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Effects of Time Horizon on Model Predictive Control for Hybrid Electric Vehicles

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Abstract: One of the challenges in Model Predictive Control (MPC) for Hybrid Electric Vehicles (HEVs), is real time implementation, Bo-Ah et al. (2012). Computation time can be reduced by limiting the time horizon of the prediction. Limiting the time horizon results in sub optimal control, but may yield nearly optimal control if the time horizon is chosen appropriately. This paper investigates the sensitivity of MPC to predicted horizon length with regard to Fuel Economy (FE). The results show that predicting Driver's Desired Power (DDP) for the next 10 seconds on the highway and 20 seconds in the city, is sufficient for MPC to perform close to the Globally Optimized Controller (GOC). In other words: Regarding fuel economy optimization on the highway, knowing DDP for the next 10 seconds is almost equivalent to knowing the DDP for the whole trip.

Keywords: Hybrid Electric Vehicles, Control Strategy, Model Predictive Control.

1. INTRODUCTION

The transportation section is the main source of global greenhouse gas emissions and it is predicted that the demand for liquid fuel for transportation will grow even faster than any other segment of the economy, Conti and Holtberg (2011). Many technologies have been introduced to improve Fuel Economy (FE) and emissions of conventional vehicles. Electric vehicles are an alternative to improve FE and emission. However, because of current restrictions on battery technologies, the range of electric vehicles is short and also their charging time is long. As a result, Hybrid Electric Vehicles (HEVs) can be considered as a temporary solution to the problem. HEVs use both conventional fuel and electricity to yield good range and good FE. Therefore, the energy management or control strategy of HEVS plays an important role in improving the FE and exhaust emissions. Control strategies can be categorized in different ways, for example: rule-based controllers, Instantaneous Optimal Controllers (IOC), predictive controllers, and a globally optimized controller, which are shown in Fig. 1. The GOC requires the advance knowledge of DDP for the whole trip. In addition, GOC has a large computational burden. For these reasons, GOC is practically impossible to implement. But since GOC yields the maximum achievable FE, it is used for evaluating the other methods.

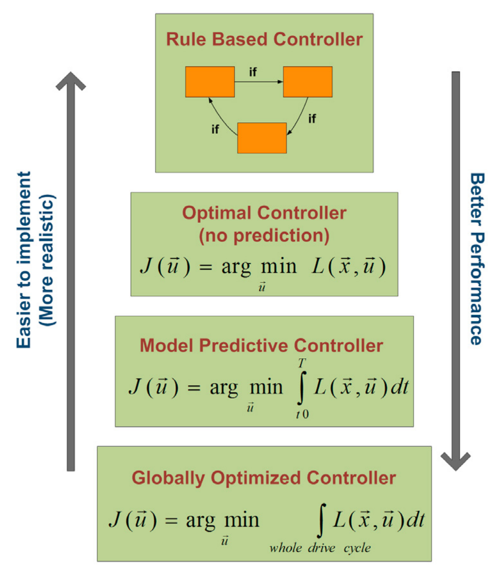

Fig. 1. A REPRESENTATION OF DIFFERENT CONTROL STRATEGIES

2. A REVIEW ON CONTROL STRATEGIES

2.1 Rule-based control

Rule-Based controllers are the most common controllers for HEVs produced by different companies. These controllers are reliable, fast and easy to implement. However, developing control rules takes time and needs extensive experimental data for a specific HEV. The rules may be defined explicitly, or in the Fuzzy domain. See Freyermuth et al. (2008), Lin et al. (2003), Salman et al. (2000), Baumann et al. (2000), and Schouten et al. (2002). The main disadvantage of rule-based controllers is that they are not optimal and there is considerable room for improving performance using other control strategies. To resolve this problem, some suggest extracting optimal rules from GOC actions, Lin et al. (2003, 2004). However, this method is drive-cycle dependent and extracting optimal rules from the distribution of GOC control actions is challenging. In Lin et al. (2004), stochastic dynamic programming is used to make extracted rules independent of drive cycle and in Moreno et al. (2006), an artificial neural network is trained

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and replaced with rules in order to avoid the process of extracting explicit optimal rules.

2.2 Instantaneous optimal control (IOC)

IOC tries to find the best control actions at each moment by minimizing a cost function as shown in Fig. 1. For example, Paganelli et al. (2001) introduced the Equivalent Consumption Minimization Strategy (ECMS) with the cost function:

$$J(\boldsymbol{u}) = \underset{\boldsymbol{u}}{argmin} \quad \{\dot{m}_{fuel}(\boldsymbol{x}, \boldsymbol{u}) + \beta(t)P_{battery}(\boldsymbol{x}, \boldsymbol{u})\} \quad (1)$$

where $\dot{m}_{fuel}$ is the rate of fuel consumption ($grams/sec$), $P_{battery}$ is the battery power ($watts$), and β is the penalty factor for using the battery power. ECMS states that using battery power $P_{battery}$ at any moment must be compensated by fuel in the future to charge the battery, so a punishment term for using battery power should be included in the cost function, Paganelli et al. (2001). The cost function in Eq.1 is shown to optimize the energy management in HEVs, Kim et al. (2011).

