A Model Predictive Control Approach to Design a Parameterized Adaptive Cruise Control

Gerrit J.L. Naus, Jeroen Ploeg, M.J.G. (René) Van de Molengraft,
W.P.M.H. (Maurice) Heemels and Maarten Steinbuch

Abstract The combination of different desirable characteristics and situation-dependent behavior cause the design of adaptive cruise control (ACC) systems to be time consuming and tedious. This chapter presents a systematic approach for the design and tuning of an ACC, based on model predictive control (MPC). A unique feature of the synthesized ACC is its parameterization in terms of the key characteristics safety, comfort and fuel economy. This makes it easy and intuitive to tune, even for nonexperts in (MPC) control, such as the driver. The effectiveness of the design approach is demonstrated using simulations for some relevant traffic scenarios.

1 Introduction

Adaptive cruise control (ACC) is an extension of the classic cruise control (CC), which is a widespread functionality in modern vehicles. Starting in the late 1990s with luxury passenger cars, ACC functionality is now available in a number of commercial passenger cars as well as trucks. The objective of CC is to control the longitudinal vehicle velocity by tracking a desired velocity determined by the driver. Only the throttle is used as an actuator. ACC extends CC functionality by automatically adapting the velocity if there is a preceding vehicle, using the throttle as well as the brake system. Commonly, a radar is used to detect preceding vehicles, measuring the distance x_r and the relative velocity v_r between the vehicles. Hence, besides CC functionality, ACC enables also automatic following of a predecessor. In Figure 1, a schematic representation of the working principle of ACC is shown.

Gerrit J.L. Naus, M.J.G. (René) Van de Molengraft, W.P.M.H. (Maurice) Heemels and Maarten Steinbuch
Eindhoven University of Technology, P.O.box 513, 5600 MB, Eindhoven, The Netherlands, email: {g.j.l.naus,m.j.g.v.d.molengraft,w.p.m.h.heemels,m.steinbuch}@tue.nl

Jeroen Ploeg
TNO Automotive, P.O.box 756, 5708 HN, Helmond, The Netherlands, email: j.ploeg@tno.nl

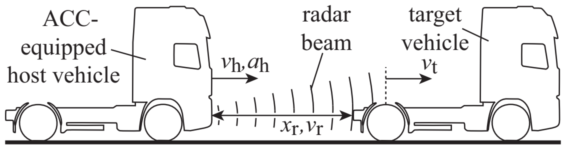

Fig. 1 The ACC-equipped host vehicle, driving with velocity v_h and acceleration a_h, automatically follows a preceding target vehicle, driving with velocity v_t.

Considering the automatic-following functionality, ACC systems typically consist of two parts: a vehicle-independent part and a vehicle-dependent part [13]. In Figure 2, a schematic representation of the ACC control loop is shown. The vehicle-independent part determines a desired acceleration/deceleration profile for the vehicle. The vehicle-dependent part ensures tracking of this profile via actuation of the throttle and the brake system through u_{th} and u_{br}, respectively. The latter part can thus be regarded as a controller for the longitudinal vehicle acceleration. As every vehicle has different dynamics, this part is vehicle dependent. The distance x_r and relative velocity $v_r = v_t - v_h$ with respect to the preceding vehicle are measured using a radar.

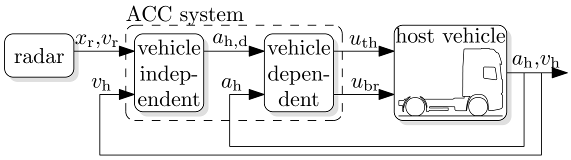

Fig. 2 Schematic representation of an ACC control loop.

