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Target Designation for Straight Road Lane Departure Scenario and ELKS Calibration

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Abstract: It is one of the most serious problems in advanced driver assistance systems (ADAS) field to find target values of Key Performance Indicators (KPIs) and to be able to calibrate these systems to achieve the desired comfort and safety. In this study, a scenario related to the lane-keeping assist system (LKAS) of the emergency lane-keeping system (ELKS) has been selected as the system to be worked on and the "Target Designation" (TD) method is proposed for the explained problem. The obtained target matrices (TM) are used for the calibration of the ELKS controller on the determined operating points. As a first step of the TD procedure, KPIs were defined for the scenario and data were collected from a vehicle that was determined as a benchmark vehicle. According to the KPI values obtained from this vehicle, optimal parameter sets were obtained for each operating point by implementing genetic algorithm (GA) and non-linear optimization (NLO) methods on the ELKS controller of a benchmark vehicle.

Keywords: target designation, emergency lane keeping system, ADAS calibration, KPI

Düz Yolda Şeritten Ayrılma Senaryosu İçin Hedef Tayini ve ELKS Kalibrasyonu

Özet: Gelişmiş Sürücü Destek Sistemleri (ADAS) alanında, temel performans göstergelerinin (KPI'lar) hedef değerlerini bulmak ve bu sistemleri istenen konfor ve güvenliği sağlamak için kalibre edebilmek, en ciddi sorunlardan biridir. Bu çalışmada acil şerit koruma sisteminin (ELKS), şerit koruma fonkisyonuna (LKAS) ait bir senaryo, çalışılacak sistem olarak belirlenmiş ve açıklanan problem için "Hedef Tayini" (TD) metodu önerilmiştir. Metodoloji sonucunda elde edilen hedef matrisler (TM), belirlenen çalışma noktalarında ELKS kontrolcü kalibrasyonu için kullanılmıştır. Belirlenen senaryo için KPI tanımları yapılmış ve denektaş araç olarak belirlenen bir araçtan veriler toplanmıştır. Bu araçtan elde edilen KPI değerlerine göre, bir test aracının ELKS kontrolcüsü için genetik algoritma (GA) ve lineer olmayan optimizasyon (NLO) metotları kullanılarak, belirlenmiş olan her bir çalışma noktası için optimal parametre setleri elde edilmiştir.

Anahtar Kelimeler: hedef tayini, acil şerit koruma sistemi, ADAS kalibrasyonu, KPI

RESEARCH PAPER

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1 Introduction

ADAS are systems that collect information from the environment through various sensors and imaging systems, alerting the driver or intervening in driving at various levels in risky situations during driving ([1]). Classification of ADAS, according to the International Society of Automotive Engineers (SAE), ranges from level zero to level five, considering intervention in horizontal or vertical axis and intervention duration ([2]). The use of ADAS aims to prevent traffic accidents caused by driver errors, thereby increasing driving safety, efficiency, and comfort ([3]).

Vehicles must undergo a series of tests before commercial deployment, which includes the approval of driver assistance control systems ([4]). Scenario-based development and testing approaches are possible solutions for validating the safe operation of autonomous vehicles. Real-life situations can be digitally replicated, including the vehicle model, controller, etc., and tested in virtual environments through simulations. In this way, all possible scenarios are tested and approved under conditions where maximum security and performance are ensured. PEGASUS ([5]) ve ENABLE-S3 ([6]) projects are leading works in scenario-based validation for autonomous vehicles. According to the approach presented in the PEGASUS Project, scenarios are defined in 6 layers: road structure, infrastructure, temporary changes on the road, objects, environment, and digital information ([5]).

One of the main causes of accidents is vehicles deviating from their lane or road. Driver assistance systems that control the lateral plane of the vehicle help prevent accidents caused by drivers unintentionally leaving their lane ([7]). This study focuses on the ELKS, mandatory in M1 (Passenger vehicles with less than 8 seat) and N1 (Vehicles used for the carriage of goods and having a maximum mass not exceeding 3.5 tonnes) type vehicles. The system's optimal response under different operational conditions is enabled through calibration of controller parameters ([8]). A study examining LKAS and Lane Departure Warning System (LDWS) designed a controller using vehicle direction deviation angle, lateral deviation from the lane center, and steering torque. Real road test data with a 500 meter curve radius was used to compare situations with and without the controller's reference path creation algorithm ([9]).

