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Cooperative energy management of electrified vehicles on hilly roads

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ABSTRACT

This paper presents a control strategy and an assessment study for the potential of minimizing fuel consumption of electrified and/or conventional vehicles driving in a hilly terrain. The main idea is to minimize the amount of energy wasted on air resistance and mechanical braking. The former is achieved by having the vehicles drive close to each other. The latter is achieved by either allowing the speed to vary and thereby reduce braking, or by using the electric machine to brake and convert kinetic energy to electric energy that is stored in the battery. We propose a control strategy that is separated into two control layers. One layer optimizes vehicle velocity and battery state of charge using convex optimization, and the other optimizes gear and engine on/off state trajectories using dynamic programming. The control strategy is then applied to several test cases, in order to evaluate the reduction in fuel consumption due to platooning, optimal battery usage and optimal velocity control in a hilly terrain.

1. Introduction

Reducing energy consumption of vehicles is desirable for both economic reasons and for mitigation of the negative effect vehicle emissions have on the environment and human health. Air pollution from transportation is the major contributor causing 40,000 deaths in 2014 in the European Union according to the European Environment Agency (2018).

One way of reducing energy consumption is to utilize a predictive cruise controller (PCC) (Björnander & Grunske, 2008) that uses information from the surrounding environment (e.g. topography of the road ahead) to optimize speed and thereby save fuel. Two examples of articles using such techniques are Hellström, Åslund, and Nielsen (2010a) and Hellström, Ivarsson, Åslund, and Nielsen (2009). The authors of Hellström et al. (2010a) and Hellström et al. (2009) propose using dynamic programming (DP) (Bellman, 1957) in a model predictive control (MPC) (Camacho & Bordons, 2007) framework. The MPC reduces unnecessary braking by optimizing vehicle speed. Still, some energy is inevitably dissipated to heat, while braking to comply to speed limits and to keep a safe distance to the preceding vehicle. An additional reduction of wasted energy can be achieved with hybrid electric vehicles (HEVs) by utilizing electric machines for regenerative braking and transferring kinetic to electric energy. The electric energy is stored in an electric battery and may be used later, thus saving fuel. Furthermore, an HEV may save additional fuel by temporarily turning off the combustion engine (Guzzella & Sciarretta, 2013).

Energy optimization of HEVs is more complex than that of conventional vehicles, mainly because the control strategy must manage an additional energy storage, i.e. the electric battery. It also introduces extra states, the battery state of charge (SOC) and an engine on/off state, as well as extra control signals for deciding electric machine power and turning the engine on or off. Energy optimization for a single HEV has previously been examined in Hellström, Åslund, and Nielsen (2010b), Johannesson, Murgovski, Jonasson, Hellgren, and Egardt (2015), Lindgärde, Feng, Tenstam, and Soderman (2015), Sciarretta, Nunzio, and Ojeda (2015), Uebel, Murgovski, Tempelhahn, and Bäker (2017), van Keulen, de Jager, Foster, and Steinbuch (2010) and van Keulen, de Jager, and Steinbuch (2011). In Johannesson et al. (2015) an MPC is proposed with velocity optimization formulated as a quadratic program (QP) and optimal gear selection formulated as a separate DP problem. The combination of QP and DP reduces computational effort compared to solving the entire problem with DP, whose computation need increases exponentially with the number of states and control signals (Bertsekas, 2000). Another computationally efficient strategy that

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manages battery energy is the equivalent consumption minimization strategy (ECMS) (Delprat, Lauber, Guerra, & Rimaux, 2004; Guzzella & Sciarretta, 2013; Musardo, Rizzoni, & Staccia, 2005; Paganelli, Delprat, Guerra, Rimaux, & Santin, 2002; Paganelli et al., 2000; Sciarretta & Guzzella, 2007; Sciarretta, Guzzella, & Back, 2004; Sezer, Gokasan, & Bogosyan, 2011). This strategy finds a fuel equivalent battery costate that relates the use of battery energy to fuel cost. The usage of the costate allows for a reduction in computational need, but does not prevent violation of battery energy limits unless additional heuristics are employed.

Another way of reducing fuel consumption and emissions is platooning (Milanes et al., 2014). The system boundary of PCC is now extended from a single vehicle to multiple vehicles. Cooperation is fundamental in platooning; information is communicated vehicle-to-vehicle (V2V) making it possible to form a coherent vehicle formation. Cooperative adaptive cruise control (CACC) is an example of a platoon strategy where a member vehicle in front limits the speed of the vehicles behind it (Alam, 2014; Alam, Besselink, Mårtensson, & Johansson, 2015a; Alam, Gattami, Johansson, & Tomlin, 2014; Alam, Mårtensson, & Johansson, 2015b; Bonnet & Fritz, 2000; Bühler, 2013; Diaby & Sorkati, 2016; Jeber, 2015; Johannesson et al., 2015; Kemppainen, 2012; Liang, Mårtensson, & Johansson, 2016; Murgovski, Egardt, & Nilsson, 2016; Wahnström, 2015; Yu, Liang, Yang, & Guo, 2016; Yu et al., 2016). Fuel is saved by driving with small inter-vehicle distances to reduce the air resistance even for the leading vehicle. Since trucks have limitations to how aerodynamically efficient they can be built, aerodynamic drag is a major contributing factor to fuel consumption at highway driving. Many articles have been published in the area of platooning; for example Alam (2014), Dunbar & Murray (2006), Levine & Athans (1966), Peppard (1974) and Swaroop & Hedrick (1996) address the subject of safety and stability for vehicle platoons. In Liang et al. (2016) the authors investigate how vehicle platoons can be formed to save fuel. A problem with platooning in hilly terrain is that the aim of saving energy by short inter-vehicle distances is not immediately in synchronization with the energy optimal speed profile of respective vehicle in the platoon. The answer to this problem is to extend predictive energy management to the platoon using V2V communication. This was observed and studied in Alam et al. (2014) and Alam et al. (2015b). Because of the large number of states, the optimization formulation of an entire platoon is often divided into multiple sub-problems. For example, an MPC is designed in Murgovski et al. (2016) to optimize velocity and gear selection separately. The velocity is optimized by formulating the problem as a convex optimization program which can be solved efficiently using commercial solvers. The gear selection is optimized using DP. The conclusion of Murgovski et al. (2016) is that up to 10 % can be saved in fuel when traveling in a platoon compared to driving alone. Another recent publication also investigates platooning with HEVs (Yu et al., 2016). The proposed controller minimizes fuel consumption while trying to track a reference battery state of charge (SOC), calculated depending on road topography. The problem is solved using the continuation/GMRES method (Ohtsuka, 2004), although gear and engine on/off trajectory are not optimized.