Focusing on the vehicle-independent part, the primary control objective is to ensure following of a preceding vehicle. Considering the corresponding driving behavior, ACC systems are generally designed to have specific key characteristics, such as safety, comfort, fuel economy, traffic-flow efficiency and minimizing emissions [18]. In general, however, these characteristics typically impose contradictory control objectives and constraints, complicating the controller design. For instance, to ensure safe following, the system should be agile, requiring high acceleration and deceleration levels, which is not desirable considering comfort or fuel economy [10]. To account for different characteristics, a weighted optimization can be employed. For example, a model predictive control (MPC) approach can be adopted, which also facilitates constraint satisfaction [3, 9].

Besides the contradictory desirable characteristics, driver acceptance of the system requires ACC behavior to mimic human driving behavior to some extent [4]. Apart from the fact that human driving behavior is driver specific and time varying, it is also situation dependent [10, 19, 20]. The desired situation dependency of the designs give rise to many tuning variables, which makes the design and tuning time consuming and error prone.

In this chapter, the design of an ACC is presented, accounting for the contradictory characteristics and the many tuning variables. The focus is on the design of the vehicle-independent part of the automatic-following functionality. The contribution is the design of an ACC, which is parameterized by the key characteristics safety, comfort and fuel economy, with at most one tuning variable for each characteristic. The setting of the ACC can then easily be changed, possibly even by the driver.

The organization of this chapter is as follows. The problem formulation and the setup are presented in Sections 2 and 3. The parameterization and results are discussed in Section 4. Finally, conclusions and an outlook on future work are given.

2 Problem Formulation

The problem formulation involves parameterization of the ACC, based on the chosen key characteristics.

2.1 Quantification Measures

In this research, safety, comfort and fuel economy are chosen as the key characteristics of the desired behavior of an ACC. Considering safety, however, we note that the ACC is not a safety system such as an emergency braking or a collision avoidance system. ACC is primarily a comfort system that incorporates safety in the sense that appropriate driving actions within surrounding traffic are guaranteed. To enable quantification of the key characteristics, desirable properties of these characteristics, so-called quantification measures, have to be defined.

Typically, the safety of a traffic situation increases for increasing inter-vehicle distance and decreasing relative velocity. Hence, regarding safety, the inter-vehicle distance and the relative velocity will be used as quantifications measures [11]. Regarding comfort, the (peak) acceleration and (peak) jerk levels will be used as quantification measures [8, 16]. Concerning fuel consumption, especially the average velocity and the deceleration time are important measures [6, 15]. Both measures are influenced by the acceleration and deceleration levels. Hence, regarding fuel economy, these levels will be used as quantification measures.

2.2 Parameterization

This research presents the design of a parameterized ACC, with, in the end, only a few design parameters, that are directly related to the key characteristics of the behavior of the ACC. The limited number of intuitive tuning variables enables quick and easy adaptation of the ACC to different desirable driving behavior. Importantly, these variables can also be used by nonexperts in (MPC) control, like the average driver, to change the behavior of the ACC system to the driver's own wishes. Enabling the driver to set these variables, really makes the ACC easily adjustable.

Correspondingly, the design parameters P_s, P_c and P_f are defined, indicating to what extent the driving behavior of an ACC-controlled vehicle is either safe, comfortable or fuel economic, with $P_s \in [0,1]$, $P_c \in [0,1]$ and $P_f \in [0,1]$. Incorporating P_s, P_c and P_f in the controller design yields a parameterized ACC, i.e., ACC(P_s, P_c, P_f), with P_s, P_c and P_f as tuning variables directly related to the behavior of the ACC. The systematic approach presented here, makes it possible to redesign the system relatively easy, and reduces the amount of time-consuming and error-prone trial-and-error techniques in the design. Although, focus lies here on safety, comfort and fuel economy, the approach is general and can be adopted for any characteristics, e.g., traffic flow efficiency or minimizing emissions.

3 Model Predictive Control Problem Setup

In this section, the control problem formulation is discussed.

