Electric Power Assist Steering System Parameterization and Optimisation Employing Computer-Aided Engineering

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Mikael Nybacka
KTH Royal Institute of Technology

Diomidis I. Katzourakis
Waymo

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Marcus Ljungberg
Volvo Car Corporation

Mikael Nybacka
Royal Institute of Technology

Gaspar Gil Gómez
Volvo Car Corporation

Diomidis Katzourakis
Volvo Car Group

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Abstract

The automotive industry strives to develop high quality vehicles in a short period of time that satisfy the consumer needs and stand out in the competition. Full exploitation of simulation and Computer-Aided Engineering (CAE) tools can enable quick evaluation of different vehicle concepts and setups without the need of building physical prototypes. Addressing the aforementioned statements this paper presents a method for optimising the Electric Power-Assisted Steering (EPAS) ECU parameters employing solely CAE. The objective of the optimisation is to achieve a desired steering response. The developed process is tested on three specific steering metrics (friction feel, torque build-up and torque deadband) for two function parameters (basic steering torque and active return) of the EPAS. The optimisation method enabled all metrics to fall successfully within the target range.

Introduction

The automotive industry is a competitive market aiming to develop new vehicles adopting the latest technology while decreasing lead time and increasing profits. A way to facilitate this goal is to further employ virtual-CAE vehicle development [1]. Virtual development can provide a fast iterative process where features can be tested and adapted without having to modify a prototype car or perform time-consuming physical tests.

The steering system feedback is an important factor in the driving experience [2] and can define the vehicle's character. The tuning-setup of the steering system aims to provide the “best” steering response; a highly subjective task [3][4] which varies between drivers of different background and experience.

The steering feedback performance is evaluated using both subjective assessments and objective testing [5]. Traditionally the tuning is performed by experienced test drivers who determine the final settings during physical vehicle testing. Dang et al. [6] presented an approach to optimise the on-centre steering force characteristics using correlations between subjective assessments and objective evaluations. This moving base driving simulator study used a nonlinear programming method in Matlab for optimisation. Guo et al. [7] also investigated how correlation studies and optimisation could be used to enhance the vehicle development process. A generic algorithm was used as an optimisation tool which focused on vehicle handling characteristics. Schoeggle and Ramschak [8] presented the tool AVL-DRIVE for drivability analysis and how that tool could be linked to test-beds for performing optimisation of driveability criteria. Borio et al. [9] described a methodology to compare longitudinal and lateral performance of AWD vehicles; this method included linking different CAE tools to target indices.

Steering System Tuning

The established tuning method of the steering system is an iterative process based on subjective and objective evaluation, i.e. physical test driving until the hardware and/or ECU software tuning provides satisfying results. An effective way to reduce the amount of iterations is to provide the tuning team an effective set of initial tuning parameters.

This paper focuses on developing and evaluating an optimisation process for the control parameters of an EPAS system employing solely CAE tools. The rationale is to perform the tuning using correlation results between subjective assessments from expert test drivers and objective metrics from physically tested vehicles [10] [11]. The optimisation is performed with the Tomlab toolbox [12] in Matlab using Efficient Global Optimisation (EGO). The gradient around the optimal point for each metric is calculated to determine the weighing factors to allow multiple-metrics optimisation; finally a global optimisation is performed for more than one parameter.

Table 1. CarMaker vehicle data set.

Vehicle Data Set	
Vehicle body	CoG position, masses, inertias (ADAMS)
Unsprung masses	CoG position, masses, inertias (ADAMS)
Suspensions	Spring stiffness, damping characteristics, buffer stiffness, stabilizer stiffness, suspension K&C (ADAMS)
Steering	Steering system geometry and masses, friction, motor parameters and gear ratios (custom SIL and plant model)
Tyres	MF tyre coefficients; longitudinal, lateral, overturning, rolling, aligning (test measured)
Brakes	Pressure distribution, response time, build-up time, pressure to brake (generic CarMaker data)
Powertrain	Parameters for engine, clutch, gearbox and driveline (generic CarMaker data)
Aerodynamics	Drag and lift coefficients (generic CarMaker data)

Method

CarMaker Vehicle Model and Setup

The vehicle simulation environment used in this project is IPG-Automotive CarMaker [13]. The setup employed kinematics & Compliance (K&C) lookup tables for the vehicle suspension and a non-linear tire-model. The steering subsystem was replaced with a custom software-in-the-loop (SIL) model emulating the corresponding hardware (HW) and software (SW) functionality used in the physical vehicle under study.

