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Model Predictive Energy Management for a Range Extender Hybrid Vehicle using Map Information ⋆

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Abstract: This paper introduces a model predictive control (MPC) strategy for the purpose of fuel-optimal operation of a range-extender hybrid vehicle. The modern navigation system nowadays can provide abundant road information. Using this information, the proposed controller solves a global optimization problem offline in order to determine a preset trajectory of the state of charge (SoC). The online MPC uses the resulting SoC trajectory as set-points for the terminal state in every moving horizon. Repeating this process, the optimal energy management along the trip to be traveled can thus be calculated. This proposed control strategy is implemented in the commercial vehicle simulation environment `IPG CarMaker`. From the first simulation results, the proposed strategy shows a promising fuel saving potential with real-time capability.

Keywords: Hybrid vehicles, Optimal control, Predictive control, Pontryagin's minimum principle, State constrained control.

1. INTRODUCTION

Many approaches for energy management for hybrid electric vehicles (HEV) have been reported, including rule-based strategies, global optimal control (GOC) strategies, and online-capable model predictive control (MPC) strategies. Although the rule-based strategies has shown great real-time ability and practicality in implementation on real vehicles, it is challenging to calibrate the controller to achieve a fuel economy near an optimal controller, as Tribioli et al. (2014) reported. Besides, it requires much effort for tuning to ensure robustness in different test scenarios (Serrao et al., 2011).

GOC and MPC are related to solving optimal control problems (OCP). One may classify the solution techniques of such problems into two main categories: dynamic programming (DP) and calculus of variations. DP splits the whole mission into a finite number of sub-problems in discrete time intervals and studies every feasible state/control sequence. The large number of thereby generated possible solutions implies a great computational effort, which is one of the biggest drawbacks for its real-time capability (Serrao et al., 2011). The latter technique can be further divided into direct and indirect search methods (Rao, 2010; Papageorgiou, 2006). The direct search method discretizes OCP along the time axis and the relationship between states at different time instances is imposed by the system dynamics as a result of the control inputs. Thus, OCP is transformed into a static optimization problem comprising a sequence of control inputs. This method seems sufficiently mature in context of energy management. General Motors Company has already published patents adopting it (Heap, 2008). As for indirect search method, the Hamiltonian function is introduced to reformulate OCP so that the necessary conditions for optimality based on calculus of variation can be applied (Papageorgiou, 2006, p. 192). In the case of control inputs being constrained, the conditions are provided by Pontryagin's Minimum Principle (PMP). In this way, OCP is cast into a two-point boundary value problem. PMP has been proven very effective in solving energy management problems in HEV (Serrao et al., 2011). Ambühl et al. (2010) presented a detailed insight of PMP implementation in HEV. Kim et al. (2011) and Stockar et al. (2011) discussed how to include state constraints elegantly by using an extended Hamiltonian formulation. The former assumed a jump in the co-state at entering the state boundary whereas the latter introduced an adjoined Lagrange multiplier for solving OCP at state boundaries. Although, to determine the valid values for either the co-state after the jump or the adjoined multiplier requires a number of trials.

Research on control strategies for externally-rechargeable HEV is growing rapidly in recent years. These HEV classes include Plug-in Hybrid vehicles (PHEV) and Range-Extender Hybrid vehicles (BEVx). The most basic control strategy for this class of HEV is charge-sustaining charge-depleting (CDCS) strategy, where the engine is switched on only if the batterie's state of charge (SoC) falls below the lower boundary. Researches have revealed that avoiding the charge-sustaining phase by switching on the engine

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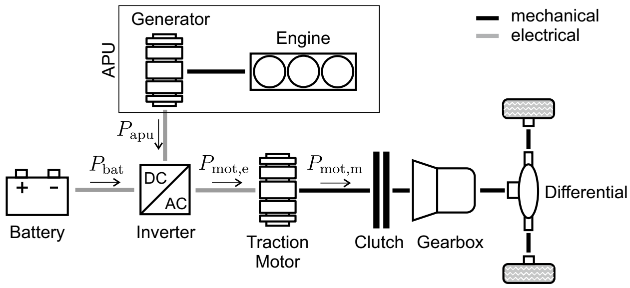

Fig. 1. BEVx powertrain topology

earlier can be beneficial for fuel economy (Larsson et al., 2010). Many articles have discussed GOC strategies using DP (Serrao et al., 2011; Gong et al., 2008) or PMP (Tribioli et al., 2014; Hou et al., 2014) to plan the optimal SoC and control policies over the whole trip. As Sun et al. (2014) suggested, the SoC trajectory generated by GOC can then be employed as the terminal state reference in each horizon of MPC. He has demonstrated an experimental application of this two-scale structure using DP algorithm.

