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Optimization of fuel consumption and battery life cycle in a fleet of Connected Hybrid Electric Vehicles via Distributed Nonlinear Model Predictive Control

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***Abstract*— This paper proposes a distributed Nonlinear Model Predictive Control (NMPC) strategy for a fleet of connected Hybrid Electric Vehicles that move in a coordinated fashion, optimizing fuel economy and battery state of charge. The numerical validation is provided by considering a commuter cycle usually exploited during real on-the-road emission tests. Results, carried out by exploiting ADVISOR - a state of the art simulation environment for modeling and control of hybrid electric vehicles - confirm the effectiveness of the approach.**

I. INTRODUCTION

In the last decades, the environmental issue has reached a dangerous hazard point. Specifically, the road transport is considerably affecting the world pollution problem since it is responsible of 16.5% of the global green house gas emissions [1]. This necessity has motivated researchers to develop more and more sophisticated approaches to reduce vehicles fuel consumption while ensuring a smooth driving behaviour as well as the improvement of the performance of all on-board devices [2], [3]. Moreover, to increase fuel savings, more efficient vehicles are being developed by employing lightweight automobiles, electric and hybrid vehicles [4], [5]. In particular, hybrid electric vehicles (HEVs) typically achieve greater fuel economy w.r.t. conventional internal combustion engine vehicles (ICEVs), as certified by the Environmental Protection Agency (EPA) [6]. Indeed, they: *i*) reduce the energy losses and the weight of the vehicle, relying on both the engine and the electric motor [7]; *ii*) recover significant amount of energy (normally wasted as heat), especially in the stop-and-go traffic that is typical of the city driving cycle [5]. However, the battery cost represents up to 30% of the total vehicle cost and its life cycle is strongly connected to its usage [8]. Therefore, it is important to select and tune an energy control system management not only for maximizing fuel economy but also for preserving the battery life duration.

On the other side, Intelligent Transport Systems (ITS) may also contribute to improve energy saving, since they reduce the traffic congestion and allow each vehicle to drive at optimal speeds with respect to fuel consumption avoiding at the same time aggressive speed variations [9], [10]. In this context, a huge effort is devoted to the design of autonomous intelligent cars, equipped with appropriate on-board tools and communication devices, with the aim of creating increasingly ecologic and safe vehicles [11]. The idea is to exploit autonomous connected vehicles sharing information in order to create fleets able to drive autonomously in the traffic flow [12], [13]. Indeed, fleets of autonomous connected vehicles are likely to provide fuel economy improvements by reducing for instance the air resistance which is proportional to the velocity square (e.g., the aerodynamic drag of a vehicles driving at 100 km/h contributes more than sixty percent of the total motion resistance force [14]). Hence, by imposing a short spacing policy among the vehicle within the fleet, the air resistance is significantly reduced, decreasing thereby traffic congestion [15]. By combining the advantages of both ITS tools and HEVs, it is possible to further improve the achievable on-the-road benefits. Moreover, it is possible to optimize battery life cycle and fuel consumption. Indeed, the battery life cycle can be extended if its State of Charge is bounded around a predefined target value [16], while the fuel consumption can be improved by imposing automatic driving strategies that consider, for example, the road topography and the spacing policy w.r.t. the predecessor (i.e., the road slope and the bumper-to-bumper distance from the previous vehicle) to name a few.

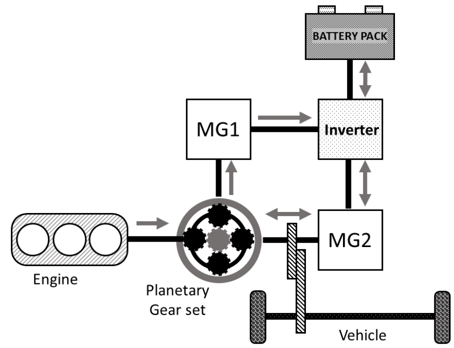

Fig. 1: Configuration of the power-split HEV system [14]. The Planetary Gear set is the key component of the vehicle that is responsible for speed coupler and continuously variable transmission. Moreover, the system is characterized by five main dynamics components: internal combustion engine, two electric motor/generators (M/G), battery and wheels.