K&C tests in ADAMS give the kinematic relation of the wheel centre in terms of x,y,z rotational (camber, wind-up, toe angles) and translation movement when subjected to x,y,z forces and torques for various rack travel positions; the inertia tensors and centre-of-gravity (CoG) also come from ADAMS (c.f. Table 1). The K&C data for the CarMaker vehicle suspension derive from a highly complex multi-body model in MSC ADAMS. Multi-body simulation can give fast results, without physical vehicle prototypes allowing different suspension/chassis setups to be tested iteratively. The non-linear tire model used is based on the magic formula [14], simulating combined slip and transient dynamics (longitudinal and lateral relaxation). The simulation environment setup is shown in Figure 1. The simulated vehicle in CarMaker was exhaustively verified and gave realistic results compared to physical measurements.

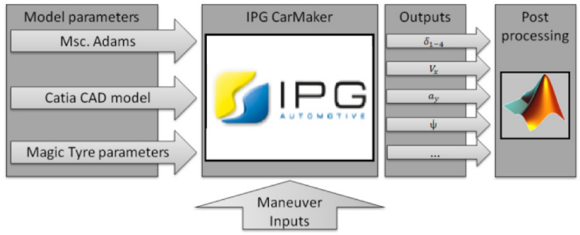

Figure 1. CarMaker simulation environment.

Steering System Modelling

The CarMaker environment (c.f. Figure 1) uses a sophisticated steering system model that emulates friction, gearing, inertias and compliances. Figure 2 shows the forces acting on the steering system. In the current implementation, the steering wheel and column dynamics are not modelled. The inputs to the system are the angle and velocity of the input shaft correspondingly.

The steering system is divided into six different components; input shaft, torsion bar, rack-to-pinion gear, servo motor with electronic control unit (ECU), ballnut gear (BNG) and the steering rack.

- The torsion bar component emulates friction of the input shaft and its peripherals and the stiffness/damping of the torsion bar itself.
- The pinion gear which translates the rotational movement of the torsion bar to the translational movement of the rack is modelled as a transmission system with friction.
- The system model for the servomotor and its ECU is a function of the voltage, driver inputs, motor temperature and motor current. The ECU itself is a SIL model of the physical ECU.
- A transmission system and inertia emulates the BNG that transfers the motor torque to rack assist force.

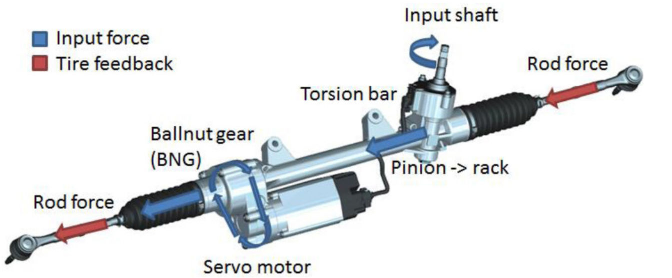

Figure 2. Forces acting on the steering system.

The forces acting on the rack (1) originate from the driver, the servo motor and the rod forces (c.f. Figure 2).

$$\ddot{x}_{rack} = \frac{F_{rack} + F_{rod}}{m_{rack} + m_{servo}} \tag{1}$$

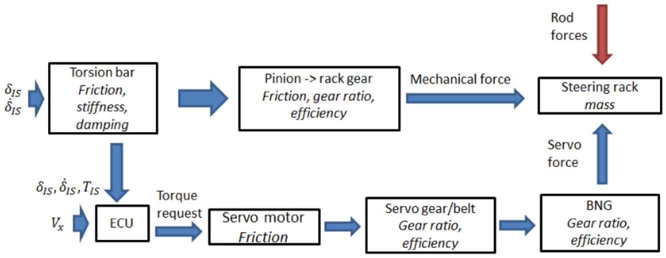

Figure 3. Steering system integration ($*_{IS}$: input shaft).

Manoeuvres

I. Ramp Steer

During ramp steer, the steering wheel angle (SWA) is increased at a slow rate while keeping constant longitudinal velocity, so as to achieve steady state (e.g. constant lateral jerk) behaviour. The metrics which can be extracted from this manoeuvre are steady state gradients (e.g. understeer gradient [°/g]). The ramp steer is also used as a pre-event to determine the magnitude of the SWA to reach a specific lateral acceleration; this angle is then used as an amplitude input for all the manoeuvres mentioned below.

II. Frequency Sweep

The frequency sweep can be used to evaluate the magnitude and phase delay of the vehicle at different SWA frequencies. The test can start from low SWA frequency and slowly increasing to the desired maximum frequency (or by going from high to low frequency). For the current study, the frequency sweeps from 0.3 Hz to 3 Hz; the SWA amplitude is determined with a pre-event (c.f. Ramp steer).