3.1 Modeling

A model predictive control (MPC) synthesis is adopted to design the ACC. The MPC synthesis requires a model of the relevant dynamics to use as a prediction model. Consider again the control structure as presented in Figure 2. Focusing on the design of the vehicle-independent control part, the model should cover the longitudinal host vehicle dynamics, the vehicle-dependent control part and the longitudinal relative dynamics, which are measured by the radar. Assuming that the vehicle-dependent control part ensures perfect tracking of the desired acceleration $a_{h,d}(t)$, the internal vehicle dynamics and the vehicle-dependent control part together can be modeled by a single integrator, relating the host vehicle velocity $v_h(t)$ and the (desired) acceleration $a_h(t) = a_{h,d}(t)$. The continuous-time equations, modeling the dynamics, are given by:

$$\begin{cases} x_r(t) = x_r(0) + \int_0^t v_r(\tau)d\tau \\ v_r(t) = v_r(0) + \int_0^t a_r(\tau)d\tau \\ v_h(t) = v_h(0) + \int_0^t a_h(\tau)d\tau \end{cases} \quad (1)$$

where $x_r(t)$ the relative position, $v_r(t) = v_t(t) - v_h(t)$ the relative velocity, $a_r(t) = a_t(t) - a_h(t)$ the relative acceleration, $v_h(t)$ the host vehicle velocity, and $a_h(t)$ the host vehicle acceleration at time $t \in \mathbb{R}^+$. The values of $x_r(t)$ and $v_r(t)$ are measured by the radar and measurements of $v_h(t)$ and $a_h(t)$ are available. As the acceleration of the target vehicle $a_t(t)$ is unknown, it is, for now as a nominal case, assumed to be zero in the MPC prediction model, yielding $a_r(t) = -a_h(t)$. In the end, $a_t(t)$ acts as a disturbance on the closed loop system.

MPC is commonly designed and implemented in the discrete-time domain. Therefore, the continuous-time equations (1) are converted into a discrete-time model via exact discretization with sample time T_s, and using a zero-order-hold assumption on $a_h(t)$. The signals are considered at the sampling times $t = kT_s$ where $k \in \mathbb{N}$ represents the discrete time steps:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}a_h(k) \quad k \in \mathbb{N} \tag{2}$$

where $\mathbf{x}(k) = (x_r(k), v_r(k), v_h(k))^T$, with some slight abuse of notation, and

$$\mathbf{A} = \begin{pmatrix} 1 & T_s & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} -\frac{1}{2}T_s^2 \\ -T_s \\ T_s \end{pmatrix} \tag{3}$$

Considering the control structure as presented in Figure 2, the host vehicle acceleration $a_h(k) = a_{h,d}(k)$ can be regarded as the control input. Furthermore, as all states of $\mathbf{x}(k)$ are measured, the output equation becomes $\mathbf{y}(k) = \mathbf{x}(k),\ k \in \mathbb{N}$, yielding:

$$\mathscr{M} : \begin{cases} \mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}u(k) \\ \mathbf{y}(k) \quad = \mathbf{x}(k) \end{cases} \quad k \in \mathbb{N} \tag{4}$$

with $u(k) = a_h(k)$ and $\mathbf{A}$ and $\mathbf{B}$ as defined in (3).

Finally, the input-output model $\mathscr{M}$ (4) is converted into an increment input-output (IIO) model $\mathscr{M}_e$ [7]. This enforces integral behavior, i.e., enabling a nonzero control output $u(k)$ for zero error $e(k)$, thus providing the possibility to prevent steady state errors in, for example, the following distance. The IIO model is given by:

$$\mathscr{M}_e : \begin{cases} \mathbf{x}_e(k+1) = \mathbf{A}_e\mathbf{x}_e(k) + \mathbf{B}_e\delta u(k) \\ \mathbf{y}_e(k) \quad = \mathbf{x}_e(k) \end{cases} \quad k \in \mathbb{N} \tag{5a}$$

where $\mathbf{x}_e(k) = (\mathbf{x}^T(k), u(k-1))^T$ is the new state vector, $\delta u(k) = u(k) - u(k-1)$ the new control input, and

$$\mathbf{A}_e = \begin{pmatrix} 1 & T_s & 0 & -\frac{1}{2}T_s^2 \\ 0 & 1 & 0 & -T_s \\ 0 & 0 & 1 & T_s \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad \mathbf{B}_e = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \tag{5b}$$

are the new model matrices. The model $\mathscr{M}_e$ (5) will be used as the MPC prediction model for the vehicle-independent control part in the remainder of this chapter.

