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Traffic Modelling Validation of Advanced Driver Assistance Systems

Robin van Tongeren, Olaf Gietelink*, Bart De Schutter and Michel Verhaegen

***Abstract*— This paper presents a microscopic traffic model for the validation of advanced driver assistance systems. This model describes single-lane traffic and is calibrated with data from a field operational test. To illustrate the use of the model, a Monte Carlo simulation of single-lane traffic scenarios is executed with application to cooperative adaptive cruise control system. The model is then validated by comparing the simulation results with data gathered from test drives.**

I. INTRODUCTION

The increasing demand for vehicle safety has stimulated the development of advanced driver assistance systems (ADASs). An ADAS is a control system that uses environment sensors to improve comfort and safety by assisting the driver. An example is adaptive cruise control (ACC), which maintains a pre-defined velocity set-point, unless a slower vehicle is detected ahead. The ACC then controls the vehicle to follow the slower vehicle at a safe distance (Fig. 1).

The demand for safety naturally increases with increasing automation of the driving task, since the driver must fully rely on a flawless operation of the ADAS. The ADAS should therefore be validated for a wide set of operating conditions.

An iterative process of *simulations* and *test drives* is often used for validation. Test drives give realistic results, but can never cover the entire set of operating conditions. Results are also difficult to analyse and not reproducible [1]. On the other hand, simulations have their limitations as well. For a realistic nonlinear model and multiple traffic disturbances, the validation problem will become difficult to solve, and eventually become *intractable* [2]. To make the simulation phase more efficient, a controller can be validated with a *grid search* over the operating range of all parameters [3]. However, an exhaustive grid search requires an intractably large number of experiments. Another possibility is a Monte Carlo strategy, where the system is simulated for a representative, but still very large, set of operating conditions, based on the probability that these conditions occur. In [4] we have introduced an efficient Monte Carlo simulation strategy. The method was illustrated with a case study consisting of an ACC controller, subjected to a one-dimensional traffic disturbance (the acceleration of only one preceding vehicle).

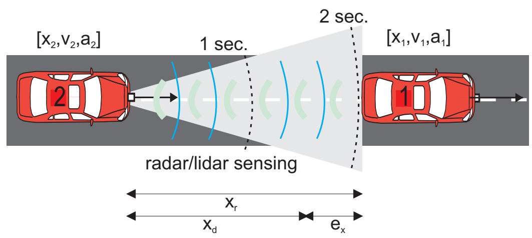

Fig. 1. Schematic representation of an ACC system.

It is the objective of this paper to develop a single-lane traffic model with multiple vehicles that include a multi-dimensional traffic disturbance. The model is applied to evaluate the performance of an algorithm for cooperative adaptive cruise control (CACC).

This paper is organised as follows. Section II presents the CACC algorithm, followed by the single-lane traffic model in Section III. Section IV presents the simulation framework and Section V the results. Section VI concludes the paper.

II. COOPERATIVE ADAPTIVE CRUISE CONTROL

Since the available literature on ACC systems is vast, the interested reader is referred to [5] for further details. Some drawbacks of ACC are mentioned though:

- ACC systems have a maximum range of about 200 m, which is insufficient for warning about an oncoming traffic jam or other potential danger further ahead.
- False and missed alarms can be caused when driving in curves or when other vehicles or road infrastructure are blocking the line-of-sight of the sensor.
- In addition, the environment sensor signals can be unreliable and inaccurate, due to multi-path reflections, weather conditions, and sensor noise.
- ACC only reacts to directly preceding vehicles, sensed by the environment sensors. The ACC will therefore not directly respond to other preceding vehicles further ahead, *e.g.* when approaching a traffic jam.

Therefore, ACC could be greatly enhanced when the field of view is extended to include reliable information from other preceding vehicles. This can be achieved by implementation of vehicle-to-vehicle communication (VVC). Current research is therefore extending ACC systems to cooperative adaptive cruise control (CACC) systems [6], where the inter-vehicle distance is accurately estimated using

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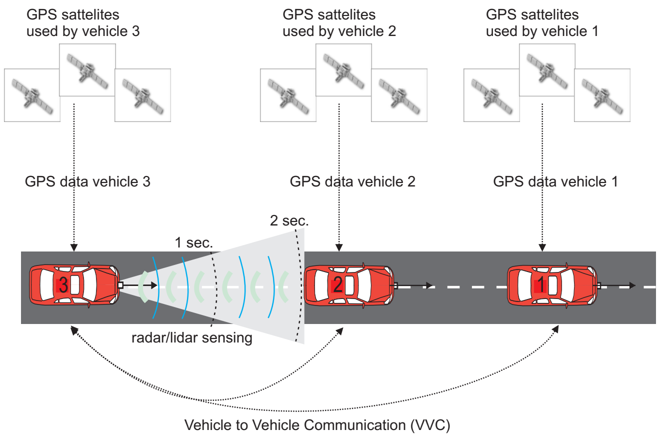

Fig. 2. Top view of the CACC principle, vehicle 1 contains the CACC.

VVC and environment sensors. The basic CACC concept is shown in Fig. 2. The advantage of CACC is that it can use a smaller distance headway and that it has an increased control bandwidth and reliability with respect to ACC.

The major improvement of CACC over ACC, is that the added communication element offers a better situation awareness, for example in detecting a traffic jam further ahead. ACC becomes aware of a traffic jam only when the directly preceding vehicle decelerates, which most likely results in severe deceleration of the ACC-equipped vehicle. On the other hand, CACC can receive an advance warning through VVC, and initiate deceleration much sooner than ACC, resulting in less severe deceleration levels.

The existing ACC longitudinal control problem is shown in Fig. 1. In distance control mode the desired acceleration a_{d} for vehicle i is provided by a feedback control law that consists of the distance separation error $e_x = x_{\mathrm{r}} - x_{\mathrm{d}}$ and its derivative $\dot{e}_v = v_{\mathrm{r}} - v_{\mathrm{d}}$, with x_{r} and v_{r} the relative distance and relative velocity, and x_{d} and v_{d} the safe following distance and safe relative velocity, respectively. The distance control law is then given by

$$a_{\mathrm{d}} = k_2 e_v + k_1 e_x, \quad k_1, k_2 > 0. \tag{1}$$

A control law for CACC can be similar to Eq. (1). However, the main advantage of CACC is that there is more information available, such as the acceleration of the preceding vehicle. Using VVC, the acceleration of the lead vehicle (which is difficult to estimate with only a environment sensor) can be communicated to the following vehicle. With information on lead vehicle acceleration a_{i-1}, as well as more reliable estimates for the range and range rate, the ACC control law Eq. (1) can be modified to

$$a_{\mathrm{d}} = k_3 a_{i-1} + k_2 e_v + k_1 e_x, \quad k_1, k_2, k_3 > 0. \tag{2}$$

Secondly, the CACC algorithm of Eq. (2) can be extended to multiple preceding vehicles. The idea behind this extension is that the CACC vehicle in Fig. 2 should not only keep a safe headway x_{d} to the first preceding vehicle, but it should also keep a headway of $2x_{\mathrm{d}} + l_{\mathrm{v}}$ to the second preceding vehicle, where l_{v} is the vehicle's effective length. Based on this idea the CACC algorithm computes a desired acceleration a_{d} for each preceding vehicle according to Eq. (2). The final desired acceleration a_{d} is chosen by taking the minimum value for all n vehicles:

$$a_{\mathrm{d}} = \min(a_{\mathrm{d},i-1}, \ldots, a_{\mathrm{d},i-n}) \tag{3}$$

In order to check the performance of this CACC algorithm, it will be evaluated using traffic simulations. A model for single-lane traffic is therefore presented in the next section.