Multi-objective optimization algorithms are applied when multiple factors in a solution set have different weights. In a study examining LDWS, optimization was performed using PID controllers and genetic algorithms ([10]). Another study used Particle Swarm Optimization (PSO) algorithms to calibrate the Adaptive Cruise Control (ACC) system for scenarios following the acceleration of the vehicle ahead, using parameters like the leading vehicle's acceleration, ego's response time, and ego's maximum acceleration ([11]). In a study that focuses on the longitudinal assessment of ADAS systems with KPIs as the basis, the approach to effectively implementing the KPI-based development process has been presented by selecting the ACC function, using scenario-based simulations ([12]).

In this study, the controller of the ELKS system is optimized and calibrated based on the considered scenarios and the KPIs to be used in these scenarios. Initially, scenarios related to the ELKS system are identified, and then KPIs are determined, leading to the extraction of target matrices for relevant maneuvers. To achieve the right controller parameters that will provide the targeted KPI values, a simulation platform is designed, incorporating the ELKS controller model of the test tool. This platform enabled the acquisition of virtual data from the benchmark vehicle, and calculation of numerous KPI values for each operating point. Finally, using GA and NLO algorithms with the help of the KPI values and the upper and lower limit values obtained in the initial phase of the target matrix, the controller parameters are calibrated. In Chapter 2, while discussing the problem to be addressed in the study, Chapter 3 introduces the ADAS function under investigation, namely ELKS. Chapter 4 covers the study parameters, KPIs, and the target values set for the validation of the system. Chapter 5 and Chapter 6 discuss how controller calibration and optimization are performed respectively. Finally, in chapter 7, the conclusion is presented.

2 Problem Definition

The first stage of the study is the identification of the ADAS function in the scope, ELKS. After the system is identified, it is determined for which scenario, operating ranges, and KPIs the target values will be derived. Then, for the determined Design of Experiments (DoE), vehicle records collected from the benchmark vehicle are fed into a Post Processing Tool (PPT). The PPT uses the records from the benchmark vehicle to detect relevant scenarios for the determined operating areas and performs related KPI calculations. Since multiple tests are conducted in each operating area, the KPI target values for these areas are found by fitting them into mathematical functions using machine learning (ML) methods. The input variables in the models are operation parameters, while the outputs are KPI values.

AVL CAMEO^{TM} is utilized to train ML models and to obtain target values for the relevant operating points. ML models are used to create the TM, which contains target values of KPIs in the relevant operating areas and the lower and upper limits of these target values. The second stage of the study involves calibrating the ELKS controller of the test vehicle using the target values obtained from the benchmark vehicle. For this purpose, an AVL VSM^{TM} block and AVL ModelCONNECT^{TM} ([13]) simulation platform has been designed, including an AVL VSM^{TM} block containing the vehicle model of the benchmark vehicle, an Functional Mockup Unit (FMU) block containing the ELKS controller model, and a Virtual Test Drive (VTD) block containing the driving simulation program. Thanks to this platform, test simulations have been conducted for a new Design of Experiments (DoE) that includes operating parameters and controller parameters, and data has been collected. The collected data is processed again with PPT, and KPIs are calculated for each detected scenario. A new data set is created from the KPIs calculated for each test simulation and the parameter sets used in the relevant test. Following this step, new ML models are trained from this data set with AVL CAMEO^{TM} ([14]). The trained ML model is optimized in AVL CAMEO^{TM} using GA and NLO algorithms to obtain an ELKS controller that performs well to keep the KPI values within the lower and upper limits of the TMs obtained from the benchmark vehicle. Thus, different optimal parameter sets are identified for each different operating point. Finally, the obtained parameter sets are validated using an iterative approach which is explained in detail on Section 7. In Fig. 1the workflow for determining the presented targets are included in this study.