This paper extends CACC of conventional vehicles proposed in Murgovski et al. (2016) to CACC of HEVs. We propose a control strategy for optimizing speed, battery energy, travel time, gear and engine state for multiple HEVs traveling in a platoon on a road with a known topography. The optimization is divided into two control layers. One layer optimizes velocity, battery SOC and travel time using convex optimization and another layer optimizes power split, gear and engine on/off state using a synergy of DP and ECMS. The control strategy proposed by Murgovski et al. (2016) is extended with a mathematical description of the electric machine and battery, and modeling steps are proposed for the convex optimization approach. The DP is modified to be able to handle power split decisions by using the battery SOC costate, without the need for including a battery SOC state. The main use of the proposed control strategy is to assess the potential fuel reduction by cooperative optimal control of HEVs and conventional vehicles driving in a hilly terrain. A guiding design principle of the proposed controller is the intention of a possible future implementation into real vehicles. The feasibility of real-time implementation due to computation demands is not the main focus of this paper, but an important aspect, nonetheless.

The paper starts with the modeling of a single HEV in Section 2, where all the physical models are presented. In Section 3, the models are extended to include the interaction between multiple vehicles. In Section 4, the control strategy is presented, which is then divided into two separate optimization problems, one regarding the real-valued decision variables and one regarding the discrete decision variables. In Section 5 some case studies and results are presented; first for the case with a single vehicle to show how the control algorithm works; and then with platoons consisting of multiple vehicles, mainly showing the potential of fuel reduction for different platoon configurations and sizes. The processing time of the proposed algorithm is also assessed. A discussion about the results and the proposed method can be found in Section 7. A conclusion and suggestions for future work are presented in Section 8.

2. Physical modeling of a single vehicle

This section describes the internal dynamics of a single HEV. The models of the vehicle components are presented, as well as the differential equations of the mechanical and electrical power balance. The models are mainly inspired by Murgovski et al. (2016), and the model data are provided by Volvo Group.

2.1. Vehicle model

An overview of an HEV is presented in Fig. 1. The vehicle is equipped with an internal combustion engine (ICE) and an electric machine (EM). The EM is powered by a battery, which can be charged by running the EM as a generator. Both the ICE and EM are connected to the same gearbox, but they deliver power to the wheels through two different sets of gears.

The HEV can be modeled as a lumped mass, with the equation of motion described as

$$m_{\mathrm{e}}\dot{v}(t) = F_{\mathrm{V}}(t) - mg\sin(\alpha(s(t))) - F_{\mathrm{air}}(v(t)) - F_{\mathrm{rol}}(\alpha(s(t))) \tag{1}$$

where m is the mass and m_{e} is the equivalent mass, which includes the actual vehicle mass and terms representing inertia of rotational parts. The force F_{V} is the total traction force delivered by the ICE and EM, g is the gravitational acceleration and α is the road gradient, which is a function of the distance traveled $s(t)$. The air resistance F_{air} depends on surrounding vehicles and will be discussed in detail in Section 3. The rolling resistance F_{rol} is modeled as

$$F_{\mathrm{rol}}(\alpha(s(t))) = mgc_{\mathrm{r}}\cos(\alpha(s(t))), \tag{2}$$

where c_{r} is the rolling resistance coefficient. The mechanical force balance is expressed as

$$\begin{aligned} F_{\mathrm{E}}(t) + F_{\mathrm{M}}(t) - F_{\mathrm{brk}}(t) &= \\ = F_{\mathrm{V}}(t) + F_{\mathrm{Td}}(\gamma(t), \chi(t), P_{\mathrm{E}}(t), P_{\mathrm{M}}(t), u_{\gamma}(t), u_{\chi}(t)) \end{aligned} \tag{3}$$

where F_{E} is the force from the ICE, F_{M} is the force from the EM, F_{Td} includes all losses from the gear shifts, ICE state change as well as losses in the transmission. Gear and ICE on/off state are denoted by γ and χ, respectively, and F_{brk} is the mechanical braking force, which is modeled as non-negative,

$$F_{\mathrm{brk}}(t) \geq 0. \tag{4}$$

The electrical power balance is expressed as

$$P_{\mathrm{B}}(t) = F_{\mathrm{M}}(t)v(t) + P_{\mathrm{Md}}(v(t), P_{\mathrm{M}}(t)) + P_{\mathrm{Bd}}(P_{\mathrm{B}}(t)) + P_{\mathrm{A}} \tag{5}$$