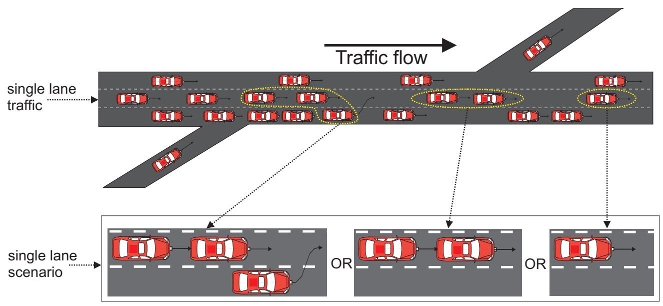

Fig. 3. Definition of a single-lane traffic scenario.

III. SINGLE-LANE TRAFFIC

A. *Single-lane Traffic Modelling*

Traffic simulations are usually based on *macroscopic* traffic models [7], consisting of several hundreds of vehicles, which do not allow the inclusion of individual vehicle models with complex control systems. Since we are concerned with the performance on *microscopic* level, we concentrate on the development of a modelling environment for microscopic traffic scenarios that allows to validate ADASs for a representative set of traffic scenarios. Therefore, the macroscopic traffic is divided into distinctive subscenarios that are representative of the scenarios that a longitudinal control algorithm should handle.

Since a human driver looks only several vehicles ahead, and a longitudinal control system only considers target vehicles that are in (or entering into) the host vehicle's lane, we focus the identification of *single-lane* scenarios. This type of scenario is defined as: *a particular setting of maximal three vehicles and their behaviour in a single-lane over a predetermined period of time*, as illustrated by Fig. 3.

B. *Driver Modelling*

In each scenario the host vehicle (i) is denoted as the subject vehicle (SV). An (optional) preceding vehicle, *i.e.* closest vehicle in front of the host in the longitudinal sense, though not necessarily in the same lane, is denoted as the primary other vehicle (POV). In case of n preceding vehicles, additional (optional) preceding vehicles are denoted by POV2, ..., POVn, where the order depends on how close the target vehicle is to the host in longitudinal direction.

The SV in a single-lane scenario requires no modelling, as its driving behaviour is controlled by the CACC. However the driving behaviour of the POV and POV2 should be modelled to provide a realistic traffic environment. Driver modelling is an intense research topic, and various types of driver models are available for traffic simulation [7]. An often used class of driver models is the class of *safety distance models*, the most famous of which is the Gipps driver model [8], which is relatively simple, but applied in this paper for reasons of transparency. The first part of the Gipps model tries to maintain a desired velocity assuming there is no preceding vehicle, the so-called *free-flow* mode. The second part tries to maintain a safe following distance, *i.e.* the *car-following* mode. Both parts calculate the velocity of the vehicle after a reaction time τ of the driver, and the resulting velocity is the minimum of the two:

$$v_1(t+\tau) = \min \left\{ \begin{array}{c} f(v_1(t)|a_{\max}, \lambda_{\mathrm{v}}) \\ f(v_1(t), v_2(t), x_{\mathrm{r}}(t)|a_{\max}, \lambda_{\mathrm{v}}) \end{array} \right. , \quad (4)$$

where $a_{\max}$ is the maximum allowable acceleration and λ_{v} the ratio between the desired velocity and the initial velocity:

$$\lambda_{\mathrm{v}} = \frac{v_{\mathrm{d}}}{v(0)}. \quad (5)$$

The parameters $a_{\max}$ and λ_{v} are the parameters by which the Gipps model can be calibrated and are different for various driver types.