III. On-Centre Test

For the on-centre test the SWA follows a sine wave with fixed frequency and amplitude. This test can be used to evaluate the steering hysteresis at different velocities and lateral accelerations. This on-centre behaviour is evaluated for three different velocities and two different lateral accelerations (c.f. Table 2) that cover both vehicle inertial response and steering wheel torque (SWT) feedback. The test consists of five "long-enough" periods which ensure that the tires operate within the linear range [15] with minimal transient behaviour.

IV. Sine-with-Dwell

This test, also known as the "Elk test," is primarily used to evaluate the vehicle's response to an evasive manoeuvre. It enables to study the delay (time lag) between the steering input and vehicle yaw response. Initially the SWA is set to the amplitude required to achieve a certain lateral acceleration (c.f. Ramp steer). This SWA is then multiplied with a factor, up to the point that the vehicle reaches its handling potentials and spins-out of control (slightly modified version of FMVSS 126 [16] where the tests are performed with an increasing SWA multiplier until either a 6.5 multiplier or 300 degrees of SWA are reached).

Test-Cases

Table 2 contains a summary of the different manoeuvres used to get the full steering characteristics; the total number of test-cases are 46, including pre-events and the different multiplication factors used in the sine-with-dwell manoeuvre. Each of these runs follows these steps:

1. Extract the appropriate SWA amplitude from the pre-event (c.f. Ramp steer).
2. Run vehicle at the desired test velocity for three to five seconds to achieve static equilibrium.
3. Perform set manoeuvre.
4. Save output data required for metric extraction.

Table 2. Summary of the simulated test-cases.

Manoeuvre	Target velocity [km/h]	Target lateral acceleration [g]
Frequency sweep	V_{x4}	a_{y3}
On-centre	V_{x1}	a_{y4}
	V_{x2}	a_{y1}
	V_{x2}	a_{y4}
	V_{x4}	a_{y1}
Sine-with-dwell	V_{x3}	a_{y2}
Ramp steer	V_{x4}	a_{y5}
	V_{x5}	a_{y5}

Objective Metric Extraction

This section compiles the post-processing method from simulated data to the steering metrics. The reader is referred to [15] for more information on the metrics calculation.

I. Complete Simulation Process

Figure 4 shows the complete simulation process with the required inputs from the different sources. The vehicle and manoeuvres are parameterized in CarMaker GUI, while the steering system model is integrated with the CarMaker vehicle dynamics model in Simulink. A total of 46 simulations (due to variations in velocities, lateral accelerations and SWA amplitudes; Table 2) are used to extract the 32 different metrics. The simulations control and post-processing are performed in Matlab.

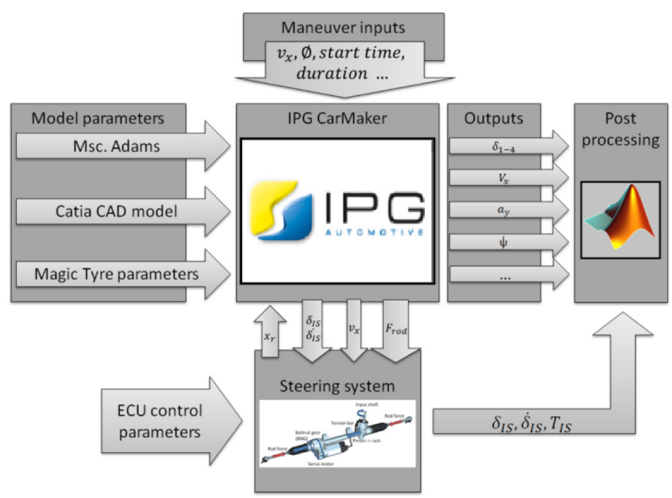

Figure 4. Complete simulation process: i) vehicle suspension properties derive from a sophisticated highly non-linear multi-body vehicle dynamics model flexible bodies in MSC ADAMS, ii) manoeuvre definition and iii) ECU control parameters for the steering system.

II. Steering Metrics

The current study focuses on three torque feedback metrics: i) torque deadband, ii) torque build-up and iii) friction feel (c.f. Straight ahead controllability in Figure 11).