3.2 Control Objectives and Constraints

Typically, the primary control objective of an ACC amounts to following a target vehicle at a desired distance $x_{r,d}(k)$. Often, a so-called desired time headway $t_{hw,d}$ is used to define this desired distance, yielding

$$x_{\mathrm{r,d}}(k) = x_{\mathrm{r,0}} + v_{\mathrm{h}}(k)\, t_{\mathrm{hw,d}} \tag{6}$$

with $x_{\mathrm{r,0}}$ a constant representing the desired distance at standstill, and the desired time headway $t_{\mathrm{hw,d}}$ a measure for the time it takes to reach the current position of the preceding vehicle if the host vehicle continues to drive with its current velocity, i.e., for constant $v_{\mathrm{h}}(k)$. Correspondingly, the tracking error at discrete time $k \in \mathbb{N}$ is defined as $e(k) = x_{\mathrm{r,d}}(k) - x_{\mathrm{r}}(k)$. Hence, the primary control objective, denoted as $\mathscr{O}_1$, comes down to minimizing the absolute tracking error $|e(k)|,\ k \in \mathbb{N}$.

Besides the primary control objective $\mathscr{O}_1$, several secondary objectives as well as constraints, related to the key characteristics safety, comfort and fuel economy, have to be included. These secondary objectives and constraints are based on the quantification measures discussed in Section 2.1: the absolute value of the relative velocity $|v_{\mathrm{r}}(k)|$ and the peak values of the host vehicle acceleration $|a_{\mathrm{h}}(k)|$ and the jerk, which will be denoted by $|j_{\mathrm{h}}(k)|$, should be kept small. Furthermore, the relative position should always be positive, i.e., $x_{\mathrm{r}}(k) > 0$, and the absolute values of the acceleration of the host vehicle $|a_{\mathrm{h}}(k)|$ and the absolute value of the jerk $|j_{\mathrm{h}}(k)|$ are constrained. The constraints on the acceleration and the jerk are given by $a_{\mathrm{h,min}} = -3.0\,\mathrm{m\,s^{-2}}$ [17], $a_{\mathrm{h,max}}(v_{\mathrm{h}}(k)) = a_{\mathrm{h,0}} - \alpha v_{\mathrm{h}}(k)$, and $|j_{\mathrm{h}}(k)| \leq j_{\mathrm{h,max}}$, where $j_{\mathrm{h,max}}$, $a_{\mathrm{h,0}}$ and α are appropriately chosen positive constants. The parameter α will allow to decrease $a_{\mathrm{h,max}}$ for increasing $v_{\mathrm{h}}(k)$. The IIO model accommodates the constraint on $|j_{\mathrm{h}}(k)|$, using the variation in the control output $\delta u(k)$ as a measure for the jerk $j_{\mathrm{h}}(k)$. Correspondingly, the constraint on the jerk is transformed into $|\delta u(k)| \leq j_{\mathrm{h,max}}$.

Summarizing, the constraints are given by:

$$\mathscr{C} : \begin{cases} 0 < x_{\mathrm{r}}(k) \\ a_{\mathrm{h,min}} \leq u(k) \leq a_{\mathrm{h,max}}(v_{\mathrm{h}}(k)) \qquad k \in \mathbb{N} \\ |\delta u(k)| \leq j_{\mathrm{h,max}} \end{cases} \tag{7}$$

where $u(k) = a_{\mathrm{h,d}}(k) = a_{\mathrm{h}}(k)$.