2.3 Model Predictive Control (MPC)

MPC is a branch of predictive control techniques that tries to find the best control actions by simulating (modeling) the plant on a predictive time horizon. As shown in Fig. 1, at the present moment t_0, MPC predicts the future reference inputs of the system for T seconds. MPC then determines the best control actions $\boldsymbol{u}(t_0)$ by optimizing the cost function $L(\boldsymbol{x}, \boldsymbol{u})$ over the time horizon $[t_0 \;\; t_0+T]$ (Fig. 2).

Knowing the reference input of the system $v(t)$ (the driver's demanded velocity) and the environmental variables $\boldsymbol{d}(t)$ at each moment, the DDP or $P_D(t)$ can be determined. The controller then tries to optimally divide $P_D(t)$ among the powertrain energy sources. So, MPC needs to predict $v(t)$ and $\boldsymbol{d}(t)$ in order to have an estimation of the future DDP. Fortunately, prediction of some of environmental variables, like speed limits, traffic conditions, road curves and road grades, is possible by using GPS devices and a geographic information system. Still, the main problem is predicting the drivers's demanded velocity $v(t)$.

3. APPLIED APPROACH FOR ANALYZING MPC

3.1 Simulation approaches

Since the goal of this work is to evaluate the performance of MPC versus time horizon, a perfect predication has been assumed. In this way, the inevitable errors in predication that happen in practice, will not affect the results. So, by using a backward simulation on a flat road, the driver's demanded power $P_D(t)$ for both city (UDDS) and highway (HWFET) drive cycles were calculated. As a result in the simulation, the MPC will have access to exact values of $v(t)$ and $P_D(t)$ for any horizon length.

3.2 HEV configuration and equations

A hybrid vehicle with parallel configuration and controllable transmission was chosen for this study. This configuration yields the power slit equations:

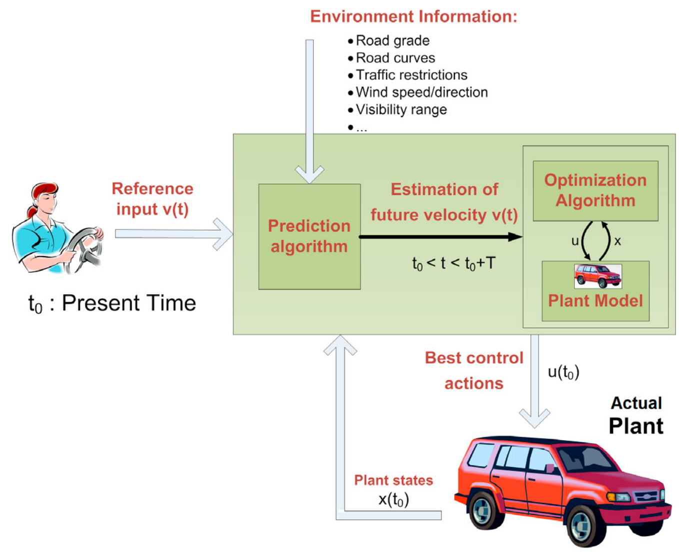

Fig. 2. UNITS OF A MODEL PREDICTIVE CONTROLLER

$$P_{eng}(t) = P_D(t)/\eta_t(g) - P_{em}(t) \quad , \; P_D(t) \geq 0 \qquad (2a)$$

$$F_{friction}(t) \cdot v(t) = P_D(t) - P_{em}(t)/\eta_t(g) \quad , \; P_D(t) < 0 \qquad (2b)$$

where t refers to time, P_D is driver's demanded power (DDP), P_{em} and P_{eng} are e-machine and engine power respectively, $F_{friction}$ is friction brake force, v is vehicle velocity, g is the transmission gear number, and η_t is the combined efficiency of the transmission and the final drive.

The constraint Eqs. 2a and 2b limit the number of variables that are used as control inputs. P_{eng} is determined by P_D (given), P_{em}, and g as shown in Eq. 2a. Similarity, $F_{friction}$ is determined by the demanded power, the velocity, P_{em}, and g as shown in Eq. 2b. Since P_D and v are specified by the driver (drive cycle), the set of control inputs can be reduced to:

$$\boldsymbol{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} P_{em} \\ g \end{bmatrix}$$

The battery power is:

$$P_{elec} = i_p(\boldsymbol{u})v_{p,oc}(x) - i_p^2(\boldsymbol{u})R_p(x) \qquad (3)$$

where P_{elec} is the electric power provided by the battery ($watts$), i_p is the battery pack current (A), $v_{p,oc}$ and R_p are the open circuit voltage and resistance of the battery pack respectively ($volts$,$ohms$), $\boldsymbol{u}$ is the vector of control variables, and x is the battery state of charge (SOC) defined by:

$$x(t) = SOC(t) = \frac{Q_p - \int_0^t i_p dt}{Q_p} \qquad (4)$$

where Q_p is the battery pack initial charge ($A.Secs$), and t is the time ($Seconds$). From the above equation and Eq. 3, the system state equation is: