016, A.T. Kearney

[8] Kalra, Nidhi and Susan M. Paddock, "Driving to Safety: How Many Miles of Driving Would It Take to Demonstrate Autonomous Vehicle Reliability?," Santa Monica, CA: RAND Corporation, 2016,

[9] Uday Singh, Jenitha B.V. and Nandini Tare, "Impact of autonomous vehicles on public transport sector," KPMG International, 2017,

[10] W. Wachenfeld and H. Winner, "Virtual Assessment of Automation in Field Operation – A New Runtime Validation Method," in 10. Workshop Fahrerassistenzsysteme, Walting im Altmühltal: Uni-DAS e. V., 2015.

[11] P. Koopman and M. Wagner, "Challenges in Autonomous Vehicle Testing and Validation," SAE Int. J. Transp. Saf., vol. 4, no. 1, pp. 2016-01–0128, 2016.

[12] J. E. Stellet, M. R. Zofka, J. Schumacher, T. Schamm, F. Niewels, and J. M. Zollner, "Testing of Advanced Driver Assistance Towards Automated Driving: A Survey and Taxonomy on Existing Approaches and Open Questions," IEEE Conf. Intell. Transp. Syst.

Proceedings, ITSC, vol. 2015–October, pp. 1455–1462, 2015.

[13] A. Koenig, K. Witzlsperger, and F. Leutwiler, "Overview of HAD validation and passive HAD as a concept for validating highly automated cars," - Autom., vol. 66, no. 2, pp. 132–145, 2018.

[14] J. Holzinger, E. Bogner, T. Schlömicher, "Objective assessment of automated driving functions ADF", (2016), Japan SAE

[15] P. Clement, P. Schoeggl, M. Oswald, P. Quinz, S. Frager, T. Schlömicher, "Cloud-based validation and optimization of highly automated vehicles: A new approach for cloud-based validation and optimization of highly automated vehicles", Japan, SAE, in press