Optimal Energy Management of HEVs with consideration of Battery Aging

Li Tang[1], Simona Onori[2] and Giorgio Rizzoni[3]
[1]The Ohio State University, 614411766, tang.437@osu.edu
[2]Clemson University, 8642837217, sonori@clemson.edu
[3]The Ohio State University, 6142925990, rizzoni.1@osu.edu

Abstract: This paper presents an optimal control-based energy management strategy for parallel hybrid electric vehicles (HEVs). This strategy not only seeks to minimize fuel consumption while maintaining the state-of-charge of the battery within reasonable bounds, but also seeks to minimize wear of the battery and extend its life. This multi-objective optimal control problem is solved numerically using Pontryagin's Minimum Principle (PMP).

Keywords: Optimal Control, Energy Management, Battery Aging, PMP, Hybrid Electric Vehicles.

I. INTRODUCTION

Thanks to the help of reversible energy storage devices and electric machines, hybrid electric vehicles (HEVs) are capable to reduce fuel consumption and emissions in contrast to conventional vehicles. The additional energy storage system, e.g. a battery pack, enables new degrees of freedom for vehicle power distribution, which provides opportunities of finding the most efficient way of power split between the engine and batteries. As a matter of fact, the fuel economy of HEVs is highly sensitive or dependent on the energy capacity of the on- board energy storage system, e.g. a Li-ion battery pack. Unfortunately, degradation of battery capacity due to several irreversible chemical processes is unavoidable. The rate of battery capacity loss is dictated by many factors including operating and environmental conditions. Factors such as extreme temperature, high c-rate, high or low level of state of charge and excessive depth of discharge are recognized to contribute to capacity degradation. Limiting stress on the battery that could accelerate its aging may result in energy management policies that are in conflict with the desire to minimize fuel consumption. This situation can be mathematically described as a multi-objective optimization problem. This paper formulates the energy problem in HEVs as an optimal control problem in which the energy management strategy is required to trade off between two objectives: minimizing fuel consumption, and minimizing battery aging. Simulation-based results are presented and analyzed to evaluate the strategy. This paper is organized as follows. First, the problem formulation is presented, and expressions of the analytical solution provided by PMP are described. Second, the model of a parallel HEV and its Simulink™ implementation are presented. Finally, the results obtained in simulation are interpreted and analyzed to provide insights into the design of implementable energy management strategy.

II. CONTENTS

- **Problem formulation**

The objectives of the optimal control problem discussed in this paper are twofold: minimizing fuel consumption, while minimizing battery capacity degradation. A crucial step in formulating such an optimal control problem consists in the development of a model to properly quantify the battery wear to be included in the cost function. In this paper, battery life with respect to a nominal cycle is defined as the total Ah-throughput when the battery undergoes the nominal load cycle (Serrao, 2009, Onori, 2011). The nominal battery life Γ can be expressed as in equation (1) where I_{nom} is the nominal current profile.

$$\Gamma = \int_0^{EOL} \left|I_{nom}(t)\right| dt \qquad (1)$$

The aging effects of any other load cycle the battery is subject to can be characterized by a severity factor which is defined as

$$\sigma(I,T,SOC) = \frac{\Gamma}{\gamma(I,T.SOC)} = \frac{\int_0^{EOL} \left|I_{nom}(t)\right| dt}{\int_0^{EOL} \left|I(t)\right| dt} \qquad (2)$$

where $\gamma(I,T,SOC)$ is the battery life (Ah-throughput) corresponding to specific operating conditions given in terms of current, temperature and SOC. The severity factor $\sigma(I,T,SOC)$ describe the aging effects of any load cycle relative to the nominal load cycle. When the battery is undergoing a more severe load cycle the severity factor is greater than one and a shorter life is expected. The severity factor σ can be obtained empirically through a battery aging model (Todeschini, 2012)(Wang, 2011). In (Suri, 2014) a method is developed to derive the severity factor map from a battery aging model. The results presented in this paper use the severity factor map developed from HEVs battery aging data (Suri, 2014). The effective life depletion due to charge exchange within the battery can be computed as effecive Ah-throughput which is defined by equation (3). Thus the battery will reach the end of life when $Ah_{eff}(t) = \Gamma$. As a reuslt, the objective of minimizing battery aging is equivalent to minimize $Ah_{eff}(t)$.

$$Ah_{eff}(t) = \int_0^{t} \sigma(I,T,SOC) \cdot \left|I(\tau)\right| d\tau \qquad (3)$$