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In this paper, we propose a distributed cooperative Model Predictive Control (MPC) approach for optimizing both fuel saving and battery usage of a fleet of connected HEVs that moves in a coordinated fashion (e.g, see [17] for a recent comprehensive review on distributed MPC strategies). Note that MPC is commonly used for a single-agent system or for multi-agent systems coordinated in centralized fashion, where the control input is hence obtained by numerically optimizing a finite horizon optimal control problem. Recently, this centralized MPC approach has been also exploited for multi-agent systems, e.g. for energy management in hybrid power systems [18], for stability control of connected vehicles equipped with only internal combustion engines [19] or for driving a fleet of hybrid electric vehicles (HEVs) by using traffic signals and slope information [14], [20]. However, leveraging a centralized implementation of the MPC strategy for fleets of autonomous connected vehicles, the control inputs are usually computed under the ideal assumption that all vehicles state information are known [21]. Moreover, the centralized control architecture is not suitable for platoons of vehicles because of the limitation to gather the information of all vehicles and the challenge to compute a large-scale optimization problem since the computational complexity sharply increases in practice with the number of the involved vehicles [22].

The distributed strategy herein drives a platoon of hybrid electric vehicles (HEVs), where each vehicle is assigned a local optimal control problem only relying both on its own state information and on its neighboring vehicles information. Since the dynamics of both engine and battery are inherent nonlinear (air drag, gravity force, rolling resistance, etc...) and strongly affected by uncertainty (e.g. due to road shape and slope) the strategy is designed following a Nonlinear Model Predictive Control (NMPC) approach [23]. The multiple aims of the control action are to minimize fuel consumption, to optimize the state of charge of the battery (preventing overcharge and discharge at single vehicle level) and to drive the whole ensemble such that each fleet member tracks the leader's state and preserves a desired spacing policy among vehicles. Note that, distributed MPC for platooning has been very recently exploited only in [24] for the different case of a fleet of vehicles powered by internal combustion engines with the only aim of reaching and maintaining a common set point corresponding to the leader motion. In order to validate the proposed control strategy, we consider an exemplar fleet of Toyota Prius HEVs, build with Power-Split technology (see Fig. 1). The performance analysis is carried out through ADVISOR, a state of the art simulation environment for modeling and control of hybrid electric vehicles. Results confirm the effectiveness of the distributed optimization in balancing fuel consumption and battery exploitation, while the autonomous driven electric fleet correctly tracks a pre-fixed time-varying motion profile while preserving at the same time the required bumper-to-bumper distances. Finally, the paper is organized as follows. In Sec. II we describe the problem statement and we provide the nonlinear dynamical model of the HEVs. In Sec. III we design the distributed nonlinear MPC preventing the battery overcharging or discharging and guaranteeing the fleet formation while minimizing the fuel consumption. In Sec. IV we present the simulation results, hence confirming the efficiency of the proposed control approach in minimizing fuel consumption and optimizing the battery state of charge. Conclusion and future work are drawn in Sec. V.

II. HEVs Fleet Dynamics

Consider N autonomous hybrid electric vehicles (HEVs) moving along a single lane. Vehicles are organized as a fleet, with vehicles following one another along a straight line and sharing their state information (e.g., the absolute position, the velocity, and the acceleration) with all the others vehicle through a Vehicle-to-Vehicle (V2V) communication paradigm [25]. The on-board integration of inertial sensors with a GPS receiver allows each vehicle to measure its absolute position, velocity and acceleration [26].

A. Vehicle and Battery Dynamical Model

Within our framework, the motion of the generic i-th vehicle in the fleet is described by its longitudinal dynamics that are inherent nonlinear and mainly governed by the drivetrain, including aerodynamics drag, rolling resistance, gravitational force [27] as:

$$\begin{bmatrix} \dot{p}_i \\ \dot{v}_i \\ \dot{a}_i \end{bmatrix} = \begin{bmatrix} v_i \\ -\frac{1}{2m_i} C_d \rho_a A_i v_i^2 - \mu g - g\sin(\theta) + a_i \\ \frac{1}{T_i}(\tilde{u}_i - a_i) \end{bmatrix}, \quad (1)$$

where p_i $[m]$, v_i $[m/s]$ and a_i $[m/s^2]$, are the position, the speed and the acceleration measured with respect to a road reference frame for each i-th vehicle ($i = 1, \cdots, N$); $m_i, C_d, \rho_a, A_i, g, \mu, \theta$ are the mass, the air drag coefficient, the air density, the frontal area, the gravitational acceleration, the rolling resistance coefficient, and the road grade respectively for the i-th vehicle; $T_i > 0$ $[s]$ is the characteristic time constant of the drivetrain depending upon specific features of the vehicle; $\tilde{u}_i$ is the control input that drives the vehicle acceleration or deceleration. It is evaluated at single vehicle level by exploiting both local measurements and networks information.

According to [28], the battery state of charge (SOC) dynamics of the i-th vehicle is instead described by the following first order dynamical system:

$$S\dot{O}C_i = -\frac{V_{OC,i} - \sqrt{V_{OC,i}^2 - 4P_{batt,i}R_{batt,i}}}{2C_{batt,i}R_{batt,i}} \quad (2)$$

where SOC is the ratio of the remaining charge to the normal charge (1 for the 100 % of the remaining charge and 0 for the 0 % of remaining charge), as defined by United States Advanced Battery Consortium (USABC) [29]; V_{OC}, $R_{batt,i}$, and $C_{batt,i}$ are the open circuit voltage, the internal resistance, and the capacity of the battery for the i-th vehicle; $P_{batt,i}$ is the control input that represents the power from and to the battery for the Motor/Generator system. It is assumed to be positive or negative depending on the charging or discharging

of the battery, respectively.
Combining the longitudinal dynamic in (1) with the state of charge one in (2) we obtain the following model for the i-th electric hybrid vehicle ($\forall i = 1, \cdots, N$): [14], [20]:

$$\dot{x}_i = f_i(x_i, u_i) = \begin{bmatrix} v_i \\ -\frac{1}{2m_i} C_d \rho_a A_i v_i^2 - \mu g - g\sin(\theta) + a_i \\ T_i(\tilde{u}_i - a_i) \\ -\frac{V_{OC,i} - \sqrt{V_{OC,i}^2 - 4P_{batt,i}R_{batt,i}}}{2C_{batt,i}R_{batt,i}} \end{bmatrix}, \tag{3}$$

where $x_i = [p_i,\, v_i,\, a_i,\, SOC_i]^\top \in \mathbb{R}^4$ is the state vector of the i-th vehicle; $u_i = [\tilde{u}_i,\, P_{batt,i}]^\top \in \mathbb{R}^2$ is the control input vector to be appropriately chosen in order to guarantee the fleet formation and the optimization of the energy management system.

B. Network Communication Structure

The communication structure among the connected vehicles can be modeled by a graph where every vehicle is a node. Hence, a network of N connected vehicles is represented as a directed graph (digraph) $\mathscr{G} = (\mathscr{V}, \mathscr{E}, \mathscr{A})$ of order N characterized by the set of nodes $\mathscr{V} = \{1, \ldots, N\}$ and the set of edges $\mathscr{E} \subseteq \mathscr{V} \times \mathscr{V}$. The topology of the graph is associated to an adjacency matrix with non negative elements $\mathscr{A} = [\alpha_{ij}]_{N\times N}$. In what follows, we assume $\alpha_{ij} = 1$ in the presence of a communication link from vehicle j to vehicle i, otherwise $\alpha_{ij} = 0$. Moreover, $\alpha_{ii} = 0$ (i.e., self-edges (i,i) are not allowed). The presence of edge $(i, j) \in \mathscr{E}$ means that vehicle i can obtain information from vehicle j, but not necessarily *vice versa*.
The generic vehicle j is said to be a neighbor of i if and only if $\alpha_{ij} = 1$. The neighbor set of vehicle i is hence denoted as $\mathscr{N}_i = \{j \mid \alpha_{ij} = 1,\ j = 1, \cdots N\}$.

III. Control Design

The energy management and fleet maintenance problem can be formulated, for each vehicle i ($i = 1, \cdots, N$), as a local optimization problem of the power flow generated by the two energy sources, i.e. fuel and battery, so to: 1) minimize fuel consumption; 2) prevent overcharge and discharge of the battery; 3) track a desired speed profile with a pre-fixed inter-vehicles spacing policy. To achieve these three control objective, each vehicle i within the fleet is equipped with: *a*) on-board sensing to measure its absolute position, speed, acceleration and SOC, i.e. $x_i(t)$; *b*) Vehicle-to-Vehicle (V2V) communication hardware to share its state information with all the other vehicles within its communication range ($\mathscr{N}_i$) and to receive the desired references behaviour for both formation and battery state of charge, i.e $v^\star$, SOC_d.
To this aim, the control input u_i ($i = 1, \cdots, N$) is designed by exploiting a distributed Nonlinear Model Predictive Control (NMPC) [23] due to the nonlinear dynamics of the engine and of the motor/generators that equip the HEVs; the variability of driving conditions; the multitude of physical constraints for involved dynamic variables [24]. Therefore the control approach allows to cope with the uncertainty of the dynamical system under investigation while anticipating future situations (e.g. road shape and road slope). See Fig. 2 for the proposed local control architecture of the vehicle i.

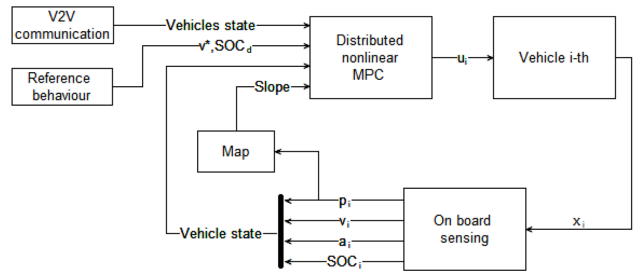


Fig. 2: Control architecture of the distributed nonlinear MPC for vehicle i.

Each vehicle locally solves the following multiple optimization problem:

$$\min_{u_i} \int_t^{t+T} \sum_{j\in\mathscr{N}_i} \mathscr{J}_{i,j}(x_i(\tau|t), x_j(\tau|t), u_i(\tau|t))d\tau \tag{4}$$

subject to:

$$\begin{aligned} &\dot{x}_i = f_i(x_i, u_i) \\ &SOC_{i,\min} \le SOC_i(\tau|t) \le SOC_{i,\max} \\ &\tilde{u}_{i,\min} \le \tilde{u}_i(\tau|t) \le \tilde{u}_{i,\max} \\ &P_{batt,i,\min} \le P_{batt,i}(\tau|t) \le P_{batt,i,\max}, \end{aligned}$$

where T is the prediction horizon; $x_i(\tau|t)$ and $u_i(\tau|t)$ are the prediction of the state variable and the control input respectively; the subscripts $_{\min}$ and $_{\max}$ denote the minimum and maximum bounds of the corresponding variable for the i-th vehicle, while the cost function $\mathscr{J}_{i,j}$ is defined as:

$$\begin{aligned} \mathscr{J}_{i,j} = \;& \omega_{i,x}L_{i,x} + \omega_{i,y}L_{i,y} + \omega_{i,z}L_{i,z} + \omega_{i,d}L_{i,d} \\ & + \omega_{i,e}L_{i,e} + \omega_{i,f}L_{i,f} + \textstyle\sum_{j\in\mathscr{N}_i}\omega_{i,j}L_{i,j}, \end{aligned} \tag{5}$$

being

$$L_{i,x} = (-\frac{1}{2M_i}C_d\rho_a A_i v_i^2 - \mu g - g\sin(\theta) + a_i)^2, \tag{6a}$$
$$L_{i,y} = (v_i - v^\star)^2, \tag{6b}$$
$$L_{i,z} = c_{f,i}(M_i a_i v_i - P_{batt,i})/(1 + e^{-\beta(M_i a_i v_i - P_{batt,i})}), \tag{6c}$$
$$L_{i,d} = (SOC_i - SOC_d)^2 \tag{6d}$$
$$L_{i,e} = (M_i a_i v_i - P_{batt,i})^2, \tag{6e}$$
$$L_{i,f} = -ln(SOC_i - SOC_{i,\min}) - ln(SOC_{i,\max} - SOC_i), \tag{6f}$$
$$L_{i,j} = (p_i - p_j - d_{ij}), \tag{6g}$$

where $\omega_{i,x}$, $\omega_{i,y}$, $\omega_{i,z}$, $\omega_{i,d}$, $\omega_{i,e}$, $\omega_{i,f}$, $\omega_{i,j}$, are positive weights; $v^\star$ is the desired speed profile reference behaviour; $c_{f,i}$ is the constant fuel consumption rate [14], [30]; β is the sharpness of the sigmoid function; SOC_d is the desired value for i-th vehicle SOC_i; $d_{ij} = d^\star + |j-i|l$ is the desired spacing policy among vehicle i and vehicle j within the fleet (being $d^\star$ the desired bumper to bumper distance and l the vehicles length, assumed to be equal for all vehicles) and $\mathscr{N}_i \subseteq \{1, \cdots, N\}$ is the set of the vehicles in the fleet exchanging information with vehicle i. Note that each term in the cost function (5) represents a different aim considered

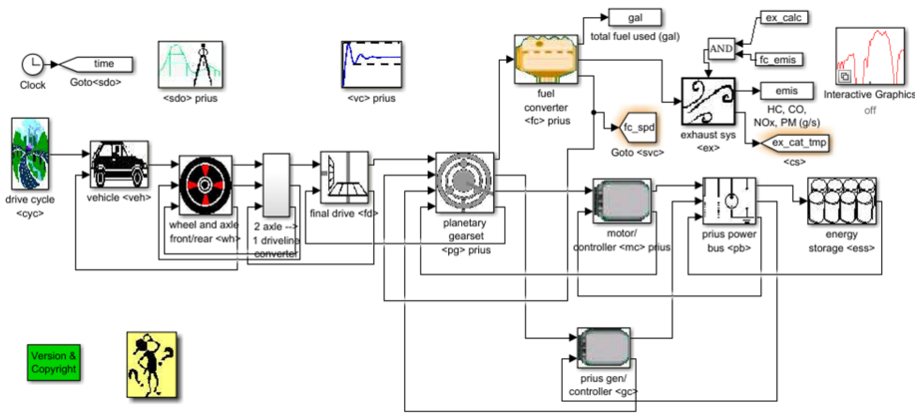


Fig. 3: ADVISOR: Toyota Prius dynamic model

in the optimal control problem, i.e. ($\forall i = 1, \cdots, N$):
- $L_{i,x}$ in (6a) limits the velocity rate a_i of i-th vehicle;
- $L_{i,y}$ in (6b) guarantees that the i-th vehicle tracks the desired reference speed behaviour $v^\star$;
- $L_{i,z}$ in (6c) ensures the fuel consumption minimization using the Willian line method [30];
- $L_{i,d}$ in (6d) guarantees that the SOC_i tend to a desired constant value SOC_d;
- $L_{i,e}$ in (6e) ensures the battery energy best use according to [14];
- $L_{i,f}$ in (6f) guarantees that SOC_i constraint is kept satisfied with the aim of extending the battery life cycle [16];
- $L_{i,j}$ in (6b) ensures the pre-fixed spacing policy among the vehicle i and the others communicating $j \in \mathcal{N}_i \subseteq \{1, \cdots, N\}$.