C. Subscenarios in Single-lane Traffic

Usually ADAS control analysis distinguishes between free driving and car-following. However, we would like to obtain a complete overview of the scenarios that an ADAS should handle. The single-lane traffic scenario is therefore divided into several subscenarios, which are recurrent behaviour patterns of vehicles. In single-lane traffic six subscenarios can be identified:

- *Free-flow*: The SV, POV, or POV2 has no preceding vehicle.
- *Car-following*: Either the SV or the POV is following the POV or POV2, respectively, with a steady velocity.
- *Cut-in*: The POV or the POV2 moves in front of the SV or the POV from a different lane.
- *Cut-out*: The POV or the POV2 moves out of the SV's or the POV's lane.
- *Lane change*: The SV, POV or POV2 changes lane.
- *Approach*: The SV or the POV drives towards the POV or the POV2 in the same lane.
- *Separate*: The POV or POV2 drives away from the SV or POV in the same lane.

Fig. 4 shows a top view of the subscenarios together with two graphs of parameters, which contain the vehicle's velocity profiles (left) and the relative distance (right) during the subscenarios.

Since a relevant microscopic scenario may include up to two preceding vehicles, we introduce the following subscenario configurations in case of zero, one, or two preceding vehicles. The most basic configuration for a single-lane scenario is in case of a single vehicle. The only two possible subscenarios for single-lane scenario with one vehicle are free-flow and lane change. For the single-lane scenarios, consisting of two vehicles (SV and POV), five configurations are possible: *car-following*, *cut-in*, *cut-out*, *lane change*, and *approach*. However the configurations for

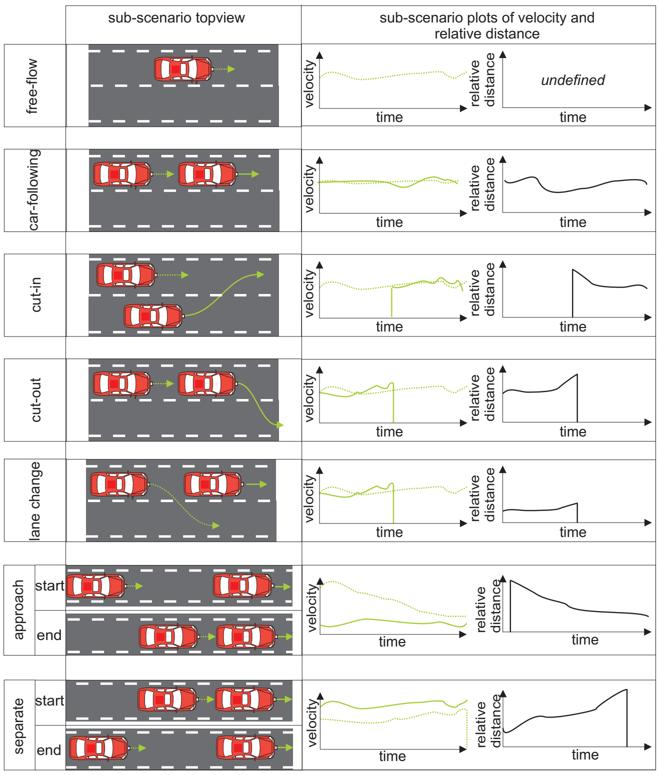

Fig. 4. The subscenarios in single-lane traffic. On the right the velocity profiles of the leading vehicle (solid line) and following vehicle (dotted line), as well as the inter-vehicle spacing, during the scenario are shown.

single-lane scenarios, consisting of three vehicles (SV, POV, and POV2) are slightly more complex. Therefore the 3-vehicle configurations are described in two steps. First, the possible subscenarios between the SV and POV are *car-following, approach* and *lane change*. Secondly, there are five possible subscenarios between POV2 and POV2: *car-following*, *cut-in*, *cut-out*, *lane change*, and *approach*. The result is a total of 15 configurations for single-lane scenarios with three vehicles.

The initial conditions for the single-lane scenario are formed by the vehicle velocities $v_i(0)$, the relative velocity $v_{\mathrm{r}}(0)$, and the distance $x_{\mathrm{r}}(0)$.

Other relevant parameters are the *occurrence rate* and *duration* of the subscenario configuration. The configuration duration is determined by the duration of the subscenario that applies to the host vehicle of the configuration. The configuration occurrence rate on the other hand, is determined by the union of the occurrence rates of the subscenarios in the configuration. The determination of both configuration parameters is illustrated in Fig. 5.

D. Scenario Parameters for Single-lane Traffic

In order to derive the probabilistic performance measures, the above mentioned *scenario parameters* are modelled by PDFs. In case a parameter is uncorrelated, the PDF of a normal, log normal or Laplace distribution will be used. The

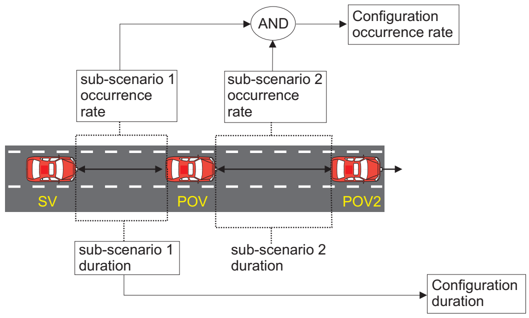

Fig. 5. Determining the configuration duration and occurrence rate.

normal distribution is given by

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, \tag{6}$$

where, x is a data value, μ is the mean, and σ is the standard deviation. The log normal distribution is given by

$$P(x) = \frac{1}{S\sqrt{2\pi x}} e^{\frac{-(\ln(x)-M)^2}{2S^2}}, \tag{7}$$

where, x is a data value, M is a location parameter, and S is the scale parameter. The Laplace distribution is given by

$$P(x) = \frac{1}{2b} e^{\frac{-|x-\mu|}{b}}, \tag{8}$$

where, x is a data value, μ is a location parameter, and b is the scale parameter.

In case of correlated parameters, the two-dimensional multivariate normal PDF is

$$P(x_1, x_2) = \frac{1}{2\pi\sqrt{|R_{x_1,x_2}|}} e^{\frac{1}{2}\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} \mu_{x_1} \\ \mu_{x_2} \end{bmatrix}\right)^T (R_{x_1,x_2})^{-1} \left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} \mu_{x_1} \\ \mu_{x_2} \end{bmatrix}\right)}, \tag{9}$$

where x_1 and x_2 are the modelled parameters, R_{x_1,x_2} is the covariance matrix for x_1 and x_2, μ_{x_1} is the mean of x_1, and μ_{x_2} is the mean of x_2.

E. Traffic Model Structure

Now that the single-lane scenario is modelled, a single-lane traffic model can be constructed as a collection of single-lane scenarios, as shown in Fig. 6. From the desired duration of the Monte Carlo simulation, the total number of single-lane scenarios is calculated. The next step is to implement this model structure into a simulation environment.

IV. MODEL IMPLEMENTATION

A. Parameter Model Calibration

In a next step these parameter models must be calibrated in order to form a representative set. Several traffic databases are available, each containing a considerable amount useful for traffic modelling. The focus of these databases ranges from crash data analysis to general driving behaviour analysis. Examples are the CAMP database [9] and the SAVME database [10]. Unfortunately these databases do not distinguish between different types of scenarios, do not

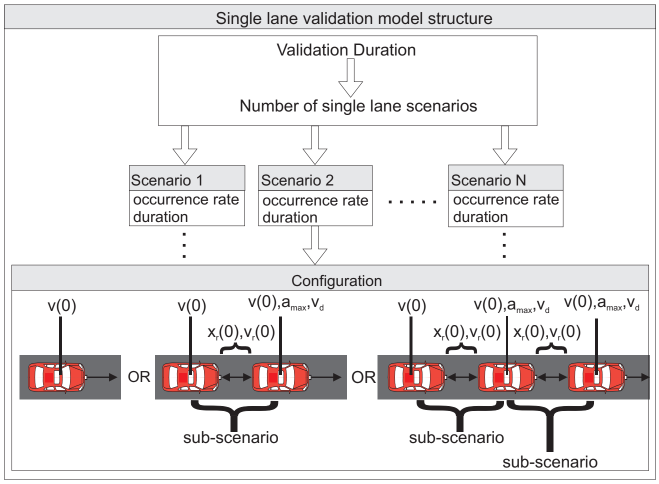

Fig. 6. The structure of the single-lane scenario simulation.

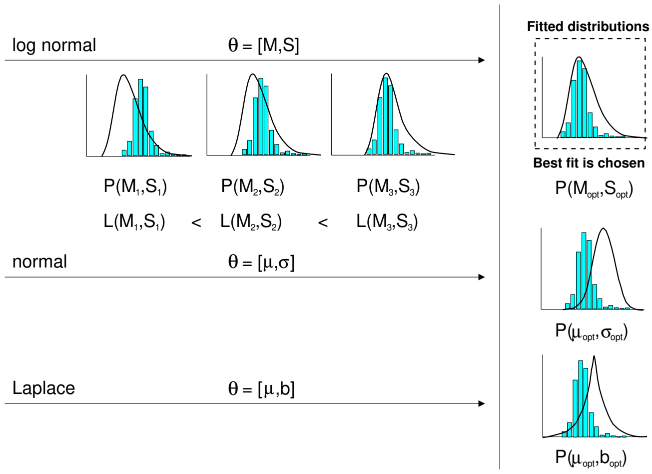

Fig. 7. An illustration of the ML fit algorithm.

contain information on the occurrence rate of each of the subscenarios, and do not provide information on the initial conditions of each subscenario.

We therefore use raw data obtained from an instrumented vehicle. This data contains measurements of relevant vehicle states, such as position, velocity, acceleration, steering angle, throttle angle, and brake use. Surrounding traffic is monitored by radar to record the distance x_r and relative velocity v_r to leading vehicles. Furthermore, video recordings of the driver and the forward scene allow to categorise the scenarios and assess driver behaviour.

Unfortunately, the large amount of raw data requires post-processing before it can be used for validation of ADASs in single-lane scenario simulations. For calibration of the parameter models two algorithms are used. Maximum likelihood (ML) estimation for calibration of uncorrelated parameters and expectation maximisation (EM) for calibration of correlated parameters. Both algorithms attempt to maximise the resemblance between a given PDF and a data distribution as shown in Fig. 7.

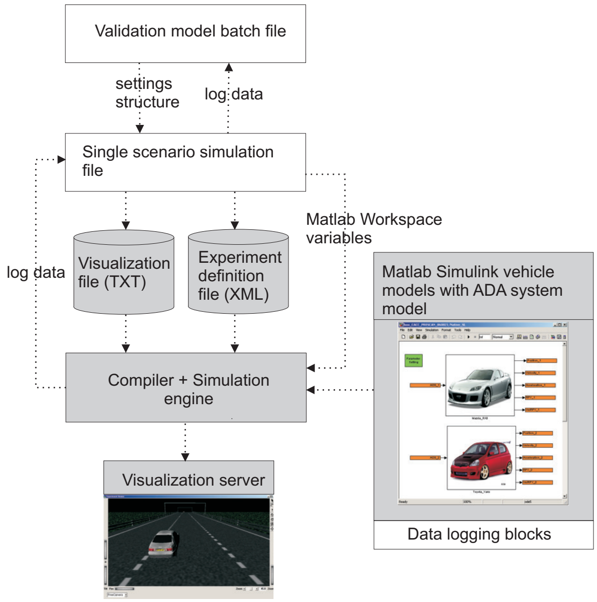

Fig. 8. The architecture of the single-lane traffic model with the PRESCAN simulation engine.

