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A model predictive controller for non-cooperative eco-platooning

Valerio Turri[1,*], Yeojun Kim[2,*], Jacopo Guanetti[2], Karl H. Johansson[1], Francesco Borrelli[2]

***Abstract*— This paper proposes an energy-saving adaptive cruise control (ACC) which exploits the future trajectory of the preceding vehicle to minimize unnecessary braking. By suitable design of the model predictive control terminal set, the proposed eco-ACC avoids unnecessary braking and improves fuel economy, while guaranteeing safety and limited online computational burden. Simulations and experiments show the efficacy of the approach and confirm fuel saving, when the eco-ACC is compared to baseline ACC formulations.**

I. Introduction

Platooning consists in running vehicles at a relatively small distance, and has been widely studied in the past decades. Early research focused on road throughput maximization, safety and stability of the vehicle stream (see e.g. [7], [10]–[12]). Recent advances in sensing and communication technologies renewed the interest both from the research community and the industrial sector. Vehicle platooning can also help to reduce energy consumption. A small inter-vehicular distance can reduce the aerodynamic resistance, which is especially important at high speed. In open-road experiments with a platoon of trucks, fuel reductions up to $7\,\%$ have been registered [1].

Several control approaches have been proposed to exploit this potential. The majority of existing theoretical and experimental studies assumes that vehicles in a platoon track a constant speed or cooperate to reach an overall fuel saving [1], [13]. Cooperation requires not only inter-vehicular communication, but also protocols to establish a consensus. This is realistic in freight transportation [13], where the objective is common to all the agents, but would probably require an adequate incentives policy in personal transportation. While an accepted policy for cooperation is lacking at present, non-cooperative solutions can still offer valuable savings. Stochastic models of the traffic speed and the road gradient have been used to define control policies able to reduce vehicle fuel consumption [4], [8]. The availability of information on the future speed of the preceding vehicle (obtained by vehicle-to-vehicle communication or by estimation) and on the road profile can be exploited in a model predictive control (MPC) framework to further reduce vehicles fuel consumption [5], [6]. However, the prediction horizon necessary to reach valuable fuel saving is typically prohibitive for real-time implementation, because of the limited on-board computational power.

In this paper we propose an adaptive cruise control (ACC) designed for energy consumption reduction (hereafter named eco-ACC). We focus on non-cooperative platooning: our eco-ACC optimizes the behavior of a vehicle following another vehicle, whose future nominal trajectory is assumed to be known. This preview is enabled by driving automation, which both plans trajectories in advance, and - removing the driver from the loop - follows them as closely as possible. Our control approach aims at avoiding power dissipation through braking. This requires a paradigm shift from classical ACC approaches, which mainly focus on tracking the trajectory of the preceding vehicle, to a formulation that allows trajectory deviations, if that reduces energy usage. The main contribution of this paper is a real-time implementable MPC formulation that can conveniently exploit long previews of the preceding vehicle by combining a short prediction horizon of few seconds with a specifically designed terminal state set. Our experimental study shows that this MPC formulation avoids unnecessary braking and can significantly improve fuel economy and ride comfort.

The remainder of the paper is organized as follows. Section II discusses the modeling assumptions on which our MPC formulation is based. Section III illustrates the proposed MPC formulation for eco-ACC. Section IV summarizes the experimental results from the implementation of the eco-ACC on a real vehicle. Section V shows with simulations how the terminal set makes the eco-ACC long-sighted. Some concluding remarks end the paper.

II. Vehicle Model and Problem Statement

In this section we discuss the vehicle dynamics and energetics that are the basis of the proposed MPC formulation. The eco-ACC control problem is then briefly stated.

A. Vehicle dynamics

The problem is to control a single vehicle (referred to as the *ego vehicle*) and its interaction with the vehicle ahead (referred to as the *preceding vehicle*). We focus on three main dynamics, (i) the distance of the ego vehicle from the preceding vehicle, (ii) the lumped longitudinal dynamics of the ego vehicle, and (iii) its actuator dynamics.