3 System Definition of ELKS

The European Union's (EU) General Safety Regulation (GSR) 2019/2144 ([15]), mandates the installation of an emergency lane keeping system in all new type M1 and N1 vehicles and compliance with EU Regulation 2021/646 ([16]). ELKS is a driving assistance system that warns the driver and corrects the route when the driver accidentally leaves the lane. Current ELKS technologies are based on lane detection, and the performance of these systems is not guaranteed in situations where such markings are not present. This system has two main functions: LDWS and corrective directional control function (CDCF). CDCF is a control function within an electronic control system that can provide wheel braking and can change the steering angle on one or more wheels for a limited time. This prevents the vehicle from leaving the desired lane and colliding with a vehicle in the adjacent lane. LDWS also provides a warning to the driver before the system intervenes. Just as on a straight road, on a curved road, when the vehicle approaches the lane markings and tends to cross them, the system intervenes to keep the vehicle within its lane, allowing the journey to continue. This system, which operates between 65 km/h and 130 km/h, can intervene to prevent the vehicle from leaving the lane by applying a lateral speed of 0.1 m/s to 0.5 m/s on a straight or curved road.

Basically, ELKS controller gives a steering wheel output as a disturbance effect, however behind this algorithm complex calculations are conducting. Roughly, 3D look-up table is using to apply optimum steering wheel angle in case of ELKS activation. Related inputs to look-up table are longitudinal speed, lateral departure speed, and lane lateral deviation of Ego. These 3 inputs based steering wheel angle calculation provides flexibility to control the Ego for different Operational Design Domains (ODDs) by interpolating for given speeds and lateral deviations. For instance, if lateral departure speed is too high during the ELKS activation, steering wheel angle should be smaller to reduce rolling effect towards out of the lane, in contrast controller output should be high enough to direct Ego into the lane as quickly as possible. When all those effects are taken into account, precisely correlated steering wheel angle among inputs have great importance.

The ELKS test scenarios in the Lane Keep Support Systems protocol of the European New Car Assessment Programme (Euro NCAP), which determine the safety capacity of cars, include scenarios where the vehicle departs from the road boundaries and goes onto the curb, grass, soil, or other areas; the vehicle departs from a continuous lane; the main vehicle departs from its lane when a vehicle is approaching from the opposite lane; and scenarios where the main vehicle, despite being in the same direction as the adjacent vehicle in the next lane, crosses the lane markings ([7]). In this study, from the test scenarios of the CDCF, which is one of the functions under ELKS, the straight road lane departure scenario and the curved road lane departure scenarios were preferred. TM has been extracted for both directions of separation (left-right) of these scenarios, but only the straight road rightward lane departure scenario was preferred for calibration. The main objectives of selecting only the rightward straight road lane departure scenario are, there were no differences between leftward and rightward lane departures, except sign of values, moreover existence of a reasonable number of real world scenario data on the straight road to train ML models.

4 Target Designation

In this study, the determination of Key Performance Indicator (KPI) target values for specific scenarios and their specific operation ranges with the aim of the validation of Advanced Driver Assistance Systems (ADAS) is referred to as TD.

4.1 Operation Parameters

For the straight road scenarios used in the study, the Ego longitudinal start speed and Ego departure speed parameters were determined. The main factor in determining these parameters in this way is the anticipation that these parameters will have a high-level impact on the KPI values. For DoE, these parameters are determined as $70, 100, 130$ km/h and $\pm\ 0.2, 0.4, 0.6$ m/s points, respectively.

4.2 Key Performance Indicators

In order to realize the TD in the selected scenarios and perform controller calibration, it was necessary to determine KPIs. Within various model types available in AVL CAMEO^{TM}, robust neural networks (RNN) and free polynomial models (FPM) were utilized due to their good model

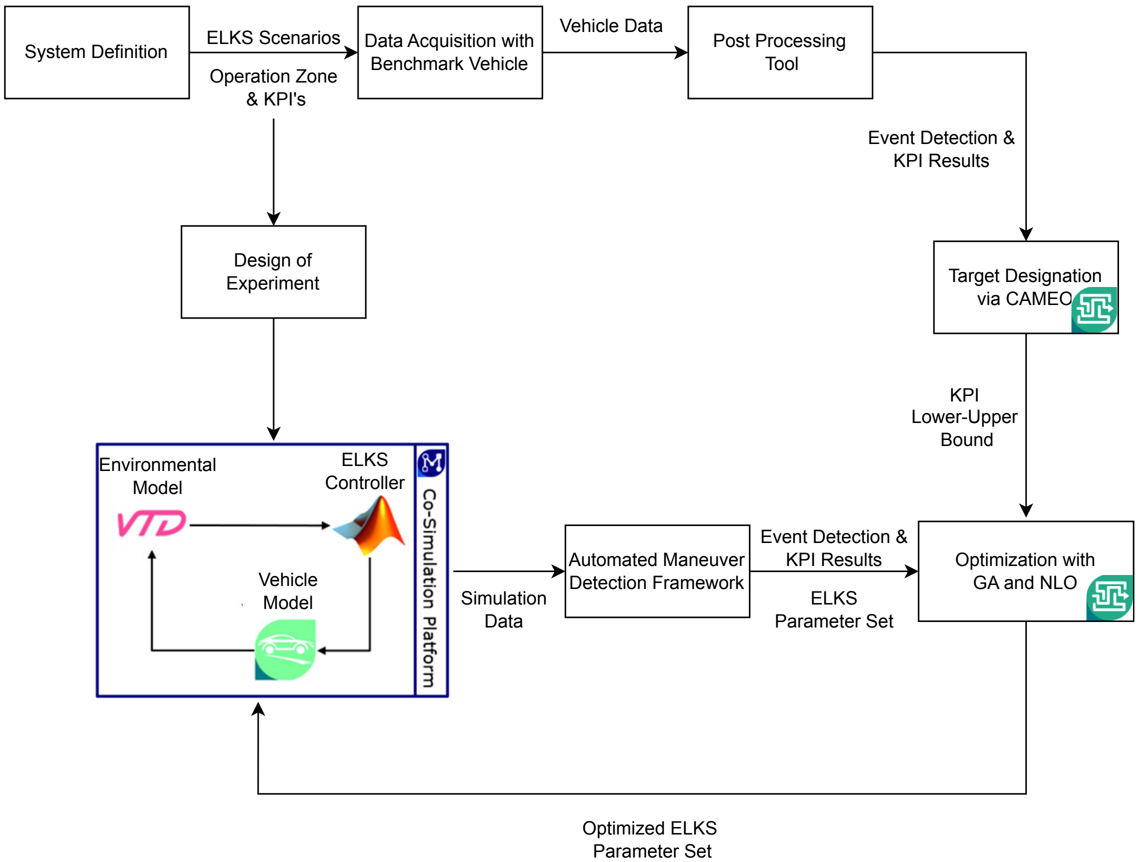

Fig. 1 Workflow

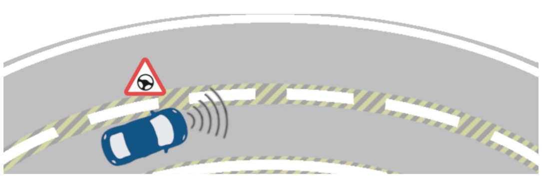

Fig. 2 Curved road lane departure scenario.

Fig. 3 Straight road lane departure scenario.

qualities. The quality of fit is determined through the statistical coefficient, called R^2, where R^2 is above 0.7 accounted as acceptable, over .0.95 is perfectly matched ([14]). The determination coefficient; signifies the extent to which model accounts for the variance of the measured values from a fixed mean. It demonstrates the level of precision of how the model conforms to the measured data. The KPIs, their descriptions, the ML models used, and R^2 values are presented in Table 1. The R^2 value specified in Table 1 directly provides insight into the model quality. The proximity of the value to 1 indicates the closeness between the data used for model training and the trained model..