Considering battery aging and fuel economy simultaneously requires defining a suitable cost function. We propose a cost function which has the form in (4). The first term represents fuel cost while the second term can be interpreted as battery aging cost. α is a weighting factor which has a value between 0 and 1. We can continuously trade off between these two costs by varying the value of α, which should yield a Pareto front. In order to make these two terms comparable numerically, normalization is needed for both. The key idea is to use a target cost of one trip to normalize the actual cost. In equation (4), M represents the target fuel consumption in kg, and Λ is the target effective Ah-throughput. Those targets can be determined by making reasonable assumptions. For instance, M can be computed by setting 50 MPG as the fuel economy target for one trip. Λ can be calculated based on the assumption of 20% battery capacity loss within a driving distance of 150,000 miles.

$$J = \int_0^t \alpha \cdot \frac{\dot{m}_f(u)}{M} + (1-\alpha) \cdot \frac{\sigma(\tau)\cdot|I(u)|}{\Lambda} d\tau \qquad (4)$$

Before trying to solve this optimization problem, one should recognize the fact that this system is subject to some dynamics or this is an optimal control problem with the state dynamics described in equation (5), where Q_{batt} is the battery capacity and u is the control input i.e. the power flow to and from the battery pack. Among methods for solving optimal control problems, Pontryagin's Minimum Principle (PMP) is chosen in this paper to give both analytical and numerical solutions.

$$S\dot{O}C = -\frac{I(SOC,u)}{Q_{batt}} \qquad (5)$$

According to Pontryagin's Minimum Principle (PMP), minimizing the cost function in (4) is equiavelent to minimize the Hamiltonian which is shown in (7). $\lambda(t)$ is the co-state which evolves with the dynamics described in (8). The optimal control input can be expressed as $u^*(t) = \arg\min_u \{H(t,SOC,u,\lambda)\}$.

$$H = \alpha \cdot \frac{\dot{m}_f(u)}{M} + (1-\alpha) \cdot \frac{\sigma \cdot |I(u)|}{\Lambda} + \lambda(t) \cdot S\dot{O}C(u) \qquad (7)$$

$$\dot{\lambda}(t) = -\frac{\partial H}{\partial SOC} = -(\frac{\alpha}{M} \cdot \frac{\partial \dot{m}_f}{\partial SOC} + \frac{(1-\alpha)}{\Lambda} \cdot \frac{\partial \sigma}{\partial SOC} \cdot |I| + \frac{(1-\alpha)}{\Lambda} \cdot \frac{\partial |I|}{\partial SOC} \cdot \sigma + \lambda(t) \frac{\partial S\dot{O}C}{\partial SOC}) \qquad (8)$$

- **Vehicle modeling**

The parallel pre-transmission hybrid architecture analyzed in this paper is shown in Figure 1, and the main characteristics of the components are listed in table 1. The internal combustion engine is a 1.6-liter in-line four-cylinder gasoline engine. The built-in electric machine allows for not only power assist but also battery charging which includes regenerative braking. The engine and electric machine are mounted on the same shaft which connects to the continuous variable transmission (CVT) through a torque damper. The system has two control inputs: T_{ice} and T_{em} the torque generated by the internal combustion engine and the electric machine respectively. Additional constraints are applied to the system, as will be explained in the paper.

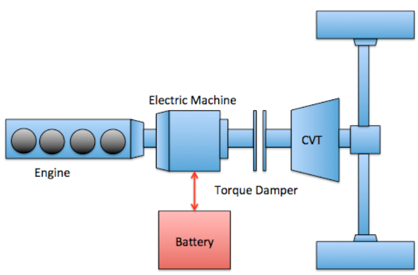

Fig. 1

Components	Specification
Vehicle Mass	1294 kg
IC Engine	1.6 liter 85 kw gasoline engine
IElectric Machine	Peak 30 kw, continuous 15 kw
CVT	Ratio: 3.172~ 0.529 Final drive: 3.94
Battery Pack	Li-ion 668 Wh\ 4.6 Ah, 20 kw

Table 1

- **Simulation results**

The key to solve this optimal control problem numerically with PMP is to solve the co-state dynamics which means implementation of the defferential equation, and determination of the initial condition for equation (8). According to equation (8), there are four terms in the co-state dynamics. The partial differentiation corresponding to the four terms are pre-calculated and implemented as lookup tables in the Simulink block. The details of creating these maps will be further illustrated in the complete version of this paper. In order to determine the initial co-state for a specific simulation condition , a two-step procedure is followed. First, an iterative method is applied to look for all the initial co-state candidates that meet the requirement of charge sustenance. Second, the total cost corresponding to each candidate is computed and the initial value that yields the lowest cost is the optimal initial co-state for that particular simulation condition.