The relative distance is dictated by the difference of velocity between preceding and ego vehicle. When traveling on a flat road, the longitudinal dynamics of the ego vehicle can be modeled using Newton's law (see e.g. [3]). A first order dynamic model is used for the actuation of traction and braking forces through engine and brakes; though simplified,

[1] ACCESS Linnaeus Centre and Department of Automatic Control, KTH Royal Institute of Technology, Stockholm, Sweden. E-mail: turri,kallej@kth.se
[2] Department of Mechanical Engineering, University of California at Berkeley, CA, USA. E-mail: {yk4938,jacopoguanetti,fborrelli}@berkeley.edu
* These authors equally contributed to this work.

TABLE I

MODEL PARAMETERS

m	vehicle mass	kg	2200
A	vehicle reference area	m^2	3.15
ρ	air density	$\mathrm{kg/m}^3$	1.206
c_d	vehicle drag coefficient	-	0.28
c_r	vehicle roll coefficient	-	0.0093
τ	actuation time constant	s	0.5
t_s	sampling time	s	0.2

this model proved effective in practice. The overall model in discrete time (where k denotes the time instant) is

$$d(k+1) = d(k) + t_s(v_p(k) - v(k)) \,, \tag{1a}$$

$$v(k+1) = v(k) + \frac{t_s}{m} F(k) - t_s g c_r - \frac{t_s}{m} \rho A c_d v^2(k) \,, \tag{1b}$$

$$F(k+1) = \left(1 - \frac{t_s}{\tau}\right) F(k) + \frac{t_s}{\tau}(F_t(k) + F_b(k)) \,, \tag{1c}$$

where the state variables d, v, and F denote the distance, speed, and longitudinal force of the ego vehicle, respectively. The longitudinal force F is commanded through the control variables $F_t \geq 0$ and $F_b \leq 0$, representing the reference traction and braking forces, respectively. The time-varying parameter v_p denotes the velocity of the preceding vehicle. The parameters of model (1) used for MPC design are listed in Table I. In the remainder of the paper, the dynamic model (1) is shortly indicated by

$$x(k+1) = f(x(k), u(k), v_p(k)) \,, \tag{2}$$

where $x = [d,\, v,\, F]^{\mathrm{T}}$ and $u = [F_t,\, F_b]^{\mathrm{T}}$.

We finally introduce the approximated dynamics of the vehicle while coasting (i.e., advancing without injecting any fuel in the engine), as it is relevant to our MPC formulation presented in Section III. Setting to zero the force F yields

$$d(k+1) = d(k) + t_s(v_p(k) - v(k)) \,, \tag{3a}$$

$$v(k+1) = v(k) - t_s g c_r - \frac{t_s}{m} \rho A c_d v^2(k) \,. \tag{3b}$$

B. Vehicle energetics

The goal of this paper is to pursue fuel economy improvements for a tailored eco-ACC strategy, when compared to basic ACC strategies tracking a certain gap from the preceding vehicle. Our objective is to influence the so-called *tank-to-wheels* energy conversion step [9]. The *wheels-to-distance* conversion step [9] is out of our scope, as it involves interaction with navigation systems and driver requirements (for applications like platoon coordination, and route optimization). In this work we only focus on the ACC problem, assuming that the decision to form a platoon has already been taken.

In the tank-to-wheels conversion for a combustion vehicle, the main factors affecting fuel economy are (i) the velocity v and longitudinal force F profiles, (ii) the gear shifting policy, and (iii) the inter-vehicular distance d. Velocity and force profiles affects both the amount of energy that is dissipated through braking, and the additional energy that is consumed due to engine operation at less-than-maximum efficiency.

In this paper we focus on the shaping of velocity and force profiles, and particularly on limiting power dissipation through braking. Clearly, taking engine efficiency into consideration could improve performance significantly, but requires a powertrain model, which is typically tuned through extensive experiments and changes from vehicle to vehicle. Conversely, our choice makes the proposed eco-ACC easily applicable to a broad class of vehicles, as the presented model can be easily identified, e.g. with coasting down tests.