Among all KPIs, R^2 has the highest value in EgoYawRateRate_min. This is because this KPI represents the first intervention by the controller to keep the vehicle within its lane, preventing it from deviating. Therefore, a correlation close to 1 for this KPI is expected and desired. Similarly, R^2 has the lowest value in EgoYawRateRate_max. The reason for this is that the second intervention movement is smoother than the first, making it more difficult to observe correlation.

The data used in TD was cleaned of outliers within the data set before being used in modeling in AVL CAMEO^{TM}, thereby improving the model quality. Values outside the specified threshold might be outliers. The tool shows the outliers values in different colors. Selecting outliers can be deactivated manually by user and the model can be rebuild provides to filter automatically. Outliers, measured values, and model predictions for the EgoP2PStrAng KPI are illustrated in Fig. 4. The deactivated outliers are red in this figure. The intersection curve depicting the variation of the same KPI according to operating parameters is provided in Fig. 5. Equation 1 was employed during the calculation of the KPI to be minimized during optimization.

t_{start} : first intervention time [s]
t_{end} : second intervention time [s]
$StrAng$: steering wheel angle [°]

$$P2PStrAng = [StrAng_{max} - StrAng_{min}]_{t_{start}}^{t_{end}} \quad (1)$$

4.3 Dataset

The data used for the TD stage of the study was collected under ideal (closed to traffic) test conditions from a vehicle considered as a benchmark vehicle in real world. It is accepted that the benchmark vehicle generates valid data since the test environment is ideal and vehicle parameters are calibrated. Tests were conducted multiple times at the working points described in 4.2 and at points between them. Thus, a data set was obtained to use benchmark data.

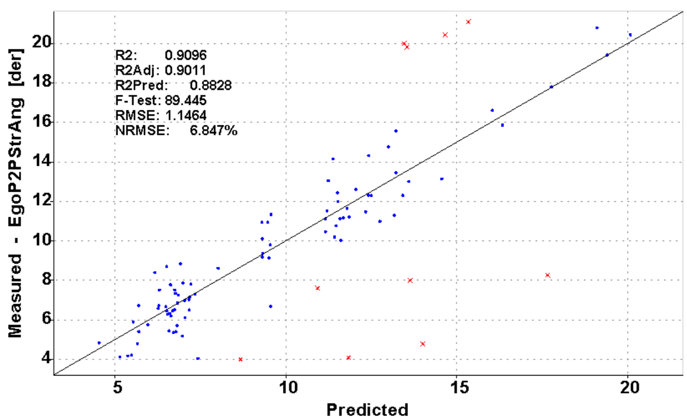

Fig. 4 P2PStrAng measured/predicted and outliers.

4.4 Target Matrices

Robust Neural Networks (RNNs) and Free Polynomial Models (FPMs) were used to model the relationship between operation parameters and KPIs through AVL CAMEO™. Between the two models, whichever ML model gave better results in terms of error metrics (R^2, $RMSE$), that model was preferred for the respective KPI.

The error metrics (R^2, $RMSE$) employed in this study have been judiciously selected due to their widespread acceptance and recognized adequacy in the context of research. $RMSE$ quantifies the disparities between predicted and actual values by computing their squared differences. Notably, $RMSE$ stands out as a metric of preference for assessing the performance of diverse machine learning algorithms

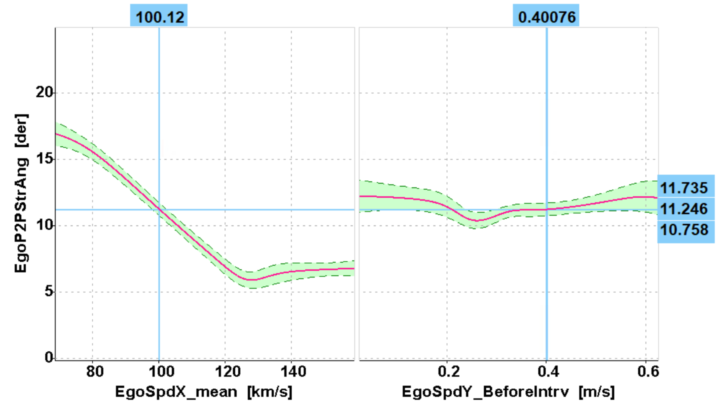

Fig. 5 P2PStrAng operation region intersection incline.