3.3 Control Problem / Cost Criterion Formulation

As we use MPC, a cost criterion J, which is minimized over a prediction horizon N_{y}, has to be defined. The future system states are predicted using the model $\mathscr{M}_{\mathrm{e}}$ (5) and the current state $\mathbf{x}_{\mathrm{e}}(k|k) := \mathbf{x}_{\mathrm{e}}(k)$ at discrete time step k as initial condition. This yields the predicted states $\mathbf{x}_{\mathrm{e}}(k+n|k)$ and the predicted tracking error $e(k+n|k)$, $n = 0, 1, \ldots, N_{\mathrm{y}}$ for a selected input sequence $\delta\mathbf{U}(k|k) = \big(\delta u(k|k), \ldots, \delta u(k+N_{\mathrm{y}}-1|k)\big)^T$, starting at discrete time step k. Based on the prediction of the future system states, the minimization problem yields an optimal control sequence, subject to constraints (7) on the inputs and outputs.

The cost criterion is typically formulated as a linear or as a quadratic criterion. To solve the corresponding optimization problem results in a linear program (LP) or a quadratic program (QP). Finding the solution of an LP is less computationally demanding than the corresponding solution of a QP, although this can also be done efficiently. The tuning of linear formulations, however, suffers from practical drawbacks, which explains why MPC is often formulated using a quadratic criterion [7, 14]. We will use the quadratic criterion:

$$\begin{aligned} J(\delta\mathbf{U}(k|k),\mathbf{x}_\mathrm{e}(k)) = & \textstyle\sum_{n=1}^{N_\mathrm{y}} \left[\xi^T(k+n|k)\,\mathbf{Q}\,\xi(k+n|k)\right] + \\ & + \textstyle\sum_{n=0}^{N_\mathrm{u}-1} \left[\delta u^T(k+n)\,R\,\delta u(k+n)\right] \end{aligned} \tag{8}$$

with $\xi(k+n|k) \triangleq (e(k+n|k), v_\mathrm{r}(k+n|k), a_\mathrm{h}(k+n|k))^T$ a column vector incorporating the primary and secondary control objectives, with $a_\mathrm{h}(k+n|k) = u(k+n|k)$, and $\mathbf{Q} = \mathrm{diag}(Q_\mathrm{e}, Q_{\mathrm{v_r}}, Q_{\mathrm{a_h}})$ and $R = Q_{\mathrm{j_h}}$ the weights on the tracking error and the secondary control objectives. Furthermore, N_y and N_u denote the output and the control horizon, respectively, where $N_\mathrm{u} \leq N_\mathrm{y}$. Moreover, for $N_\mathrm{u} \leq n < N_\mathrm{y}$ the control signal is kept constant, i.e., $\delta u(k+n|k) = 0$ for $N_\mathrm{u} \leq n < N_\mathrm{y}$. Finally, $u(k+n|k) = u(k+n-1|k) + \delta u(k+n|k)$, for $n \geq 0$.

Given a full measurement of the state $\mathbf{x}_\mathrm{e}(k)$ of the model $\mathscr{M}_\mathrm{e}$ (5) at the current time k, the MPC optimization problem at time k is formulated as

$$\begin{aligned} \underset{\delta\mathbf{U}(k|k)}{\text{minimize}} \;& J(\delta\mathbf{U}(k|k),\mathbf{x}_\mathrm{e}(k)) \\ \text{subject to the dynamics } & \mathscr{M}_\mathrm{e} \ (5) \\ \text{the constraints } & \mathscr{C} \ (7) \end{aligned} \tag{9}$$

The controller will be implemented in a receding horizon manner, meaning that at every time step k, an optimal future input sequence $\delta\mathbf{U}^*(k|k) = (\delta u^*(k|k), \ldots, \delta u^*(k+N_\mathrm{y}-1|k))^T$ is computed in the sense of the minimization problem (9). The first component of this vector, $\delta u^*(k|k)$, is used to compute the new optimal control output $u^*(k) = u(k-1) + \delta u^*(k|k)$. This $u^*(k)$ is applied to the system, i.e., $u(k) = u^*(k)$, after which the optimization (9) is performed again for the updated measured state $\mathbf{x}_\mathrm{e}(k+1) = (\mathbf{x}^T(k+1), u(k))^T$.