IV. Numerical Validation

A. Simulation scenario

In order to show the effectiveness of the proposed control strategy, we exploit ADVISOR (ADvanced VehIcle SimulatOR) that is a simulator often used by automotive companies (e.g. by Ford and Toyota) for modeling and control design of hybrid electric vehicles [31]. It allows an accurate performance analysis and accounts for fuel consumption and emissions for electric, hybrid-electric and fuel cells vehicles. The distributed MPC control strategy has been hence integrated in ADVISOR for controlling a fleet of Toyota Prius, which is one of the most popular vehicle in the hybrid market equipped with the Power-Split technology depicted in Fig. 1. Each Toyota Prius is modeled with an high level of accuracy since ADVISOR emulates all the electro-mechanical components along the kinematic chain of the HEV with the power-split architecture (see Fig. 3). The exemplar validation scenario in ADVISOR

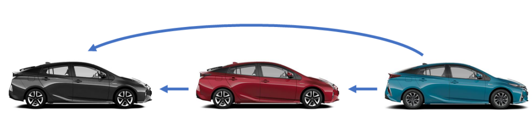


Fig. 4: Fleet of three Toyota Prius moving along a single lane and sharing their state information.

TABLE I: Simulation Parameters

Parameters	Value	Measure unit
Mass of vehicle m_i ($\forall i = 1,2,3$)	1368	$[kg]$
Length of vehicle l_i ($\forall i = 1,2,3$)	4	$[m]$
Gravity acceleration g	9.81	$[m/s^2]$
Front vehicle area A	1.746	$[m^2]$
Aerodynamic coefficient C_D	0.3	$[\cdot]$
Air density ρ	1.225	$[kg/m^3]$
Rolling friction with dry asphalt μ	0.8	$[\cdot]$
Slope - θ	0	$[rad]$
Bumper to bumper distance $d^\star$	15	$[m]$
Drivetrain constant $\frac{1}{T_i}$	0.5	$[s]$
Open circuit Voltage $V_{OC,i}$ ($\forall i = 1,2,3$)	307.9	$[V]$
Battery internal resistance $R_{batt,i}$ ($\forall i = 1,2,3$)	1.0	$[\Omega]$
Minimum state of charge $SOC_{i,min}$ ($\forall i = 1,2,3$)	60	$[\cdot]$
Maximum state of charge $SOC_{i,max}$ ($\forall i = 1,2,3$)	80	$[\cdot]$
Desired state of charge SOC_d	65	$[\%]$
Minimum power of battery $P_{batt,i,min}$ ($\forall i = 1,2,3$)	-23.684	$[kW]$
Maximum power of battery $P_{batt,i,max}$ ($\forall i = 1,2,3$)	23.684	$[kW]$
Minimum acceleration $\tilde{u}_{i,\max}$ ($\forall i = 1,2,3$)	2.0	$[m/s^2]$
Maximum acceleration $\tilde{u}_{i,\min}$ ($\forall i = 1,2,3$)	-2.0	$[m/s^2]$
Weight $\omega_{i,x}$ ($\forall i = 1,2,3$)	10000	$[\cdot]$
Weight $\omega_{i,y}$ ($\forall i = 1,2,3$)	1000	$[\cdot]$
Weight $\omega_{i,z}$ ($\forall i = 1,2,3$)	10	$[\cdot]$
Weight $\omega_{i,d}$ ($\forall i = 1,2,3$)	500	$[\cdot]$
Weight $\omega_{i,e}$ ($\forall i = 1,2,3$)	100	$[\cdot]$
Weight $\omega_{i,f}$ ($\forall i = 1,2,3$)	10000	$[\cdot]$
Weight $\omega_{i,j}$ ($\forall i, j = 1,2,3 \quad i \neq j$)	5000	$[\cdot]$

considers three connected Toyota Prius that move along a single lane as a fleet sharing their state information with a Leader-predecessor-follower network topology (see Fig. 4). Specifically, the leading vehicle (vehicle 1) tracks a desired speed profile (a commuter cycle usually exploited during real on-the-road emission tests that consider an acceleration maneuver followed by a braking, as depicted in Fig. 5), while vehicles 2 and 3 have to correctly follow the leading vehicle while preserving a fixed bumper-to-bumper distance. Each vehicle embeds the Model Predictive Control strategy illustrated in Sec. III, while simulation parameters are summarized in Table I.