([17]). Concurrently, R^2 constitutes a pivotal statistical measure gauging the extent to which the model explains the underlying data. It is noteworthy that within the academic literature, the combined utilization of R^2 and $RMSE$ has become customary for the comprehensive evaluation of model performance ([18]).

After the models were trained with the data set described in Section 4.3, target values for each KPI at all working points and the lower and upper limits of these values were obtained. The lower and upper limits were determined as the lower and upper limits of the confidence interval. Obtained target values for EgoP2PStrAng KPI, which is also the target function, are given in Table 2.

5 Controller Calibration

The second phase of the study, as mentioned in Section (4.4), is to calibrate the ELKS controller parameters of the test vehicle using the obtained target matrices, taking the benchmark vehicle as a reference. The intended objective here is to align the controller performance of the test vehicle as closely as possible to that of the reference vehicle's controller performance.

5.1 Simulation Platform

For simulations, the test vehicle model AVL VSM™; for the ELKS controller in the vehicle, Simulink/FMU; and for the road and environment models, VTD are used. In VTD, the road curve radius, speed, and the deviation of the Ego vehicle from the center axis of the lane obtained from the radar sensor are processed in the controller, thus the necessary steering angle information is calculated. This steering angle is recalculated in the vehicle model according to the vehicle's speed and dynamic model and then fed back to VTD continuously.

Basically, ELKS controller gives a steering wheel output as a disturbance effect, however behind this algorithm complex calculations are conducting. Roughly, 3D look-up table

Table 1 Straight road lane departure scenario for KPI Table

KPIs	Description	ML Model	R^2 Value
EgoAccY_AfterIntrv_max	Maximum lateral acceleration after the move that returns the ego vehicle to the lane	RNN	0.76
EgoP2PStrAng	Difference of maximum steering angles in the move that turns the ego vehicle into the lane and the move made to put it back in the lane	RNN	0.91
EgoStrWhlAng_std	Ego steering wheel angle standard deviation	FreePolyModel	0.87
EgoDTLC_min	Ego distance to lane center minimum	RNN	0.79
EgoYawRate_max	Ego yaw rate maximum	RNN	0.84
EgoYawRate_min	Ego yaw rate minimum	FreePolyModel	0.82
EgoYawRateRate_max	Ego yaw rate acceleration maximum	FreePolyModel	0.72
EgoYawRateRate_min	Ego yaw rate acceleration minimum	RNN	0.96

Table 2 Ego P2PStrAng [$\circ$] Target Matrice

Longitudinal velocity [km/h] \ Lateral velocity [m/s]	0.2	0.4	0.6
70	13.54	16.80	21.16
100	11.47	11.27	12.24
130	6.52	5.91	7.25

is used to apply optimum steering wheel angle in case of ELKS activation. Related inputs to look-up table are longitudinal speed, lateral departure speed, and lane lateral deviation of the Ego vehicle. These 3 inputs based steering wheel angle calculation provides flexibility to control the Ego for different Operational Design Domains (ODDs) by interpolating for given speeds and lateral deviations. For instance, if lateral departure speed is too high during the ELKS activation, steering wheel angle should be smaller to reduce rolling effect towards out of the lane, in contrast controller output should be high enough to direct the Ego vehicle into the lane as quickly as possible. When all those effects are taken into account, precisely correlated steering wheel angle among inputs have great importance. The controller intervenes when the Ego vehicle starts to leave the lane, inserting a sharp steering angle to bring the vehicle back into the lane, and then the lane tracking system ensures that the vehicle stays in the center of the lane. In the controller, steering angles, which vary depending on the lateral distance to the lane markings (DTLM) representing how far the vehicle deviates from the lane centerline, have been optimized.

5.2 Design of Experiment

The experimental design for the simulation environment resulted from changing controller parameters ($k1$, $k2$, $k3$, $k4$, $k5$) and operation parameters (Ego vertical speed and Ego departure speed) within certain ranges. Here, while parameters k1...k5 were used in the experimental design, $k1 > k2 > k3 > k4 > k5$ limitation was considered. The reason for this limitation is that these parameters are calibration table parameters that vary depending on the lane lateral deviation amount, and it is anticipated that a high steering angle intervention is required for a high amount of lane deviation.

