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Optimal Control Policy Tuning and Implementation for a Hybrid Electric Race Car

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Abstract: The Formula 1 car is a state-of-the-art hybrid electric vehicle. Its power unit is composed by a turbocharged gasoline engine and two electric motor/generator units connected to the traction system and to the turbocharger. Such a powertrain offers an additional degree of freedom and therefore requires an energy management system. This supervisory controller has a significant influence on the vehicle's fuel consumption and on the achievable lap-time. Therefore, a thorough, systematic optimization of the energy management system is a crucial prerequisite to win a race. The complexity of the system and the strict regulations make the time-optimal energy management problem non-trivial to solve and an effective implementation of its solution on the car difficult to achieve. In Ebbesen, S. et al. (2016) and Salazar, M. et al. (2016) a convex numerical solver was designed and the optimal strategies were derived analytically using a non-smooth version of Pontryagin's Minimum Principle, respectively. Building on these results, we design a nonlinear program to tune an efficient version of the optimal control policy, in order to precisely match various boundary conditions on the fuel consumption and on the battery usage. This allows a simple and robust implementation of the time-optimal control strategies on the vehicle, and guarantees compatibility with the FIA rules. A simulator is then used to test the obtained feedforward controls on one race lap in Barcelona. The results stand comparison with the optimal solutions obtained with the numerical solver and validate the effectiveness of this strategy.

Keywords: Optimal Control, Formula 1, Hybrid Electric, Energy Management, Nonlinear Programming, Intelligent Vehicles and Robotics Technology in Vehicles

1. INTRODUCTION

The effectiveness and the promising results obtained with hybrid technologies in terms of sustainability and fuel efficiency have appealed to the Formula 1 (F1) world. Starting in the 2014 season, a downsized and turbocharged 1.6l V6 Internal Combustion Engine (ICE) was combined with two Motor/Generator Units (MGU). The first one is used to recover kinetic energy from breaking (MGU-K) and the second one as an electric turbo-compound system (MGU-H), Algrain (2005); Katrašnik et al. (2003); Wei et al. (2010). Moreover, the energy flows within this power unit are subject to strict regulation and the overall fuel consumption per race is limited to 100 kg gasoline, 201 (2013). The authors Picarelli and Dempsey (2014) investigate different power unit configurations and present simulations of the complete physical model. The increasing complexity of the system and the strict regulations given by the Fédération Internationale de l'Automobile (FIA) demand a systematic analysis of the time-optimal control problem, in order to understand and implement a control strategy that allows minimum lap-time to be achieved.

A review of the various methodologies that have been employed to tackle the time-optimal control problem of hybrid electric race cars can be found in Limebeer and Rao (2015). The racing path and the power unit energy flows are optimized simultaneously for a sports series HEV using the indirect method in Lot and Evangelou (2013). Direct multiple shooting is employed in Casanova (2000) to solve the same problem for the F1 car. The optimal control of the power unit is addressed in Limebeer et al. (2014) together with the optimization of the race trajectory by using orthogonal collocation methods. Direct transcription and Nonlinear Programming (NLP) are exploited in Perantoni and Limebeer (2014) to also optimize the design parameters of the car.

In contrast to the presented methodologies, here the energy management problem was separated from the optimal driving problem. In Ebbesen, S. et al. (2016), the optimal control problem is addressed for the F1 power unit, and the optimal racing path is precomputed and fed to the solver in form of maximum speed constraint and track slope. The system is modeled in a convex form, which allows the time-optimal energy management problem to be solved by means of convex optimization, Boyd and Vandenberghe (2004) and Rockafellar (1997), and guaranteeing existence and uniqueness of the optimum and computational times three orders of magnitude lower than the state of the art methodologies. The implementation of the presented strategies is altogether non-trivial, as the forward implementation of pre-computed input trajectories lacks in robustness and adaptability. In Salazar, M. et al. (2016), the time-optimal control of the power unit is treated analytically using Pontryagin's Minimum Principle (PMP) Pontryagin (1987) combined with non-smooth analysis, in order to understand the optimal behavior and implement it in a simple way.

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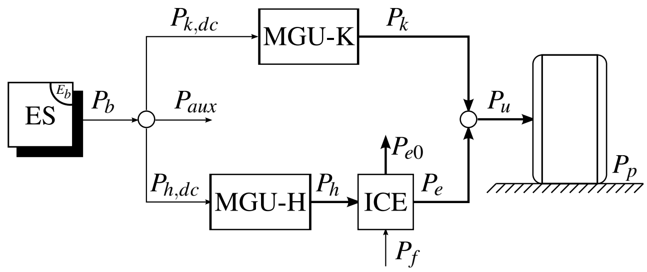

Fig. 1. Schematic representation of the F1 power unit taken from Ebbesen, S. et al. (2016). Bold lines indicate mechanical connections and arrows denote positive energy flow directions. The blocks represent the Energy Storage (ES), the MGU-K, the MGU-H and the ICE.

This paper continues along the same lines. The optimal control policy obtained in Salazar, M. et al. (2016) depends on the co-state variables of the system, whose values are constant except for the first one, which is space-dependent and can be used as decision variable. If the terminal constraints on fuel and battery consumption are changed, the co-state variables also change, whereby the first one only slightly. Choosing a fixed first co-state as decision variable, a Nonlinear Program (NLP) is designed to tune the remaining co-state values, and thus the optimal control policy, to match the desired terminal conditions. Similar ideas are employed in Jiao and Shen (2014), Ahmad et al. (2013) and Hagura et al. (2013) to tune the energy management strategies for HEVs and to improve their fuel efficiency. The resulting control policy can be effectively implemented on the car with a 1-D look-up table, as shown in Section 4 with a forward simulator.

The structure of this paper is as follows: the optimization problem is presented together with a summary of the results obtained in Ebbesen, S. et al. (2016) and Salazar, M. et al. (2016) in Section 2. Thereafter a NLP is designed in Section 3. Section 4 describes the control policy implementation in a forward simulator for one race lap on the Barcelona circuit and the obtained state trajectories are compared to the optimal ones. Conclusions and an overview of further research work are presented in Section 5.

2. BACKGROUND

In this section, the time-optimal energy management problem for the F1 power unit shown in Figure 1 will be presented. Furthermore, the model derived and validated in Ebbesen, S. et al. (2016) and the results obtained in Salazar, M. et al. (2016) will be summarized. For the sake of clarity, the optimal solutions obtained numerically with the convex optimizer, Ebbesen, S. et al. (2016), will be denoted as $(\cdot)^o$ henceforth, whereas the ones derived analytically in Salazar, M. et al. (2016) with $(\cdot)^*$.

2.1 Optimization Problem

In order to express the optimization problem in a form compatible with PMP, the state variables are defined as $x = (E_{kin}, E_f, \Delta E_b, E_{ES2K}, E_{K2ES}, s)^{\mathrm{T}}$, i.e. kinetic energy, fuel energy used, battery energy deployment [1], energy transferred from the ES to the MGU-K and vice versa, and position on track. The inputs are represented by the fuel, the MGU-K and the braking power $u = (P_f, P_k, P_{brk})^{\mathrm{T}}$. The minimum lap-time energy management problem is then

$$\min_u \int_0^T g(x,u)dt + h\big(x(T)\big)$$
s.t.
$$\begin{cases} \dot{x}_1 = c_{s,1}P_u^2 + c_{s,2}P_u - P_d(x_1,x_6) - P_{brk} \\ \dot{x}_2 = P_f \\ \dot{x}_3 = -P_i(P_k, -\eta_h P_f) \\ \dot{x}_4 = \max\{0, P_{k,dc}(P_k) + P_{h,dc}(-\eta_h P_f)\} \\ \dot{x}_5 = \min\{0, P_{k,dc}(P_k)\} \\ \dot{x}_6 = \sqrt{2x_1/m} \end{cases}$$
$$\begin{cases} P_f(t) \in [0, P_{f,max}] \\ P_k(t) \in [P_{k,min}, P_{k,max}] \\ P_{brk}(t) \in [0, P_{B,max}] \\ x_1(t) \le E_{kin,max}(x_6(t)) \\ x_1(T) \in \{x_1(0)\} \\ x_2(T) \le E_{f,max} \\ x_3(T) \ge \Delta SOC \\ x_4(T) \le 4\text{MJ} \\ x_5(T) \ge -2\text{MJ} \\ x_6(T) = S \ , \end{cases} \tag{1}$$

where the power of the power unit, the converter power, and the battery internal and terminal power flows are defined as

$$\begin{aligned} P_u &= \underbrace{\eta_e P_f - P_{e0}}_{=:P_e} + P_k \\ P_{x,dc}(P_x) &= \alpha_x P_x^2 + P_x \ \text{ for } x = k,h \\ P_i(P_k,P_h) &= \alpha_b P_b(P_k,P_h)^2 + P_b(P_k,P_h) \\ P_b(P_k,P_h) &= P_{k,dc}(P_k) + P_{h,dc}(P_h) + P_{aux} \ . \end{aligned} \tag{2}$$

The stage cost function of the constrained PMP is

$$\begin{aligned} g(x,u) =& 1 + \Psi_{[-\infty,0]}(x_1 - E_{kin,max}(x_6)) + \Psi_{[0,P_{f,max}]}(P_f) + \\ &+ \Psi_{[P_{k,min},P_{k,max}]}(P_k) + \Psi_{[0,P_{B,max}]}(P_{brk}) \ , \end{aligned} \tag{3}$$

whereas the terminal cost function is

$$\begin{aligned} h(x(T)) =& \Psi_{\{x_1(0)\}}(x_1(T)) + \Psi_{[-\infty,E_{f,max}]}(x_2(T)) \\ &+ \Psi_{[\Delta SOC,\infty]}(x_3(T)) + \Psi_{[-\infty,4\text{MJ}]}(x_4(T)) \\ &+ \Psi_{[-2\text{MJ},\infty]}(x_5(T)) + \Psi_{\{S\}}(x_6(T)) \ , \end{aligned} \tag{4}$$

and $\Psi_{\mathscr{X}}(x)$ is the indicator function to the closed convex set $\mathscr{X}$ [2]. The Hamiltonian is then

$$\begin{aligned} H(x,u,\lambda) =& 1 \\ &+ \lambda_1\big(c_{s,1}P_u(P_f,P_k)^2 + c_{s,2}P_u(P_f,P_k) - P_{brk} - P_d(x_1,x_6)\big) \\ &+ \lambda_2 P_f - \lambda_3\big(\alpha_b P_b(P_k,-\eta_h P_f)^2 + P_b(P_k,-\eta_h P_f)\big) \\ &+ \lambda_4 \max\{0, P_{k,dc}(P_k) + P_{h,dc}(-\eta_h P_f)\} \\ &+ \lambda_5 \min\{0, P_{k,dc}(P_k)\} + \lambda_6\sqrt{2x_1/m} \\ &+ \Psi_{[-\infty,0]}(x_1 - E_{kin,max}(x_6)) + \Psi_{[0,P_{f,max}]}(P_f) \\ &+ \Psi_{[P_{k,min},P_{k,max}]}(P_k) + \Psi_{[0,P_{B,max}]}(P_{brk}) \ , \end{aligned} \tag{5}$$

where λ_i are the co-state variables.

In Salazar, M. et al. (2016), it was shown that the last co-state variable $\lambda_6(t)$ is not needed to derive the optimal control policy. Therefore, the relevant co-state variables are $\lambda_1(t)$, which is time-dependent, plus four other co-state values, which

[1] i.e. the change in State of Charge over one lap

[2] For detailed information refer to Vinter (2010) and Rockafellar (1997).