C. Eco-ACC problem statement

The eco-ACC problem addressed in the paper is now briefly stated. The ego vehicle knows a preview of the preceding vehicle velocity profile from the current time t to time $t+N_c$. The ego vehicle dynamics are given in (1). Safety, i.e. avoidance of collisions with the preceding vehicle, must be guaranteed. The goal is to maintain a desired distance from the preceding vehicle, while avoiding unnecessary braking.

III. MPC FORMULATION

In this section we propose an MPC approach for the eco-ACC problem outlined above. At each time step the MPC algorithm computes the optimal control and state trajectories solving the following finite horizon optimization problem:

$$\underset{u(\cdot|t)}{\text{minimize}} \quad J = \sum_{k=t}^{t+N_p} \|d(k|t) - d_{\text{des}}\|_Q \tag{4a}$$

$$+ \sum_{k=t}^{t+N_p-1} \|F_b(k|t)\|_B \tag{4b}$$

$$+ \sum_{k=t}^{t+N_p-1} \|F(k|t) - F(k+1|t)\|_D \tag{4c}$$

$$\text{subject to} \quad x(k+1|t) = f(x(k|t),\, u(k|t),\, v_p(k)) \,, \tag{4d}$$

$$v_{\min} \leq v(k|t) \leq v_{\max} \,, \tag{4e}$$

$$0 \leq F_t(k|t) \leq F_{\max} \,, \tag{4f}$$

$$F_{\min} \leq F_b(k|t) \leq 0 \,, \tag{4g}$$

$$d_{\text{safe}} \leq d(k|t) \,, \tag{4h}$$

$$x(t|t) = x(t) \,, \tag{4i}$$

$$\forall k = t, \ldots, t+N_p-1,$$

$$\begin{bmatrix} d(t+N_p|t) \\ v(t+N_p|t) \end{bmatrix} \in \mathcal{C} \,, \tag{4j}$$

where $x(k|t) = [d(k|t),\, v(k|t),\, F(k|t)]^{\mathrm{T}}$ and $u(k|t) = [F_t(k|t),\, F_b(k|t)]^{\mathrm{T}}$ represent the state and input at time k predicted at time t, respectively.

The cost function J includes a penalty for tracking the (constant) desired distance d_{des} (4a), a penalty on braking (4b), and a penalty on jerk (4c). The weighting term B on the braking force is chosen relatively large compared to the other weighting terms in order to avoid braking unless strictly necessary (i.e., if required by the activation of the constraints). The minimization of the cost function is subject

TABLE II

MPC PARAMETERS

d_{des}	desired distance	m	20
d_{safe}	safety distance	m	5
v_{min}	minimum velocity	m/s	0
v_{max}	maximum velocity	m/s	45
F_{min}	minimum braking force	kN	-43
F_{max}	maximum traction force	kN	3
N_p	MPC horizon	-	30
N_c	coasting horizon	-	330

to the vehicle prediction model (4d) defined by (2). The reference traction and braking forces, F_t and F_b, and the velocity, v, are bounded by constraints (4e), (4f), and (4g) enforcing the physical limitations of the vehicle and its actuators. The safety constraint (4h) is enforced throughout the prediction horizon, to avoid collisions with the preceding vehicle. The initial state is set in (4i). The MPC parameters in (4) are listed in Table II.

In problem (4) the set $\mathcal{C}$ is the terminal state condition (4j), whose aim is to give long-sight to the MPC eco-controller, otherwise myopic. In detail, it prevents that the excessive throttling of the ego vehicle leads to braking, and therefore power dissipation, after the end of the prediction horizon. This is achieved by exploiting a preview of the preceding vehicle velocity that at time t is supposed to be known until time $t + N_c$, where $N_c > N_p$. The terminal set $\mathcal{C}$ is an approximation of the largest invariant set at time $k = t + N_p$ for the coasting dynamics (3) that satisfies the safety constraint (4h). It is defined as the set of the pairs distance-speed at time $t + N_p$ from which the coasting dynamics (3) does not lead to the violation of the safety constraint (4h) for $k = t + N_p + 1, \dots, t + N_c$, i.e.,

$$\begin{aligned} \mathcal{C} = \{(d(t+N_p), v(t+N_p)) \quad &| \quad \text{dynamics in (3)}, \\ d(k) \geq d_{\text{safe}}, \, \forall k = t + N_p + 1, ...t + N_c\} \,. \end{aligned} \tag{5}$$

In other words, if the preceding vehicle preview is perfect and the predicted trajectory of the ego vehicle falls into the terminal set $\mathcal{C}$, no braking will be necessary to avoid violations of the safety constraint.

In order to construct the terminal set $\mathcal{C}$, we first notice that the speed trajectory $v(k|t)$ between time $k = t + N_p$ and $k = t + N_c$ can be computed (assuming coasting behavior) integrating equation (3b) with intial condition $v(t + N_p|t)$. The distance trajectory $d(t|k)$ between time $k = t + N_p$ and $k = t + N_c$ can be expressed now as

$$d(k|t) = d(t + N_p|t) + t_s \sum_{j=t+N_p}^{k-1} (v_p(j) - v(j|t)), \tag{6}$$

for $k = t+N_p, \dots, t+N_c$. If we impose the safety constraint (4h) to the obtained distance trajectory we obtain

$$d(t + N_p|t) \geq d_{\text{safe}} - t_s \sum_{j=t+N_p}^{k-1} (v_p(j) - v(j|t)), \tag{7}$$

that should hold for $k = t + N_p, \dots, t + N_c$. Recalling that the speed trajectory $v(k|t)$ between time $k = t + N_p$ and $k = t+N_c$ can be computed as a function of $v(t+N_p|t)$, the terminal set $\mathcal{C}$ can be constructed gridding the space of the terminal speed $v(t + N_p|t)$ and exploiting (7). Fig. 1 shows the terminal set computed when the preceding vehicle runs at a constant velocity of $25\,\mathrm{m/s}$.

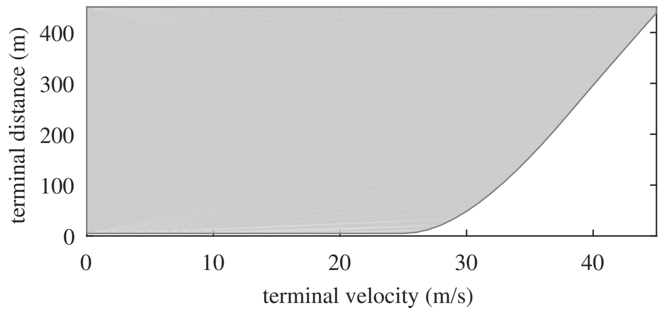

Fig. 1. Terminal set $\mathcal{C}$ with $v_p(k) = 25\,\mathrm{m/s}$, $\forall k \in [t + N_p + 1, t + N_c]$.

IV. EXPERIMENTAL RESULTS

In this section we present the experimental study that we conducted on a full scale vehicle. The goals of this experimental study are to illustrate the proposed eco-ACC strategy in a representative set of driving scenarios, to demonstrate its practical implementation, and to compare its performance with other baseline approaches.

A. Experimental Setup

The experiments were conducted at the Hyundai-KIA Motors California Proving Grounds, California City, CA.

The proposed eco-ACC concept involves at least two vehicles, playing the roles of preceding and ego vehicle. Testing requires vehicle-to-vehicle communication, to transmit the velocity preview v_p from the preceding vehicle to the ego vehicle. In this paper we adopted a simplified setting: the experiments were run with the ego vehicle only, while the preceding was a virtual vehicle.

The ego vehicle used for experimental tests is equipped with a 3.8 liter V6 engine and an 8-speed automatic transmission. The precise localization of the vehicle in the inertial frame is guaranteed by an OTS RT2002 system, which includes a differential GPS (global positioning system), an IMU (inertial measurement unit) and a DSP (digital signal processor). Other signals of interest and the control signals are directly obtained from and sent to the vehicle ECUs via the CAN bus. These signals include wheel speed, fuel flow rate, traction and braking forces.

Problem (4) is an optimization problem that must be solved in real-time, with sampling time $t_s = 200\,\mathrm{ms}$. Our implementation used FORCES Pro [2] to automatically generate a tailored solver. The resulting MPC controller and the necessary data processing were implemented and executed in real time on a dSpace MicroAutobox, which consists of an IBM PowerPC processor capable of running at 900 MHz. In the experiments presented below and with the proposed $N_p = 30$ steps horizon, the maximum computation time to solve problem (4) was $76.4\,\mathrm{ms}$.

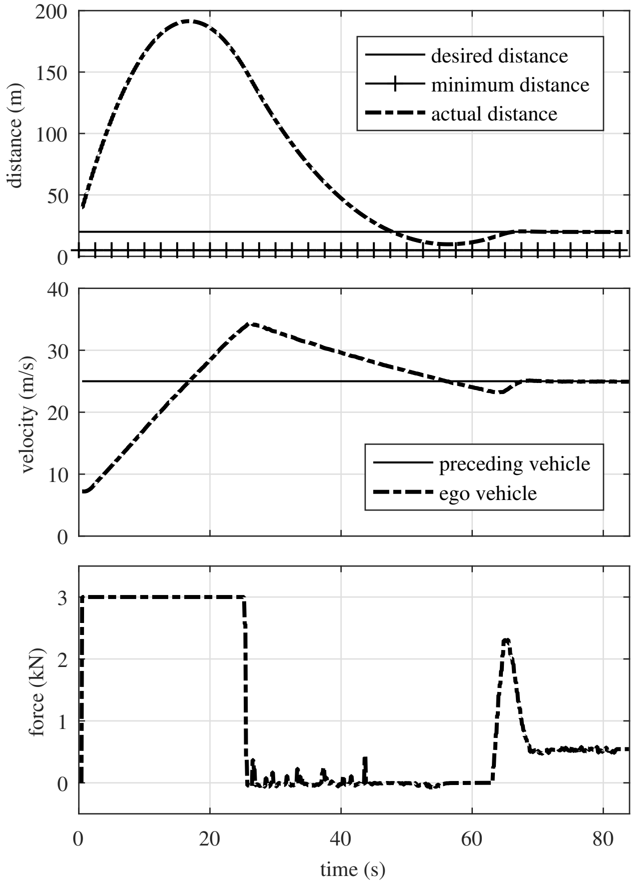

Fig. 2. Catch-up of a vehicle traveling at constant velocity: inter-vehicle distance, velocity, traction (positive values) and braking (negative values) force.

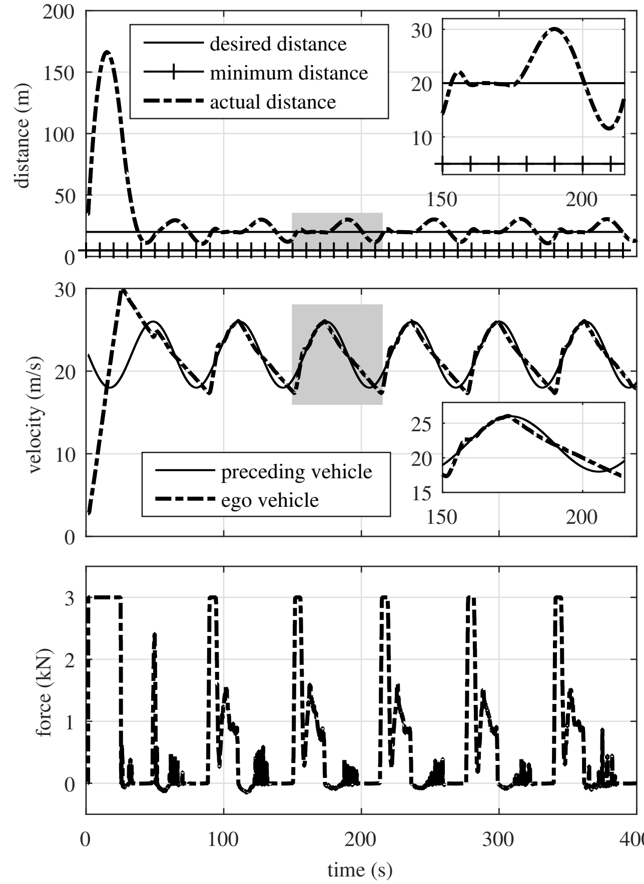

Fig. 3. Catch-up of a vehicle traveling with sinusoidal velocity profile: inter-vehicle distance, velocity, traction (positive values) and braking (negative values) force. Zoomed portions shows the behavior during one period of the sinusoidal profile.

B. Constant Velocity Catch-up

The first experiment reproduces the catch-up of a preceding vehicle driving at a constant velocity of $25\,\mathrm{m/s}$. The ego vehicle starts $40\,\mathrm{m}$ behind the preceding at a velocity of $7\,\mathrm{m/s}$.

Fig. 2 shows the measured behavior of the ego vehicle, in terms of distance from the preceding vehicle, velocity, and traction and braking force. Initially, the eco-ACC applies the maximum traction force, so that the big velocity gap between ego and preceding vehicle is compensated.

The coasting phase is started when the eco-ACC predicts that air drag, friction, and inertia will decelerate the ego vehicle, keeping it behind the safety distance d_{safe} without additional braking. Coasting brings the ego vehicle to a distance from the preceding vehicle smaller than d_{des}. Therefore, a second, short acceleration phase is applied to adjust the relative distance to the desired value. Afterwards, the traction force is kept to the constant value that maintains the ego vehicle at the same speed of the preceding vehicle.

As seen in Fig. 2, the force input commanded by the eco-ACC assumes almost only non-negative values throughout the experiment. Only small deviations from zero are observed in the coasting phase; these deviations are explained by the unavoidable mismatch between the prediction model and the vehicle response in closed loop. Power dissipation through braking is successfully avoided, exploiting the knowledge of future velocity profile.

C. Sinusoidal Velocity Catch-up

This experiment also considers a catch-up scenario, however, in this case the preceding vehicle follows a sinusoidal velocity profile. The main objective is to show that the eco-ACC can successfully catch-up and track the preceding vehicle also when this has a non-constant velocity profile. The latter has an average of $22\,\mathrm{m/s}$, an amplitude of $4\,\mathrm{m/s}$ and a period of $62.8\,\mathrm{s}$ for this experiment. The ego vehicle is initially $40\,\mathrm{m}$ behind the preceding vehicle.

Fig. 3 shows the closed-loop trajectories of the ego vehicle, in terms of distance, velocity, and input force. During the first $25\,\mathrm{s}$, the eco-ACC applies the maximum input to catch up with the preceding vehicle. Afterwards, the ego vehicle decelerates by coasting, and starts tracking the sinusoidal velocity profile. The behavior during the tracking phase can be observed in the zoomed axes in Fig. 3 for one period of the sinusoid. A few remarks follow.

- The ego vehicle tracks the sinusoidal velocity trajectory of the preceding vehicle without applying any hard braking, nor violating the minimum safety distance. Due to model mismatch, some braking is applied during the coasting phases.

- During the coasting phases, the relative distance consistently oscillates around the desired value d_{des}. While the preceding vehicle follows a sinusoidal velocity, the ego vehicle aims at coasting; hence the relative distance first increases over and then decreases below d_{des}.
- During the accelerating phase, the maximum input force is first applied to match the desired d_{des}, then the sinusoidal profile is tracked at constant distance until the coasting phase starts.

D. Performance Comparison

This subsection compares the performance of the proposed eco-ACC and of two baseline ACC controllers. Both use tracking MPC to follow the velocity profile of the preceding vehicle. The first uses the same formulation as eco-ACC except for the terminal set (hereafter named NT-ACC). The underlying optimization problem is the same as (4), removing the terminal constraint (4j). The second baseline controller only knows v_p at the current time step, and assumes that velocity is kept constant afterwards (hereafter named CV-ACC). The underlying optimization problem is the same as NT-ACC, except that v_p is constant throughout the prediction horizon, and the predicted distance d is computed accordingly.

The preceding vehicle has a sinusoidal velocity profile, with an average of $14\,\mathrm{m/s}$, an amplitude of $4\,\mathrm{m/s}$ and a period of $10.47\,\mathrm{s}$. The ego vehicle starts $40\,\mathrm{m}$ behind the preceding vehicle at an initial velocity ranging from $6.5\,\mathrm{m/s}$ to $9\,\mathrm{m/s}$.