- *Torque deadband* (derives from the ramp steer test) is the SWA (with respect to zero SWA) required to achieve a specific SWT (c.f. Figure 5). A small value for this metric gives a "stiff" and "heavy" (no backlash sensation) steering feel while a large value a "compliant" and "light."
- *Torque build-up* (derives from the ramp steer test) is the gradient of the SWT to SWA (2). The average gradient is used if the relation between these two variables is non-linear. A large value means "heavy" steering feel while a low value the opposite.
- *Friction feel* (derives from the on-centre test) is the SWT value at 0g lateral acceleration.

$$TorqueBuildup = \frac{\Delta T_{IS}}{\Delta \phi_{is}} \tag{2}$$

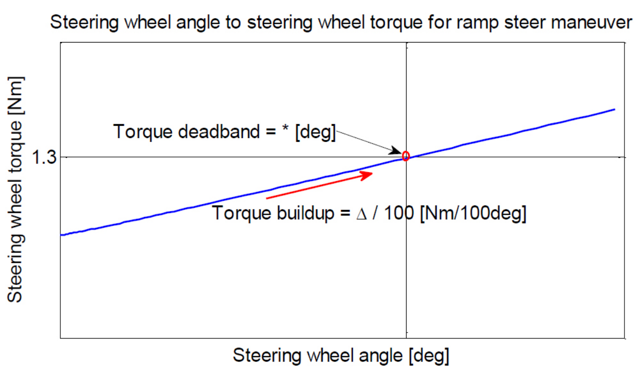

Figure 5. Torque deadband and torque build-up metric calculation.

Steering System Control Parameters and Sensitivity Analysis

There are numerous parameters to adapt in the steering servo controller; some are related to motor performance and mechanical limitations (e.g. one function limits the SWA so that the rack does not hit its mechanical end stops, thus reducing wear) while others are related to the torque assist. The torque assist parameters of interest for this study are: i) the basic steering torque, ii) active return and iii) active damping.

I. Basic Steering Torque

Common parameters in EPAS systems are the velocity dependent basic steering torque (BST) curves [4][17]. These determine the assist level using the relation between the rack assist force and the SWT (c.f. Figure 6). At low speeds (e.g. parking manoeuvres, c.f. V0 Figure 6) the assist rack force is high at low SWT; the steering feels "light." As the velocity increases, a larger amount of SWT is needed (the assist level is lower); the steering feels "heavier."

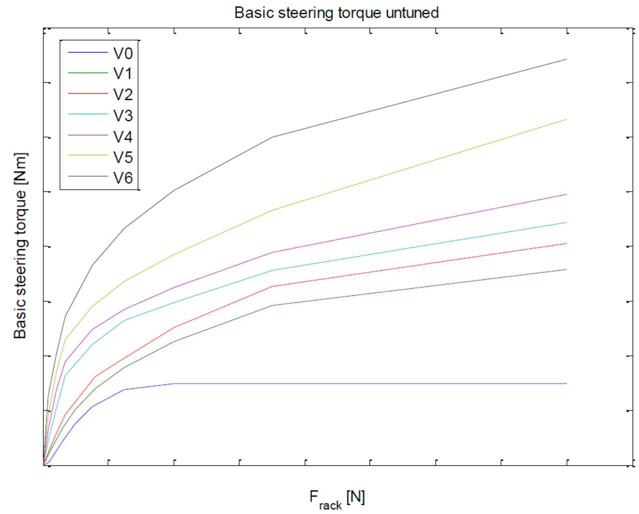

Figure 6. Basic steering torque (BST): rack assist force as a function steering wheel torque (SWT) for various travelling speeds (V6>V0).

II. Active Return

This function is responsible for the self-centring of the steering wheel and is a function of SWA, SWT and longitudinal velocity; this function heavily influences the steering feel metrics, acting like a spring-damper system around a reference SWA.

III. Active Damping

This function adds damping to the steering response and is a function of the SWA, SWT, vehicle speed and the rotational velocity of the rotor of the servomotor.

Sensitivity Analysis

A sensitivity analysis was performed to study the effect of the three aforementioned functions in the metric values. This was performed by changing only one parameter value at a time from 0 to its maximum allowable value (the SW allows only plausible parameterization). Figure 11 shows the effect of multiplying the BST by a factor (Multiple from 0 to 2 for the BST).

Figure 12 shows the percentage change between the minimum and maximum metric value achieved (3) by changing one parameter at a time (c.f. Figure 12; Parameter 1.1 to 3.4) to its allowable extremes (minimum to maximum allowed value).

$$\Delta_{i,n} = \frac{\max(M_{i,n})}{\min(M_{i,n})} \cdot 100 \tag{3}$$

In (3), $M_{i,n}$ is the vector containing the values for the i^{th} metric estimated by adapting the n^{th} parameter.

Optimisation Process

The optimisation process is performed in three steps: i) single metric, ii) multiple metrics and iii) global parameter optimisation.

i. Initially a single metric parameter optimisation is performed for the three different metrics using the Tomlab toolbox and EGO. The EGO framework uses stochastic processes and tries to model a response surface based on the objective and the constraint function. This method is suitable for modelling nonlinear and multimodal functions. The fitting of stochastic process to the data calibrates the model which informs how the function behaves and the subsequent point to evaluate the function [18].

ii. The gradient around the optimal point for each metric is calculated to determine the weighing factors for the optimisation of multiple metrics.

iii. Finally the global optimisation is performed by assuming the tuning from ii) as starting point for optimising the "next" parameter.