4 Controller Design

The final controller design, the implementation, and simulation results are presented in this section.

4.1 Parameterization

The MPC controller design incorporates all quantification measures regarding safety and comfort. This yields a significant number of MPC tuning parameters, given by the desired time headway $t_{\mathrm{hw,d}}$, the constraints on the acceleration and jerk, $a_{\mathrm{h,min}}$, $a_{\mathrm{h,max}}$ and $j_{\mathrm{h,max}}$, respectively, the weights $\mathbf{Q} = \mathrm{diag}(Q_{\mathrm{e}}, Q_{\mathrm{v_r}}, Q_{\mathrm{a_h}})$ and $R = Q_{\mathrm{j_h}}$, and the control and prediction horizons N_{u} and N_{y}.

Using affine relationships between the MPC tuning parameters on the one hand and the ACC design parameters for safety, P_{s}, for comfort, P_{c}, and for fuel economy, P_{f}, on the other hand, the MPC tuning parameters are explicitly related to the key characteristics safety, comfort, and fuel economy. In this way, the MPC tuning parameters are all determined as a function of these three essential design parameters. The setting of these design parameters indicates to what extent the driving behavior is either safe, comfortable or fuel economic, with $P_{\mathrm{s}} \in [0,1]$, $P_{\mathrm{c}} \in [0,1]$ and $P_{\mathrm{f}} \in [0,1]$. Due to space limitations, we will not discuss in detail how these affine relationships are actually constructed, see [12].

In this specific case in which we considered comfort, safety and fuel economy as key characteristics, it can be assumed that the key characteristics are complementary: the design of the relationships between the MPC tuning parameters and the ACC design parameters indicates a decrease in comfort of the driving for increasing safety, and vice versa. For example, small acceleration and jerk peak values, indicating a high level of comfort, induce a long time to steady state, which is not desirable regarding safety. Furthermore, the quantification measures chosen to indicate comfort, are similar to those indicating fuel economy. Consequently, in this case, a single parameter $P \in [0,1]$ results:

$$P = P_{\mathrm{c}}, \quad P_{\mathrm{s}} = 1 - P, \quad P_{\mathrm{f}} = P, \quad P \in [0,1] \tag{10}$$

If other characteristics would be considered in the design, typically more design parameters would remain in the end.

Parameterization of the ACC with safety, comfort and fuel economy amounts to incorporating in the original optimization problem (9) the relationships between the MPC tuning parameters, $t_{\mathrm{hw,d}}$, $a_{\mathrm{h,min}}$, $a_{\mathrm{h,max}}$, $j_{\mathrm{h,max}}$, $\mathbf{Q}$, R, N_{u} and N_{y}, and the design parameters, P_{s}, P_{c} and P_{f}, accounting for (10). This yields

$$\begin{aligned} \underset{\delta\mathbf{U}(k|k)}{\text{minimize}}\ & J(P, \delta\mathbf{U}(k|k), \mathbf{x}_{\mathrm{e}}(k)) \\ \text{subject to the dynamics } & \mathscr{M}_{\mathrm{e}}\ (5) \\ \text{the constraints } & \mathscr{C}\ (7) \end{aligned} \tag{11}$$

where $\mathscr{C} = \mathscr{C}(P)$ as a result of the parameterization. Changing the behavior of the ACC system comes down to adjusting P. Allowing the driver to change $P \in [0,1]$, enables him to influence the behavior of the controller focusing on either safe, or comfortable and fuel economic driving, depending on the driver's own desire.