This paper presents a two-scale PMP solution for externally rechargeable HEV, applying it on BEVx as an example. With modifications, the proposed algorithm is also applicable on other HEV configurations. Another novelty may consist in handling constraints on the state regarding PMP without numerous trials to determine required parameters. Through a driver model for speed prediction, the necessary a priori knowledge of the road load for GOC can be acquired, which is the required torque and rotational speed at the wheels. In the offline phase, i.e. before the BEVx starts off, the global optimization problem for best fuel economy is solved based on the predicted road-load information over the entire trip. Thus we obtain a set-point trajectory over the traveled distance for SoC. In the online phase, i.e. during the driving, our MPC algorithm solves one time-finite optimization problem with terminal state constraints at every discrete time instance.

2. SYSTEM MODEL AND OPTIMIZATION PROBLEM

The following section introduces the powertrain topology of BEVx discussed in this paper, the optimization control problem formulation and the mathematical models that appear in the problem formulation.

2.1 Powertrain Topology

The powertrain of BEVx is a so-called serial hybrid configuration. The electric generator is mechanically coupled with an engine and converts the mechanical power from the engine into electrical power. The generator operates as a motor only when it starts up the engine. The generated electrical power joins the power flow from the battery to supply the traction motor whose torque drives further the wheels through the final drive. The powertrain topology of BEVx is depicted in Fig. 1.

2.2 Optimal Control Problem Formulation

According to the classical optimization problem definition (Papageorgiou, 2006), we can describe OPC discussed in this paper as follows:

$$\min_{u(\cdot)} \quad J = \int_{t_0}^{t_\text{f}} P_\text{f}(u(t))\,\mathrm{d}t \tag{1a}$$

subject to

$$\dot{x} = f(x,u,d,t) \tag{1b}$$
$$x(t_0) = x_0 \tag{1c}$$
$$x(t_\text{f}) = x_\text{f} \tag{1d}$$
$$u_\text{min} \le u \le u_\text{max} \tag{1e}$$
$$x_\text{min} \le x \le x_\text{max}, \tag{1f}$$

where P_f is the equivalent fuel power as a function of the control u, which is the electric power P_apu delivered by the auxiliary power unit (APU). APU is the combined set out of the generator and the engine. x stands for SoC of the battery. d denotes the disturbance to the dynamic system. At the beginning of a trip $t = t_0$, SoC starts at the initial state x_0. Note that the terminal state constraint (1d) at $t = t_\text{f}$ does not exist in offline GOC. That is because SoC is *not* required to be held at a certain level to ensure the sustainability for hybrid functionality, as in the case of HEV without Plug-in.

The only state variable in a HEV energy management problem is the SoC of the battery (Sciarretta and Guzzella, 2007). Thus, the system function (1b) can be described as (cf. Hou et al., 2014),

$$\dot{x} = c_1\left(V_\text{oc}(x) - \sqrt{V_\text{oc}^2(x) - c_2 P_\text{bat}(t)}\right), \tag{2a}$$

with the coefficients

$$c_1 = -\left(2\,Q_\text{bat} R_\text{bat}\right)^{-1}, \tag{2b}$$
$$c_2 = 4\,R_\text{bat}, \tag{2c}$$

where Q_bat is the full electric charge and R_bat the internal resistance of the battery. The open-circuit voltage $V_\text{oc}(x)$ is a function of SoC. Fig. 1 shows that the electric power flows from the battery and APU converge to the traction motor. Neglecting the power loss on the inverter, we can express the output power of the battery P_bat according to Kirchhoff's laws:

$$P_\text{bat}(t) = P_\text{mot,e}(t) - P_\text{apu}(t) = d(t) - u(t), \tag{3}$$

where the time-variant disturbance is defined as $d(t) := P_\text{apu}(t)$.

After substituting P_bat in (2a) with (3), we get

$$\begin{aligned}\dot{x} &= f(x,u,d)\\ &= c_1\left(V_\text{oc}(x) - \sqrt{V_\text{oc}^2(x) + c_2(u-d)}\right).\end{aligned} \tag{4}$$

2.3 Battery Model

We adopt the modeling method in Chen and Rincon-Mora (2006) to build up an equivalent circuit model for the Li-ion battery in the BEVx. Note that since the transient response in the circuit is much quicker than the dynamical characteristic in reference to SoC, the capacitors in the model can be neglected. The circuit can thus be simplified into a combination of a controlled voltage source $V_\text{oc}(SoC)$ in dependance of SoC and a single internal resistor. The relationship between SoC and V_oc is depicted in Fig. 2.

Typically, the battery's open-circuit voltage is considered constant when modeling HEV. Different than in the case