The process repeats steps i) to iii) until the end-optimisation target is reached.

I. Cost Function

The objective of the optimisation is to minimize the cost function shown in equation (4). The cost function is the RMS of the normalised value of the weighed difference between the desired and the actual metric.

$$J = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \omega_i \left(\frac{M_{a,i} - M_{d,i}}{M_{a,i}} \right)^2} \tag{4}$$

In (4) J is the cost function to be minimised, n is the number of metrics being optimized, ω_i is the i^{th} weighing factor, $M_{a,i}$ is the actual value of the i^{th} metric and $M_{d,i}$ is the desired value of the i^{th} metric. Since each metric has to lie within a target range (and not a constant) the mean value within that range serves as the $M_{d,i}$. The three selected metrics are highly affected by the steering system parameters (c.f. Figure 12).

II. Single Metric Optimisation

The first step is to optimise individual parameter for a single metric. The first parameter to study is the velocity dependent BST. The V5 BST curve (c.f. Figure 6) was fit to an exponential function (5) using the least square curve-fit function in the Matlab optimisation toolbox.

$$BST(F_{rack}) = A \cdot F_{rack}^{B} \tag{5}$$

In equation (5), F_{rack} is the rack force, A and B are constants. The initial optimisation objective is to adjust the parameters A and B so that the metric values fall within range. The optimisation problem can then be formulated as in (6).

$$\min_{A,B} J(A,B)$$

$$s/t \begin{cases} A_L \leq A \leq A_U \\ B_L \leq B \leq B_U \end{cases}$$

$$\text{Initial conditions} = \begin{bmatrix} A_0 \\ B_0 \end{bmatrix} \tag{6}$$

In (6), $J(A, B)$ is the cost function as defined in Equation (4), A_L, B_L, A_U and B_U are the lower and upper boundaries of the linear constraints and A_0 and B_0 are the initial values. Table 3 shows the optimisation settings for Tomlab EGO solver.

Table 3. Tomlab EGO settings for optimisation.

Metric	Torque deadband	Torque build-up	Friction feel
A_L	0.1	0.1	0.1
B_L	0.25	0.25	0.25
A_U	0.4	0.4	0.4
B_U	0.4	0.4	0.4
A_0	0.2864	0.2864	0.2864
B_0	0.3421	0.3421	0.3421

III. Weighing Factors for the Metric Optimisation

The initial single metric parameter optimisation will provide different A and B values (c.f. equation (5)) for the different corresponding metrics. To enable parameter optimisation for multiple metrics an analysis is performed to determine how sensitive individual metric is to changes in the power function (5). By varying the A-value (5) between its extreme (minimum and maximum) values it allows to study the gradient around the optimal -value. A large (in magnitude) gradient value around the optimal A-value means that the metric is sensitive to changes and vice-versa. This was used to determine the weighing factors, where the relative gradient is calculated according to equation (7).

$$\left(\frac{dM}{dA}\right)_{opt} \cdot \frac{1}{M_{opt}} = \omega_F \tag{7}$$

Where $\left(\frac{dM}{dA}\right)_{opt}$ is the gradient around the optimal A-value, $\frac{1}{M_{opt}}$ is a normalisation factor and ω_F is the weighing factor.

IV. Multiple Metrics Optimisation

The cost function for the multiple (three) metric optimisation can be seen in equation (8) having the weighing factors calculated as in (7).

$$J = \sqrt{\frac{1}{3} \cdot \sum_{i=1}^{3} \omega_{F,i} \left(\frac{M_{a,i} - M_{(d,i)}}{M_{a,i}} \right)^2} = \sqrt{\frac{1}{3} \left[\omega_{a,TDB} \left(\frac{M_{a,TDB} - M_{d,TBD}}{M_{a,TBD}} \right)^2 + \omega_{a,TDU} \left(\frac{M_{a,TBU} - M_{d,TBU}}{M_{a,TBU}} \right)^2 + \omega_{F,FF} \left(\frac{M_{a,FF} - M_{d,FF}}{M_{a,FF}} \right)^2 \right]} \tag{8}$$

In (8), the indices TDB, TBU and FF are the torque deadband, torque build-up and friction feel metric correspondingly.

The optimisation results from the multiple (three) metrics optimisation (3) are used as a starting point for adapting the active damping parameterization (mentioned as "next" parameter in the Optimisation process). The optimisation method followed was the same as with the BST.

