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Least costly energy management for series hybrid electric vehicles

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ABSTRACT

Energy management of plug-in hybrid electric vehicles (HEVs) has different challenges from non-plug-in HEVs, due to bigger batteries and grid recharging. Instead of tackling it to pursue energetic efficiency, an approach minimizing the driving cost incurred by the user – the combined costs of fuel, grid energy and battery degradation – is here proposed. A real-time approximation of the resulting optimal policy is then provided, as well as some analytic insight into its dependence on the system parameters. The advantages of the proposed formulation and the effectiveness of the real-time strategy are shown by means of a thorough simulation campaign.

1. Introduction

Hybrid electric vehicles (HEVs) are generally regarded to as an effective solution to improve the fuel economy and reduce CO_2 emissions with respect to Internal Combustion Engine (ICE) vehicles. Since HEVs are usually equipped with (at least) two energy sources, a critical energy management problem arises, that is, a supervisory system is needed to determine how to generate the requested power. In the so-called "mild HEVs", the downsized battery and the electrical motor do not allow to drive the vehicle based just on the electric power, but only to assist the ICE in low efficiency operating points. In this framework, heuristics and rule-based algorithms have shown to provide satisfactory results. On the other hand, highly hybridized powertrains call for more sophisticated control approaches for their higher flexibility (Sciarretta and Guzzella, 2007).

In the latter configuration, given a model of the hybrid powertrain, the best performance theoretically achievable over a driving schedule can be computed by means of optimization techniques, see, e.g., Delprat, Lauber, Guerra, and Rimaux (2004) and Barsali, Miulli, and Possenti (2004). A classical approach in HEVs aims at minimizing the overall fuel consumption, concurrently penalizing excessive deviations of the battery state of charge (Won and Langari, 2005; Won, Langari, and Ehsani, 2005). Such a penalty term is very important for conventional HEVs, in which the minimization of the fuel consumption *tout court* may lead to excessive battery charge depletion.

The above optimization approach usually yields a non-causal control policy, which defines a useful upper bound in terms of performance for a given driving cycle. A good approximation of the above optimal policy can be found using the so-called Equivalent Consumption Minimization Strategy (ECMS) – based on the Pontryagin Minimum Principle – in which the knowledge of future power requests is replaced by a cycle-dependent parameter, see Sciarretta and Guzzella (2007), Sciarretta, Back, and Guzzella (2004), Serrao and Onori (2009), Paganelli, Guerra, Delprat, Santin, and Combes (2000), and Kim, Cha, and Peng (2011) for further details. Adaptive variants of the ECMS have also been developed and successfully implemented in real-time (Ambühl and Guzzella, 2009; Musardo, Rizzoni, Guezennec, and Staccia, 2005). Nonetheless, other real time approaches have been explored, based, e.g., on Model Predictive Control (Borhan et al., 2012; Poramapojana, 2012) or Robust Control (Pisu and Rizzoni, 2007; Pisu, Silani, Rizzoni, and Savaresi, 2003).

The above strategies were originally conceived for conventional, non-plug-in HEV powertrains, that is when the battery can be recharged exclusively during vehicle operation, e.g., by regenerative braking or thermal power surplus. However, more recent plug-in HEVs make it possible to recharge the battery from the grid (Axsen and Kurani, 2013; Bradley and Frank, 2009). Quite simultaneously, progresses in battery technology are making big battery packs more affordable, thus extending the electric autonomy of such vehicles.

Upcoming HEVs are then more and more conceived as plug-in vehicles with a relatively large battery and a significant "all-electric range", with a thermal unit often playing the role of a range

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extender. In view of this trend, on the one hand, the need for charge sustenance becomes less critical. On the other hand, since the battery has a more significant impact on the overall vehicle cost, the battery operating conditions leading to fast aging should be avoided.

Supervisory strategies have been proposed also for the energy management of plug-in and series HEVs. Sticking as a relevant case to the ECMS strategies mentioned above, some implementations for a plug-in HEV are presented, e.g., in Sciarretta et al. (2014); quite intuitively, here the charge sustenance constraint can be relaxed, by taking into account the characteristics of the powertrain and the available information on the trip to be performed. A general framework for energy optimization of plug-in HEVs has been recently introduced in Guardiola, Pla, Onori, and Rizzoni (2014), where the optimal data-driven tuning of the ECMS policy is also discussed. In some recent works, battery aging is accounted for in the optimization problem. In Moura, Stein, and Fathy (2013) battery aging and energy consumption are both regarded as relevant phenomena for the optimal depletion strategy of the battery in a plug-in HEV. In Serrao, Onori, Sciarretta, Guezennec, and Rizzoni (2011) and Ebbesen, Elbert, and Guzzella (2012) a similar problem is tackled for HEVs with a hard charge sustenance constraint; in these works, ECMS-based strategies are developed, with an additional tuning parameter affecting the weight of the aging in the cost function.