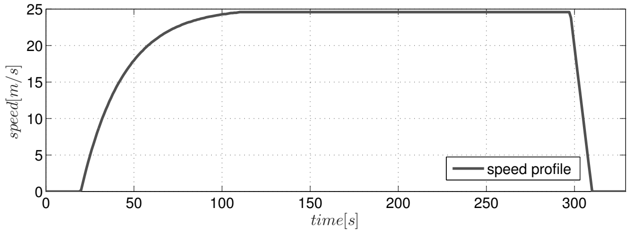
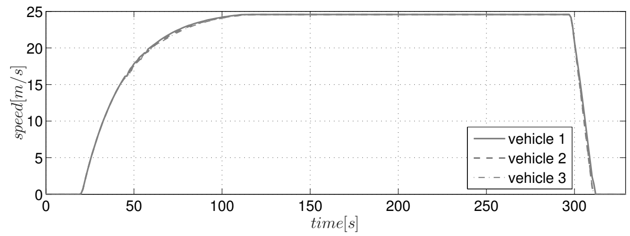
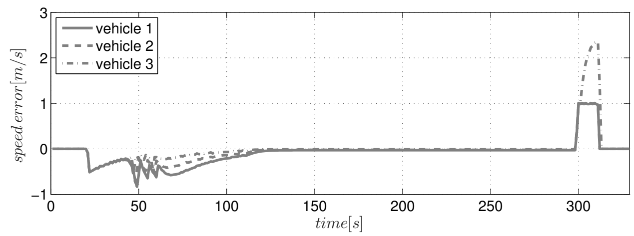


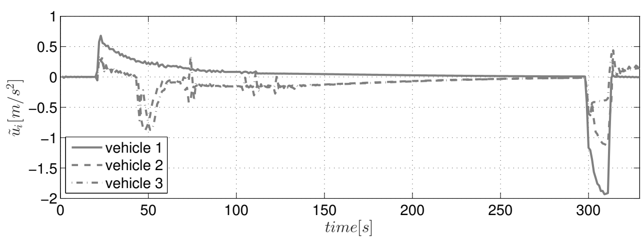
Fig. 5: Desired speed profile $v^{\star}(t)$ for HEVs fleet.



(a)



(b)

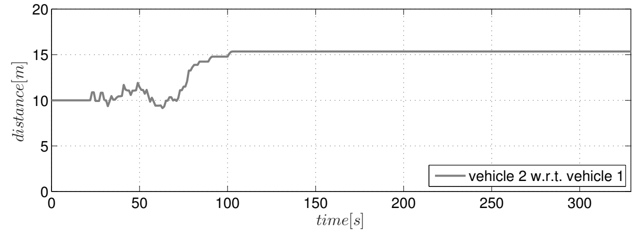


(c)

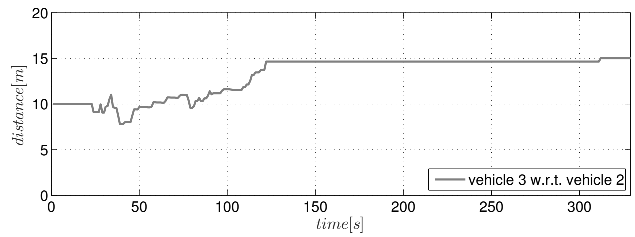
Fig. 6: Tracking performance of distributed Nonlinear Model Predictive Control strategy: (a) time history of vehicles speed $v_i(t)$ $(i=1,2,3)$; (b) time history of the speed error computed as $v_i(t)-v^{\star}(t)$ $(i=1,2,3)$; (c) time history of the vehicle acceleration/deceleration control input $\tilde{u}_i$ $(i=1,2,3)$.