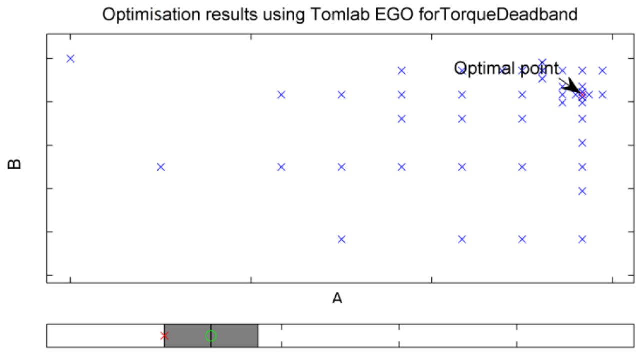

Figure 7. Single metric optimisation; torque deadband. The subplot (top) shows show the intermediate *A* and *B*-factors before the EGO solver reaches the Optimal point. The red cross in the bar (bottom) is the metric value with the initial tuning, the green circle the optimized metric value and the grey area its target range.

Results

The current section compiles the results of the ECU parameter optimisation using the aforementioned three step optimisation process: i) single metric, ii) multiple metrics and iii) global parameter optimisation.

I. Single Metric Optimisation

The three metrics chosen for the single metric optimisation (due to their high sensitivity; c.f. Figure 11 and Figure 12) are the torque deadband (c.f. Figure 7), torque build-up and friction feel. The optimisation resulted in metric values with small deviations from the target and all within range (c.f. Table 4).

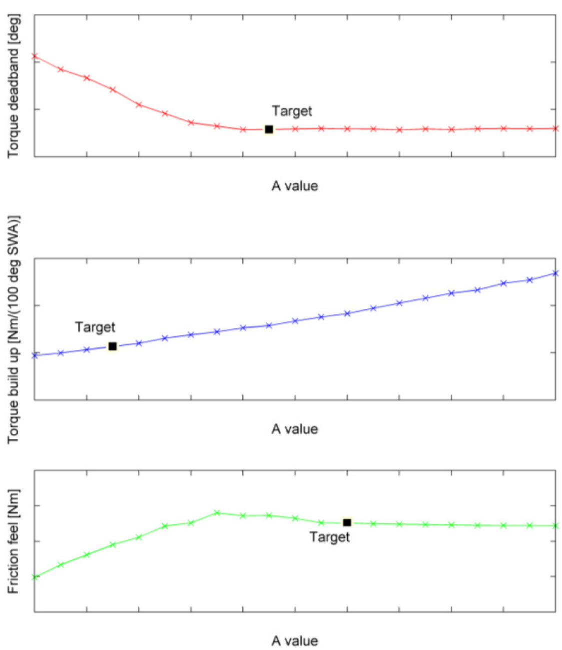

Figure 8. Weighing factors for the multiple (three) metrics with respect to the *A*-factor of the BST power function.

Table 4. Deviation from target after the single metric optimisation.

Metric	Deviation (%)
Torque deadband	0.17
Torque build-up	0.102
Friction feel	0.05

II. Weighing Factors for the Multiple Parameter Optimisation

The single metric parameter optimisation provided three different *A* and *B* values (c.f. equation (5)) for the three corresponding metrics. A sensitivity analysis was performed to determine how sensitive individual metric is to changes in the power function (5) so as to enable parameter optimisation for the multiple (three) metrics together. Figure 8 displays the gradient around the three optimal *A*-values for the three metrics.

The resulting weighing factors (calculated as in (7)) are:

$$\omega_{TD} = 0.01$$
$$\omega_{TBU} = 0.21$$
$$\omega_{FF} = 0.007 \tag{9}$$

The indices TD, TBU and FF in (9) stand for torque deadband, torque build-up and friction feel correspondingly.

III. Multiple Metric Optimisation

Figure 9 shows the results from the multiple metric optimisation using the weighing factors (9) and the method described in the Optimisation process. Both torque deadband and torque build-up fall within their target range while friction feel does not.