After defining the operation parameters and their ranges for the DoE, it is clear that test cases resulting from the combination of variation parameters (operation parameters and controller parameters) increase abruptly. To overcome this problem, DoE has to be optimized in a way that it still offers a reasonable coverage over the experiment and also is not computationally expensive.

In this study, to optimize the DoE, S-Optimal Design was exploited. The S-optimal design plans, they are identified as encompassing a methodology that ensures a thorough dispersion of test points across the designated experimental field. This approach meticulously considers the spatial distribution between existing design points and potential candidates, aiming to optimize a set of predefined criteria. This strategic optimization facilitates a uniform distribution across the testing environment, which is instrumental in identifying non-linear patterns through a structured modeling process. At its core, the S-optimal design seeks to extend the minimal distance among adjacent points, mirroring the repulsive force seen between magnets. Moreover, it possesses a flexible structure that allows for division into smaller segments without compromising the space-filling attribute of the design, underscoring its versatility and applicability to diverse experimental setups ([19]).

6 Optimization Method

To find the optimal parameter set, the KPI lower and upper limits 4.4 for each working point have been defined in AVL CAMEO™, and the solution space for optimization has been limited. Since the identified controller parameters directly affect the steering angle command, it has not been possible to find a single parameter set that works commonly at different working points. Instead, a solution for a parameter set specific to each working point using the relevant lower and upper limits has been pursued. When setting the KPI limits, the upper limits for the minimum yaw rate and minimum yaw rate rate KPIs; and the lower limits for the maximum yaw rate and maximum yaw rate rate KPIs are removed. Additionally, the lower limit for the maximum lateral acceleration KPI is not used. The reason for removing these limitations is that trying to minimize these KPI values in absolute terms would lead to an improvement in driving experience, and two-sided limitations for these KPIs would make the optimization process difficult. The target function for the optimization process has been defined as minimizing the P2PStrAng KPI. Here, the function aims to keep both the initial counter steering intervention and the final lane centering intervention as smooth as possible, thereby improving driving experience, comfort, and safety.

The optimization algorithm can be described as a combination of GA and NLO. The GA operates as a stochastic process, leading to varying outcomes across different iterations. Its primary objective is to pinpoint the region where the optimum solution resides. The process begins with an initial population of solutions. Through iterative steps involving selection, modification, and mutation, the algorithm generates a new population with enhanced target values. Termination occurs when any of the specified stopping criteria are satisfied. NLO on the other hand aims to initiate with an initial interior solution. If the current solution meets the required quality criteria, the algorithm halts. However, if improvements are needed, the algorithm systematically explores various directions, employing increasingly complex operations in each iteration to identify a more favorable trajectory. The algorithm selects the most promising direction, advancing towards a better interior solution until the solution reaches the desired quality or one of the specified termination criteria is met. To summarize, with the GA algorithm, the optimum position is first found. After the optimum point is found, the algorithm is automatically switched to NLO to complete the optimum search and overcome the local optimum problem.

6.1 Optimization Result and Comments

When an optimization is performed in such a way that the design space cannot be extrapolated, a solution was found in 7 out of 9 points; whereas, when the design space is left free, a solution was found at all 9 working points. The main reason for this is that the limitations made in the DoE regarding controller parameters ($k1>k2>k3>k4>k5$) are not actually fully compatible with the controller of the benchmark vehicle. In the results obtained by leaving the design space free, it has been observed that the relationships between these parameters can change according to working points. This observed relationship reveals that there is not always a directly proportional relationship between lateral deviation amount and steering angle correction in the benchmark vehicle.