B. Results

The good tracking performance is shown in Fig. 6a where the time history of the speed of each vehicle within the fleet is reported. This is confirmed by time history of the speed error w.r.t. the imposed reference behaviour $v^{\star}$ depicted in Fig. 6b. Here the tracking error is bounded during the all maneuver and it is zero when the leading vehicle reaches its constant speed of 24,6 $[m/s]$. Moreover, the accelerations/decelerations of each vehicle are always within the limitation bound of the optimization problem (see Fig. 6c). Moreover, the distributed strategy also guarantees that each vehicle correctly achieves the required spacing policy (see Fig. 7). Indeed all vehicles, starting with positions, velocities and accelerations that are different from one to another, after a small transient reach and maintain both the desired reference speed and the required distance w.r.t. the predecessor. The optimization of battery SOC is presented in Fig. 8a where the time history of the SOC is reported. Results show that the SOC is always within the required optimal bounds (between 60% and 80%) with values of the electric power required from the battery P_{batt} always within admissible ranges (see figs. 8a, 8b). Finally, results in Fig. 9 also confirms that the MPC strategy succeed in reaching the minimization of fuel consumption. Note that, as expected, results in Fig. 9 disclose that the fuel consumption of the leading vehicle (vehicle 1) is higher on average than the fuel consumption on the two followers (vehicles 2 and 3) due to the effect of the weights on the (6g) contribute within the control strategy. Accordingly, the battery State Of Charge of the leading vehicle is lower on average than the one of vehicles 2 and 3 (see Fig. 8a).



(a)



(b)

Fig. 7: Tracking performance of distributed Nonlinear Model Predictive Control strategy: (a) time history of bumper to bumper distance $d_{21}(t)$; (b) time history of bumper to bumper distance $d_{32}(t)$.

V. Conclusions

In this paper, the optimization problem of fuel consumption and battery life cycle for a fleet of connected HEVs is addressed and solved by designing a distributed NMPC. Numerical results, carried out through ADVISOR simulator, confirm the effectiveness of the control strategy in guaranteeing both the minimization of fuel consumption and the prevention of overcharge/discharge of the battery, while all vehicles move in a coordinated fashion tracking the behavior of the leading vehicle with a desired inter-vehicles spacing policy.

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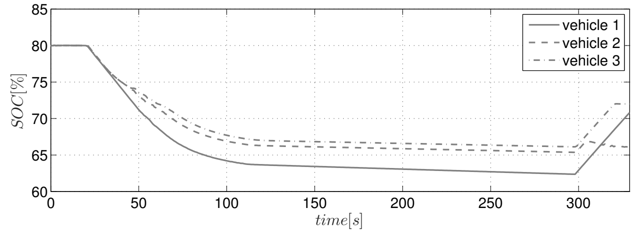
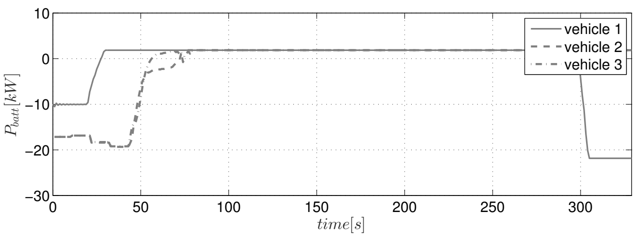


(a)



(b)

Fig. 8: Performance of distributed Nonlinear Model Predictive Control strategy: (a) time history of battery state of charge $SOC_i(t)$ $(i = 1, 2, 3)$; (b) time history of electric power flow $P_{batt,i}$ $(i = 1, 2, 3)$.

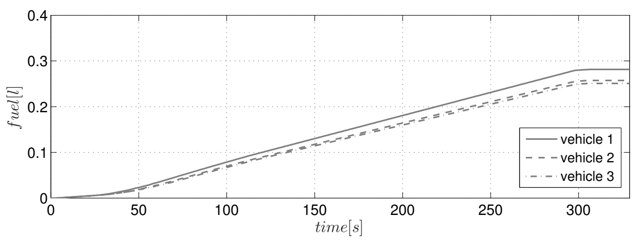


Fig. 9: Performance of distributed Nonlinear Model Predictive Control strategy. Time history of fuel consumption for a three Toyota Prius fleet.

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