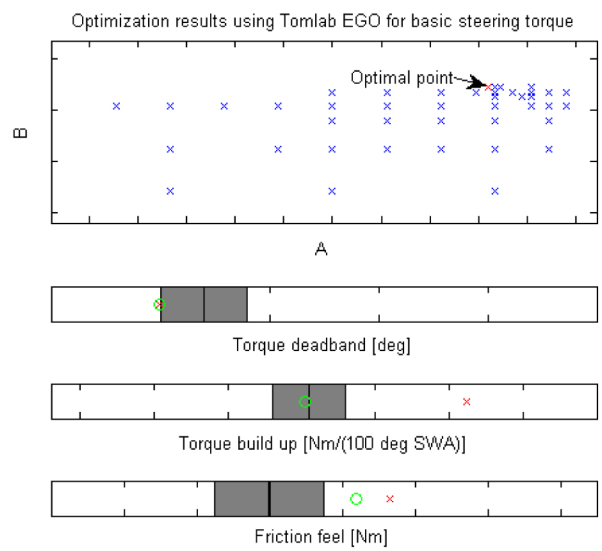

Figure 9. The optimisation results from the multiple metric optimization of the BST. The subplot (top) shows show the intermediate *A* and *B*-factors before the EGO solver reaches the Optimal point for the multiple metric optimisation. The red cross in the bar (bottom) is the metric value with the initial tuning, the green circle the optimized metric value and the grey area its target range.

IV. Global Metric Optimisation

Consulting the sensitivity analysis in Figure 11, the active damping was selected as the optimisation parameter to enable the friction feel to also fall within the target range. The active damping was optimised using the results of three metrics optimisation from the previous paragraph (the optimised BST). The results are shown in Figure 10, with the green circle representing the optimized metric value and the grey area the target range; all metrics fall successfully within the target range.

Conclusions

This paper presented a method on how to mathematically optimise the ECU parameters of an EPAS system in simulation. The simulation environment used was IPG CarMaker where the vehicle was modelled using kinematics & compliance (K&C) lookup tables for the vehicle suspension and a non-linear tire-model. The steering subsystem was replaced with a software-in-the-loop (SIL) model emulating the corresponding HW and SW functionality used in the physical vehicle under study. The mathematical optimisation was performed with the EGO framework in Tomlab toolbox in Matlab [12]. The optimisations' objective was to enable the objective steering metrics torque build-up, torque deadband and friction feel [4][10][11] to fall within their prescribed targets. The optimisation process was performed in three steps: i) single metric, ii) multiple metrics and iii) global parameter optimisation. The global optimisation step used previously optimised parameters (BST) for the steering metrics as a starting point and optimised a second parameter (active damping) so that all metrics fall successfully within the target range.

Although the proposed method can provide numerically optimised parameters for a certain target set and metrics, the definition of the objective metrics and the target values does constitute a problem by itself. The metrics have to capture the subjective perception of the steering feedback and the target values are optimal for the attribute leader who assigned them; not necessarily for everyone. There is however plenty of research in the area of developing new objective metrics and finding ways of correlating objective metrics with subjective assessments [10][11]. Using results from [10] and [11] in combination with the presented method could prove to be an efficient way of parameterising not only ECU parameters but also complete physical vehicle properties (suspension setup etc.). Determining the weighing factors is also a complicated task since they will dictate the results of the optimisation process.

The authors expect that drivers would welcome systems which would automatically adapt to their own inherent properties with solely objective to promote a safety task; maybe something to expect in future Volvo cars [19].

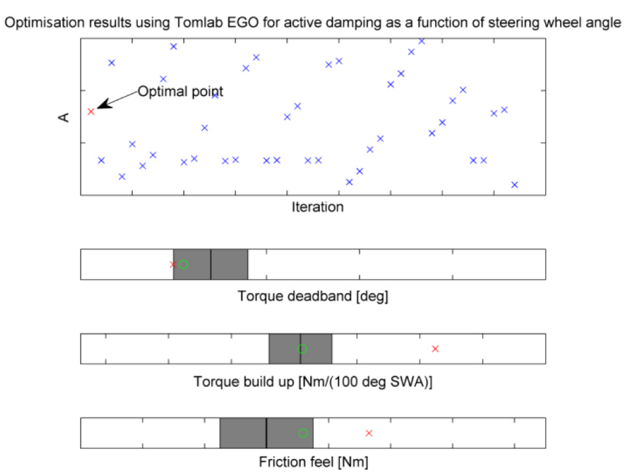

Figure 10. The global optimisation uses the optimised BST for the three multiple metrics and optimises the active damping so that all metrics fall within the target range. The subplot (top) shows show the intermediate *A* and *B*-factors before the EGO solver reaches the Optimal point for the multiple metric optimisation. The red cross in the bar (bottom) is the metric value with the initial tuning, the green circle the optimized metric value and the grey area its target range.