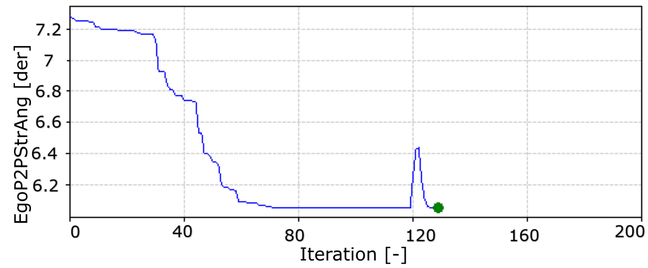

Fig. 6 Optimization result of P2PStrAng KPI

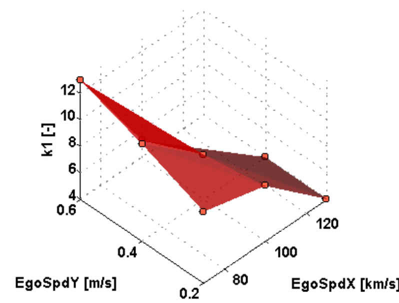

Fig. 7 k1 paremeter's changes in operation points

7 Validation

The optimized controller paramater sets proposed by AVL CAMEO^{TM} has to be validated because of the potential performance gap between proposed KPI responses by AVL CAMEO^{TM} and the actual KPI values obtained from the co-simulation platform. The main factor behind this gap is that, AVL CAMEO^{TM} proposes optimal controller parameters truly based on a data-driven approach by fitting a model between variation parameters and response parameters. Thus, this data-driven model bypasses the vehicle dynamics and controller dynamics represented in the co-simulation platform. Thus, the main problem of this methodology is to obtain a ML model that represents the co-simulation platform precisely. To achieve a more representative model, an iterative validation method was exploited. First, a DoE consists of the 9 operation parameters was created in the co-simulation platform. Then, optimized controller parameter sets obtained from AVL CAMEO^{TM} were plugged in to the controller for each operation point - test case with the corresponding sets. Obtained data for each test case were then processed with AMDF and the reuslting KPIs were compared with the proposed KPI values from AVL CAMEO^{TM}. This comparison is here mainly done for the P2PStrAng KPI since it is also the target function. To enhance the model and consequently to reduce the similarity gap, a new DoE with varying controller parameter breakpoints were created and for each test case again the variation parameters and response parameters were recorded. Training data set then were enriched with this additional data and with this new data set, model precision was aimed to be enhanced.

Table 3 EgoP2PStrAng KPI values obtained with opmtized calibratable sets for first and final iteration

EgoP2PStrAng [degree]					
Min	Initial Iteration	Deviation	Final Iteration	Deviation	Max
12.42	8.46	31.88	13.03	4.91	14.64
15.94	13.51	15.24	15.7	1.50	17.65
19.66	18.33	6.76	20.71	5.34	22.00
10.61	5.61	47.12	8.19	22.80	12.19
10.8	10.07	6.75	10.3	4.62	11.78
11.15	13.94	25.02	9.73	12.73	13.5
5.85	4.81	17.77	5.3	9.40	7.2
5.33	8.44	58.34	7.55	41.65	6.66
6.01	8.44	40.43	8.23	36.93	8.5

Deviation values on Table 3 were calculated with respect to minimum values of EgoP2PStrAng since this KPI is targeted to be minimized for the given min-max interval. Each distinct row represents a different operation point combination starting from 70 kph - 0.2 m/s. After the data collection and model enhancement processes, deviations were decraesed dramatically in most operation points. For the other KPIs, since the limitation was one sided for these KPIs, the main goal there was to minimize the magnitude of those KPIs since they represent the lateral movement of the Ego vehicle and also to not overshoot the upper limit which are both satisfied in the final iteration.

8 Conclusion

This study proposes an end-to-end methodology for obtaining KPI target values for ADAS controllers and calibrating these controllers according to obtained target values. TD promises to fill an important gap in the ADAS field, allowing quantitative definition and validation of the desired performance from ADAS functions. The calibration methodology aims to enable an ADAS controller to perform according to desired KPI values at different operating points. For future work, enabling the controller to update parameter sets adaptively and specifically for each operating point and validating the calibration performed can be targeted. Additionally, replacing the reference data set obtained from a benchmark vehicle with a larger data set obtained from subjective ratings by multiple participants can be considered for the TD process.

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