B. Implementation of the Single-lane Traffic Model

With the realistic PDFs of the model parameters, a useful model of single-lane traffic can be implemented on a software platform. The implementation of the model is performed in combination with the simulation tool PRESCAN [11]. PRESCAN is developed for microscopic traffic simulation, and can be considered as a simulator in which three different worlds are integrated and controlled:

- one or more sensor worlds;
- a visualisation world; and
- a combined controller/dynamics world represented by a PRESCAN controlled Matlab/Simulink session.

The compilation and simulation of traffic scenarios is controlled by the PRESCAN simulation engine. The complete structure of the single-lane traffic model together with PRESCAN is shown in Fig. 8.

V. SIMULATION RESULTS AND TEST DRIVES

The simulation results are first illustrated using two examples of single-lane scenarios. Then the results of the Monte Carlo simulation are presented.

A. Example 1: Lane Change Scenario

The first scenario simulation is a 3 vehicle configuration, where the middle vehicle (POV) performs a *lane change*. As a result the following vehicle (SV) has to follow the lead vehicle (POV2). The results are shown in Fig. 9, where it can be seen that the CACC starts following the POV2 after the POV has made a lane change. This is according to expectations. Another observation shows that the velocity profile of the SV with the CACC system is not damped well in this configuration. The poor velocity damping can be explained from the fact that the CACC first has to decelerate considerably for the POV. However when the POV cuts-out, the SV has to start following the POV2, which is at a larger distance and therefore requires less deceleration.

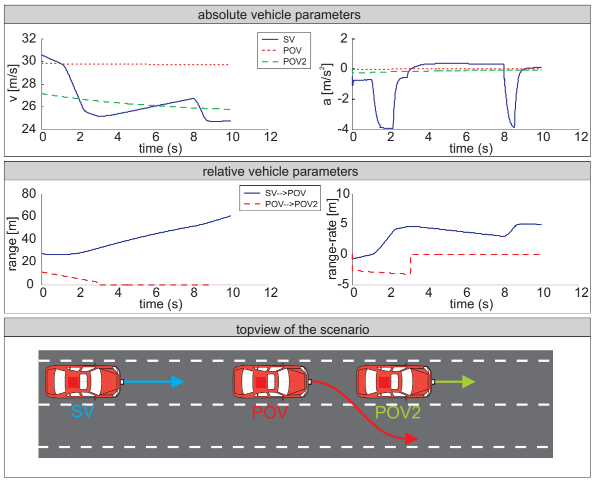

Fig. 9. Simulation results for a lane change scenario.

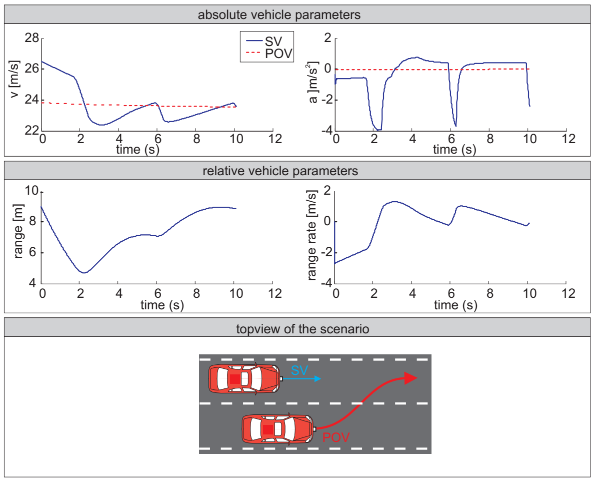

Fig. 10. Simulation results for a cut-in scenario.

B. Example 2: Cut-in Scenario

Another simulation is shown in Fig. 10, where a vehicle makes a *cut-in* in front of the SV with a much lower velocity. The SV decelerates rapidly when it detects the POV cutting in. The results show the same poor velocity damping as the first example. For this scenario the poor damping is due to the close *cut-in* of the POV combined with the lower velocity of the POV. These conditions cause the CACC to decelerate considerably at the start of the experiment. Because the same severe deceleration was required in Example 1, it can be concluded that the CACC velocity damping in case of severe deceleration is poor.