Figure 4 compares the trajectories of distance, velocity, input force, and fuel flow rate. The minimum safety distance d_{safe} is maintained throughout the experiments. Every tested controller produces some oscillation in the distance from the preceding vehicle when following the sinusoidal velocity reference. Eco-ACC and NT-ACC produce smaller distance oscillations, while CV-ACC has the biggest oscillation.

Eco-ACC produces the least fluctuation in velocity, resulting in minimum traction force, almost no braking and minimum fuel rate. During the tracking phase (approximately after second 20), NT-MPC behaves similarly to eco-ACC. This is expected, because in this experiment the prediction horizon is long enough to preview about half period of the sinusoid. Nonetheless, during the catch-up phase (up to second 20), the improvement due to the terminal set is evident, as NT-ACC applies significant braking. CV-ACC poorly tracks the profile with large fluctuations in velocity, requiring higher traction forces, braking, and fuel rate.

Tables III, IV summarize the performance of the three controllers, in terms of the fuel consumption and jerk RMS, during the catch-up and tracking phases, respectively. We defined as catch-up phase the segment from 0 to $20\,\mathrm{s}$, and the tracking phase as the segment from 20 to $55\,\mathrm{s}$. Fuel consumption is simply the integral of the measured fuel flow rate divided by the distance traveled. Both metrics are computed relatively to CV-MPC.

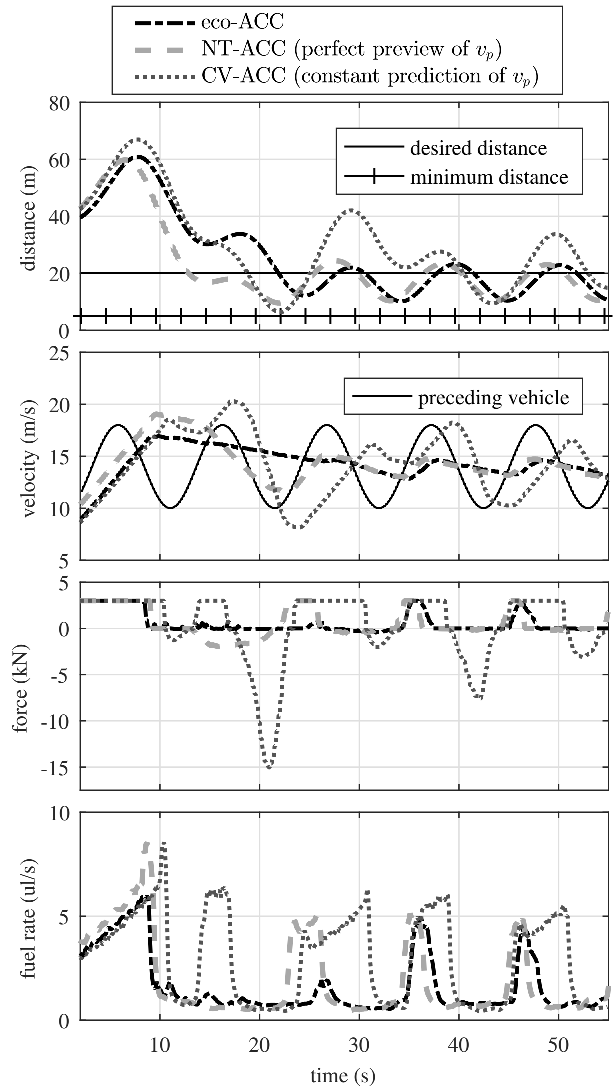

Fig. 4. Catch-up of a vehicle traveling with sinusoidal velocity profile: inter-vehicle distance, velocity, traction and braking force, fuel rate. Comparison between the proposed eco-ACC and baseline ACC using tracking MPC (with and without preview of the velocity profile).