4.2 Implementation Issues

The total controller design is implemented via the Multi Parametric Toolbox [5]. Online solving of the optimization problem (9) at each time step yields an implicit solution. Solving (9) as a multi-parametric quadratic program (mpQP) with parameter vector $\mathbf{x}_\mathrm{e}$ enables an explicit form of the solution by offline optimization. The resulting explicit controller inherits all stability and performance properties of the implicit controller and has the form of a piecewise affine (PWA) state feedback law [1, 2]. Solving the mpQP, provides a set $\mathscr{X}_\mathrm{f} \subseteq \mathbb{R}^{n_\mathrm{x}}$, with n_x the dimension of $\mathbf{x}_\mathrm{e}$, of states for which the constrained optimization problem (9) is feasible. Since the control law is given by a PWA state feedback law, the feasible set $\mathscr{X}_\mathrm{f}$ is partitioned into R polyhedral regions $\mathscr{R}_\mathrm{i}$, $i = 1,\dots,R$, such that

$$\mathscr{X}_\mathrm{f} = \bigcup_{i=1}^{R} \mathscr{R}_\mathrm{i} \tag{12}$$

where $\mathrm{int}\mathscr{R}_\mathrm{i} \cap \mathrm{int}\mathscr{R}_\mathrm{j} = \emptyset$, for $i = 1,\dots,R,\ j = 1,\dots,R$ and $i \neq j$. At time step k, the optimal input $\delta u^*(k|k)$ is then given by

$$\delta u^*(k|k) = \mathbf{F}_\mathrm{i}\mathbf{x}_\mathrm{e}(k) + f_\mathrm{i}, \qquad \text{for } \mathbf{x}_\mathrm{e}(k) \in \mathscr{R}_\mathrm{i}, \qquad i = 1,\dots,R \tag{13}$$

To compute the control input at discrete time step $k \in \mathbb{N}$, (13) has to be evaluated.

Regarding the explicit solution, the most time-consuming part is determination of the region $\mathscr{R}_\mathrm{i}$ that contains $\mathbf{x}_\mathrm{e}(k)$. However, online tuning is prohibited by the offline optimization. As a solution, one might store various explicit controllers for a finite number of values $P \in n/N$ for $n = 0,1,2,\dots,N$. For implementation of the implicit controller, solving an optimization in every time step is required. Hence, the computational demand depends on the available solver, which is not desirable targeting industrial acceptance. However, P can be changed online in a continuous manner. Depending on the system requirements, one may adopt either solution.

4.3 Results

To illustrate the influence of varying $P \in [0,1]$, simulations are performed for some relevant traffic scenarios using an explicit controller. For a finite number of values $N = 10$ for P, the number of regions in the explicit ACC laws ranges from 110 to 120. In Figures 3 and 4 the results of *the approach of a vehicle at standstill* and *a negative cut-in scenario* for different settings $P \in \{0.2, 0.5, 0.8\}$ are shown, showing the proper working of the parameterization. By changing the setting of the design parameter $P \in [0,1]$, the behavior of the ACC system changes, with respect to the comfort, the safety and the fuel economy of the resulting driving action.

In Figure 3, the results of *the approach of a vehicle at standstill* are shown. At 13 s, the vehicle at standstill is detected by the radar, which has a range of 180 m.

Before that, no vehicle is detected. The following behavior of the ACC system becomes more comfortable as well as more fuel economic for increasing P. Firstly, the deceleration peaks decrease, and secondly, the total deceleration time increases. As a result, the average velocity decreases, which is beneficial regarding fuel economy.