C. Monte Carlo Simulation Results

The experimental goal is to execute a Monte Carlo simulation of single-lane traffic. To illustrate this simulation strategy, 1 hour of single-lane traffic (equivalent to 280 simulated single-lane scenarios) is simulated and the per-

Fig. 11. The three demonstrator vehicles. From left to right: INCA, Smart12, Smart09.

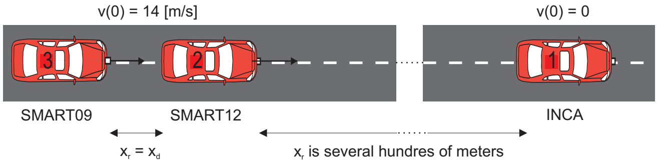

Fig. 12. The set-up of the performed single-lane scenario.

formance of the CACC evaluated. The following parameters were checked:

- The number of potential collisions.
- The acceleration level.
- Inter-vehicle spacing between SV and POV/POV2.
- Damping of oscillations in velocity.

In 1 hour of simulated single-lane traffic, the CACC-equipped vehicle collided 9 times. In 7 cases the collisions occurred because of unrealistic environment settings. The remaining 2 collisions occurred, because required deceleration of the vehicle was beyond the capability of the CACC.

The acceleration levels were comfortable for 95 % of the time. Only in safety-critical single-lane scenarios (*e.g.* emergency braking) the acceleration levels tended more toward noticeable and uncomfortable levels.

The spacing was assumed to be safe for 85 % of the time. Finally, the velocity damping of the CACC is acceptable, except when severe deceleration of the vehicle is required. A more proper tuning of the CACC could solve this damping problem for severe accelerations.

D. Validation of Simulation Results with Test Drives

Finally, the simulation results are compared with data from test drives. For the test drive two CACC-equipped Smarts (designated Smart09 and Smart12) and one Volkswagen (INCA) were used, as shown in Fig. 11, all equipped with VVC [12]. In one of the tests the Volkswagen is at standstill and the two Smarts approach as shown in Fig. 12.

The velocity profiles of both Smarts during the test drive are compared to those during a simulation with equal initial conditions. Fig. 13 shows that the POV model resembles the real-life behaviour of Smart 12 in single-lane traffic. The CACC-equipped SV model however, decelerates earlier than during the test drive (Smart09). This is caused by the fact that during the test drive the environment sensors and VVC are perturbed by environmental disturbances. As a result the standing vehicle is detected earlier in the simulated environment than during the test drive.

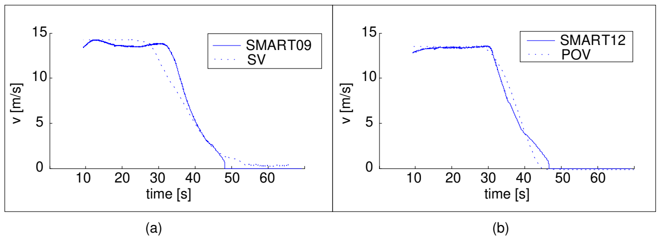

Fig. 13. Comparison of the velocity profiles between (a) Smart 09 and the SV, and (b) Smart 12 and the POV.

VI. CONCLUSIONS AND FUTURE WORK

In this paper the validation process of ADASs was illustrated with a CACC system, implemented in a vehicle model. In a Monte Carlo simulation of single-lane traffic, the CACC was subjected to several hundred single-lane traffic scenarios. The results are promising and the CACC performance proved to be satisfying.

Future research focusses on creating more realistic traffic simulations, by extending the model to multi-lane scenarios with more vehicles and more advanced driver models.

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