During tracking, NT-ACC produces intermediate results ($39\,\%$ less fuel and $62\,\%$ lower jerk). Eco-ACC outperforms both baseline controllers according to both metrics ($50\,\%$ less fuel and $73\,\%$ less jerk compared to NT-ACC). During the catch-up phase, the controllers have closer performance. The eco-ACC is still improving, with about $36\,\%$ less fuel and $36\,\%$ lower jerk compared to CV-ACC. Clearly, the relative improvement strongly depends on the preceding velocity profile. Remarkably, the performance of NT-ACC strongly depends on the information contained in the preview v_p from time t to time $t + N_p$, i.e. during the MPC horizon. Generalizing the performance improvement to some average driving conditions is out of the scope of the present work. Nonetheless, in the representative scenario that we selected, performance improvement is consistently attained both during catch up and during tracking.

TABLE III

COMPARISON OF ACC CONTROLLERS IN CATCH-UP PHASE

ACC strategy	Fuel (%)	Jerk RMS (%)
eco-ACC	63.8	63.7
NT-ACC (perfect preview of v_p)	72.0	83.5
CV-ACC (constant prediction of v_p)	100.0	100.0

TABLE IV

COMPARISON OF ACC CONTROLLERS IN TRACKING PHASE

ACC strategy	Fuel (%)	Jerk RMS (%)
eco-ACC	50.0	26.8
NT-ACC (perfect preview of v_p)	61.0	37.9
CV-ACC (constant prediction of v_p)	100.0	100.0

V. SIMULATION RESULTS

In this section we present a simulation study conducted in absence of model mismatch. The purpose is to demonstrate how the proposed eco-ACC combines a limited prediction horizon with the presented terminal state constraint to approach the performance of a long-sighted controller. We compare the proposed eco-ACC with a short-sighted ACC and a long-sighted ACC. Eco-ACC and short-sighted ACC have the same prediction horizon of $N_P = 30$. Long-sighted ACC has a longer prediction horizon of $N_P = 250$ and is regarded as an approximation of the acausal optimum. Short-sighted ACC and long-sighted ACC use the formulation in (4) except for the terminal state constraint (4j). The three controllers follow the velocity profile of a preceding vehicle that was recorded in real urban driving. The ego vehicle starts $40\,\mathrm{m}$ behind the preceding at a velocity of $5\,\mathrm{m/s}$.

Figure 5 compares the closed loop velocity trajectories. Eco-ACC and long-sighted ACC exhibit very similar behaviors, as both coast whenever possible and avoid excessive throttling and braking. Conversely, short-sighted ACC is myopic and braking becomes often inevitable. All of the controllers make the ego vehicle track the preceding vehicle without violating the safety distance constraint.

We solved the optimization problem (4) on a laptop with a tailored solver generated by FORCES Pro. Eco-ACC and short-sighted ACC require similar average computational times ($8.62\,\mathrm{ms}$ and $5.45\,\mathrm{ms}$ respectively), while the long-sighted ACC requires significantly higher time ($47.12\,\mathrm{ms}$), because of the longer prediction horizon.

VI. CONCLUSIONS

In this paper, we proposed an eco-ACC aiming at energy consumption reduction. Key aspects are (i) the use of the velocity prediction from the preceding vehicle, and (ii) the design of a terminal set for the MPC, which prevents unnecessary braking of the ego vehicle without violating a minimum safety distance. Experimental results show the effectiveness of the approach and the improvement with respect to baseline ACC approaches. Future work includes experiments with vehicle-to-vehicle communication and studying the sensitivity to errors in the preceding vehicle preview.

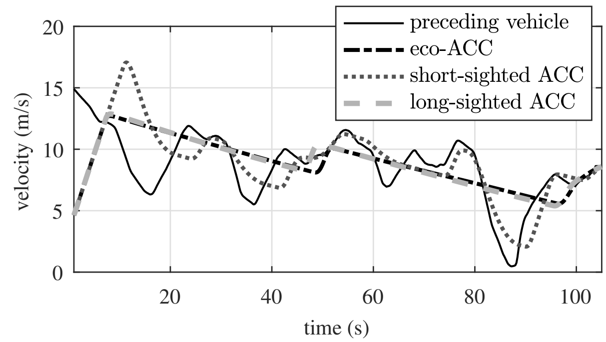

Fig. 5. Simulated tracking of a vehicle in urban driving: inter-vehicle distance, velocity, traction (positive values) and braking (negative values) force.

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