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APPENDIX

Sensitivity Analysis Parameters and Results

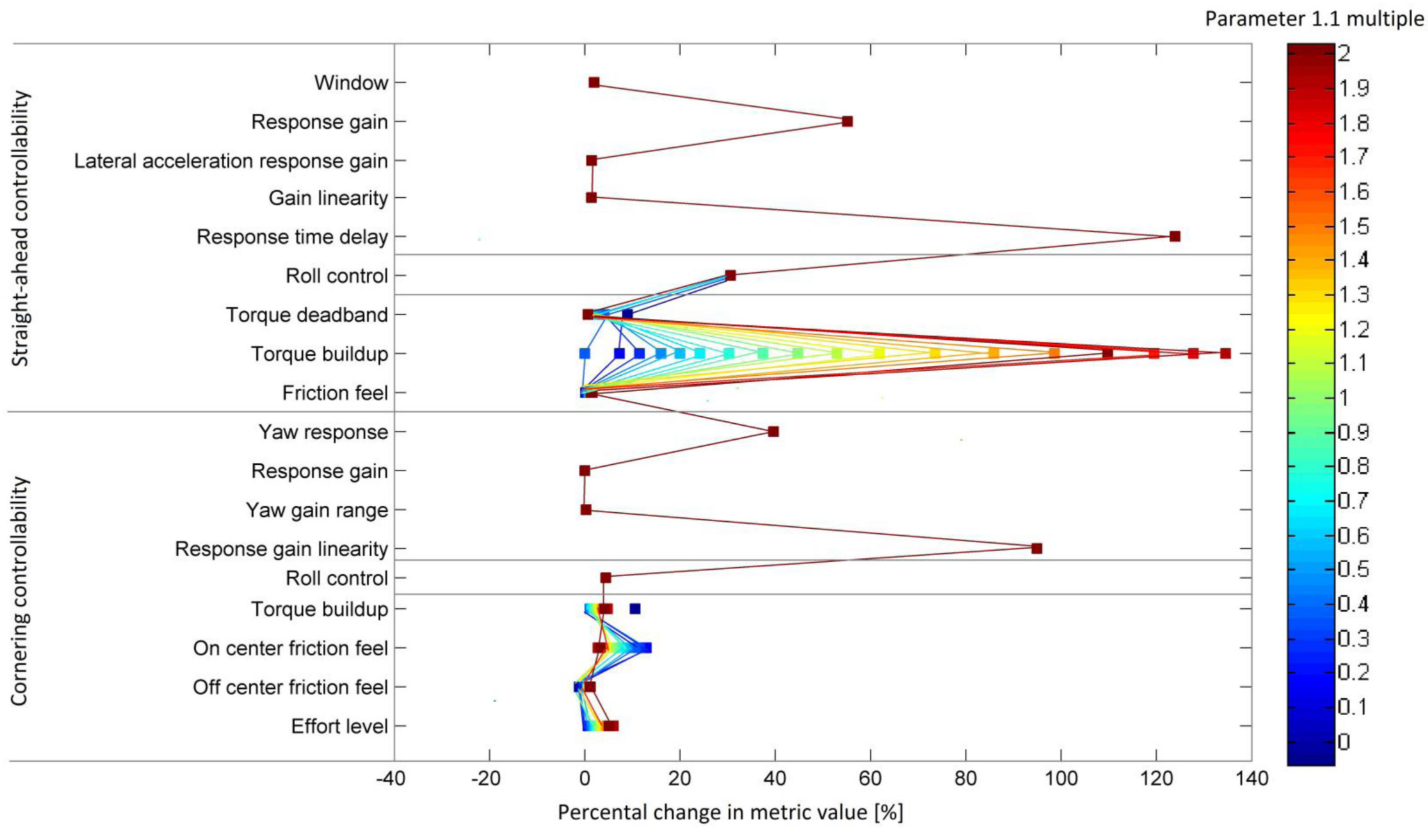

Figure 11. The percentile change of steering characteristics metrics achieved by changing the basic steering torque (BST) parameter.

		Function	Function 1	Function 2					Function 3			
		Function parameter	Parameter 1.1	Parameter 2.1	Parameter 2.2	Parameter 2.3	Parameter 2.4	Parameter 2.5	Parameter 3.1	Parameter 3.2	Parameter 3.3	Parameter 3.4
		Metric	% Change	% Change	% Change	% Change	% Change	% Change	% Change	% Change	% Change	% Change
Straight-ahead controllability	Response	Window	60%									
		Response gain	52%	4%	4%	3%	3%			2%		1%
		Lateral acceleration response gain	17%									
		Gain linearity	35%									
		Response time delay	3%		1%						5%	3%
	Roll control	Roll control										
	Torque feedback	Torque deadband	347%	3%	3%	3%	3%				3%	3%
		Torque buildup	1224%	1%	1%	1%	1%				1%	1%
		Friction feel	688%	17%	28%	13%	23%				16%	10%

Colour scale: 0% to >15%

Figure 12. The results of the sensitivity analysis.

The Engineering Meetings Board has approved this paper for publication. It has successfully completed SAE's peer review process under the supervision of the session organizer. The process requires a minimum of three (3) reviews by industry experts.

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