A *negative cut in scenario* involves the cut in of a vehicle driving with a velocity $v_{\mathrm{t}}(k) < v_{\mathrm{h}}(k)$ at an inter-vehicle distance $x_{\mathrm{r}}(k) < x_{\mathrm{r,d}}(k)$, see Figure 4: at 20 s, a vehicle cuts in 30 m in front of the host vehicle with a velocity of $50\,\mathrm{km\,h^{-1}}$, while the host vehicle is driving at $80\,\mathrm{km\,h^{-1}}$. Before that, no preceding vehicle is detected and, hence, no distance is measured. From a safety point of view, direct reaction and substantial braking are required, disregarding the setting of P, i.e., comfort or fuel-economy-related measures. The results in Figure 4 indeed show this behavior, indicating that safe behavior is guaranteed for any value of P. Furthermore, the results show that for decreasing P the desired steady state distance increases, which is a result of the parameterization $t_{\mathrm{hw,d}} = t_{\mathrm{hw,d}}(P)$, and is desirable regarding safety.

5 Conclusions and Future Work

In this chapter, a systematic procedure to design an ACC is presented, which is directly parameterized by the key characteristics safety, comfort and fuel economy of

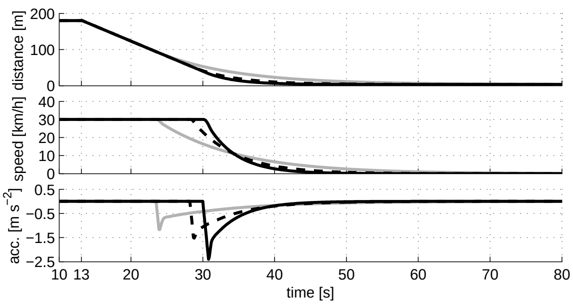

Fig. 3 The distance x_{r}, the host vehicle velocity v_{h} and the acceleration a_{h}, corresponding to *the approach of a vehicle at standstill*. The solid black, the dashed black and the solid gray lines show the results for increasing $P \in \{0.2, 0.5, 0.8\}$.

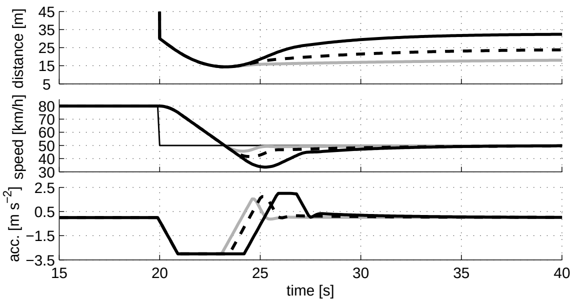

Fig. 4 The distance x_{r}, the host vehicle velocity v_{h} and the acceleration a_{h}, corresponding to a *negative cut in*. The solid black, the dashed black and solid gray lines represent the results for increasing $P \in \{0.2, 0.5, 0.8\}$, respectively. The narrow black line in the middle figure represents the velocity of the target vehicle v_{t}.

the ACC behavior. The goal of the parameterization of the ACC is to reduce the time it takes to tune the system and to enable the tuning for nonexperts in (MPC) control, such as the driver. This requires that the tuning should be simple and intuitive with only a few design parameters that are directly related to the key characteristics of the ACC. To this end, the corresponding design parameters P_s, P_c and P_f are defined. Due to the generality of the approach, other characteristics can be straightforwardly incorporated in the design, using the same systematic design procedure.

The approach is based on (explicit) MPC. The parameterized ACC is obtained by carefully mapping the many tuning parameters of the MPC setup to the three design parameters P_s, P_c and P_f only, which, in this specific case, could be united in one design parameter P. Simulations have shown the proper functioning of the parameterized ACC for some relevant traffic scenarios. Changing the behavior of the system by changing the setting of the design parameter P, has proven to work in a desired manner.

Future research will focus on experiments, and on extending the two-vehicle model to multiple vehicles. Taking vehicle-to-vehicle communication into account too, allows for the design of so-called cooperative ACC (CACC) systems. The communication provides additional information concerning the surrounding traffic in addition to the radar data, which can be very beneficial to the system behavior.

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