The contributions of this paper can be summarized as follows. Firstly, a *least costly* formulation of the energy management is proposed, aiming to fully exploit series hybrid powertrains. The underlying model also accounts for battery aging and the optimal control problem accounts for all the *cost entries* related to both the electrical part and the thermal unit.

Secondly, by applying Dynamic Programming (DP) (Bertsekas, 1995), it is shown that the resulting energy management policy does not necessarily yield minimum fuel consumption. As a matter of fact, cheap fuels like CNG (Compressed Natural Gas) can prove cheaper than driving entirely on electric power, especially if battery purchase cost is considered; in such a scenario, a formulation in terms of *total driving cost* is desirable from the point of view of the user. Moreover, limited diffusion of alternative fuels may boost the adoption of multi-fuel range-extenders (http://www.fuerex.eu/). In the latter case, a total driving cost formulation allows to find a compromise e.g., between a relatively expensive fuel that is easy to find, like gasoline, and a cheaper less widespread fuel, like CNG.

Unfortunately, the above DP-based solution relies upon the *a priori* knowledge of the driving cycle. Therefore, as a further contribution of the paper, two causal implementations of the least costly energy management strategy are proposed. The optimal policy is first derived based on a simplified model of the powertrain in an explicit way: although the model is less general, in this case the policy is expressed as a set of explicit rules, hence its implementation requires substantially less memory and computational power. Furthermore it is shown that, when a more complex model of the powertrain is necessary, the optimal policy can still be computed numerically, attaining very close results to the acausal benchmark. Finally, the paper includes a sensitivity analysis that investigates the performance of the numerical policy for a broad range of model parameters and energy costs.

The remainder of the paper is as follows. A general formulation of the energy management problem – as well as some specific formulations in terms of energy consumption minimization – is given in Section 2, where the full-fledged simulator of the vehicle and the simulation scenarios used in the following sections are also presented. By deriving a suitable control-oriented model and an economic cost function, the least costly energy management approach is presented in Section 3, where the resulting non-causal policy is also derived by Dynamic Programming. Section 4 provides the causal policies for the least costly energy management problem, while Section 5 discusses the limits of applicability of such a strategy by means of a sensitivity study. The potential of the new approach is shown in each section by employing both a urban and a mixed urban-motorway driving cycle. The paper is ended by some concluding remarks.

2. Problem formulation and simulation setup

In this section the HEV energy management problem is presented and the way it is commonly addressed in the literature is discussed. Moreover, the simulation setup and the driving cycles – employed in the remainder of the paper to test the proposed strategy – are introduced.

2.1. Problem formulation

With "energy management problem" it is meant the problem of designing a supervisory control layer with the aim of managing the power dispatch between multiple sources in a HEV. More specifically, such a problem is commonly formalized as an optimal control problem over a finite time horizon. With reasonable knowledge of the vehicle, the speed and slope profiles of the trip can be converted into a profile of requested electrical power in series HEVs, or mechanical power in parallel HEVs. The remainder of the paper is focused on series HEVs.

Formally, an energy management problem can be written as

$$\begin{aligned} \min_u \quad & J = h(x(T)) + \int_0^T g(t, x(t), u(t), w(t))\, dt \\ \text{s. t.} \quad & \dot{x} = f(t, x(t), u(t), w(t)) \\ & x(0) = x_0 \\ & x(t) \in X \\ & x(T) \in X_T \\ & u(t) \in U \end{aligned} \tag{1}$$

where J is the cost function to minimize, x collects the state variables, u is the control variable, w represents the exogenous input variable, f denotes the state function, g is the running cost and h is the terminal cost. x, u, w are assumed to be scalar variables and f, g, h are assumed to be scalar, possibly nonlinear functions. $X = [\bar{x}_{min}, \bar{x}_{max}] \subseteq \mathbb{R}$ is the set of admissible values for the state variable; the bounds $\bar{x}_{min}, \bar{x}_{max}$ are assumed to be static. X_T is the set of admissible values for the final state. $U = [u_{min}(t), u_{max}(t)] \subset \mathbb{R} \times \mathbb{R}^{T-1}$ is the set of admissible values for the input variable; the bounds u_{min}, u_{max} are assumed to possibly be time-varying.

Many approaches proposed in the literature aim at minimizing the fuel consumption for a given trip; therefore, the fuel mass flow rate is often chosen as the running cost as

$$g(u(t)) = \dot{m}_f(u(t)). \tag{2}$$

The fuel mass flow rate reasonably depends on the control policy $u(t)$. The control input may be the battery current, the battery power, the generated power or the ratio between battery and generated power. The state variable is typically the battery state of charge, which requires the introduction of a battery model.

A possible strategy is the Full Electric mode, i.e. the simple minimization of the fuel consumption, without any constraint or penalization on the final state

$$\begin{aligned} & h(x(T)) = 0 \\ & X_T = X. \end{aligned} \tag{3}$$