To illustrate the results, we consider an urban driving cycle, and two different environmental temperature (15 ^{0}C and 30 ^{0}C). In order to have Pareto sets, four different values of α are tested in the simulations. In addition we impose a constraint that the initial SOC equals 0.5 and the final SOC is limited between 0.49 and 0.51. The main results of the simulation are listed in the table below,which only shows the results for T=15 ^{0}C. The definitions of the entries in the table are shown in (9).

Alpha	Initial Co-state	SOC_{final}	Total Cost	Fuel Cost	Aging Cost	Fuel Weighted	Aging Weighted
0.3	**0.19**	**0.50**	**0.61**	**1.11**	**0.39**	**0.33**	**0.27**
0.5	**0.1095**	**0.49**	**0.75**	**1.10**	**0.40**	**0.55**	**0.20**
0.7	**0.026**	**0.50**	**0.89**	**1.09**	**0.42**	**0.76**	**0.13**
0.9	**-0.0666**	**0.49**	**1.02**	**1.08**	**0.45**	**0.97**	**0.04**

Table 2. Simulation results with T=15 ^{0}C

According to the simulation results, when α increases, the fuel economy improves, but battery aging increases. This observation matches with the cost function in (7) which shows that increasing α gives more weight on fuel consumption while less on battery aging. In addition, battery aging cost changes up to 13.3% by varying the value of α while fuel cost changes only up to 2.7%. This means that by choosing an appropriate value of α, the battery life can be extended with an modest sacrifice in fuel economy. If we look into the details of the simulations, the optimal controller gives the commonds which lead to a more aggressive way of using batteries when α increases. The SOC profiles in Fig.2 show that the DOD at $\alpha = 0.9$ is deeper then what it is at $\alpha = 0.3$. Moreover, according to Fig.3, the battery power outputs have many big peaks at $\alpha = 0.9$ while the power is gentle at $\alpha = 0.3$. These differences in the way of being used make a difference in terms of battery aging rate.

$$\text{Total cost} = \int_0^t \alpha \cdot \frac{\dot{m}_f(u)}{M} + (1-\alpha)\cdot\frac{\sigma(\tau)\cdot|I(u)|}{\Lambda}d\tau \qquad \text{Fuel cost} = \int_0^t \frac{\dot{m}_f(u)}{M}d\tau$$

$$\text{Aging cost} = \int_0^t \frac{\sigma(\tau)\cdot|I(u)|}{\Lambda}d\tau \qquad \text{Fuel weighted} = \int_0^t \alpha\cdot\frac{\dot{m}_f(u)}{M}d\tau \qquad (9)$$

$$\text{Aging weighted} = \int_0^t (1-\alpha)\cdot\frac{\sigma(\tau)\cdot|I(u)|}{\Lambda}d\tau$$

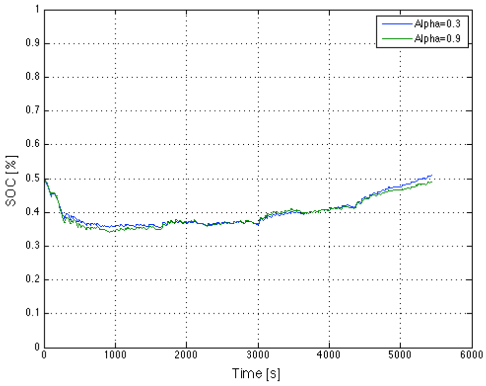

Fig.2

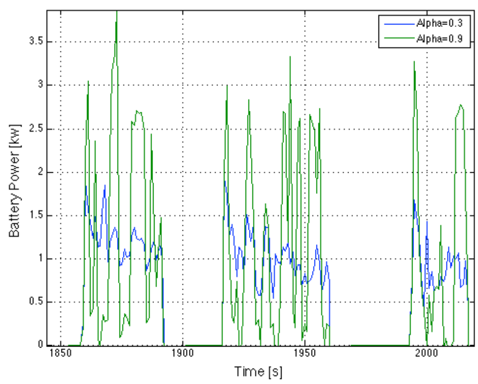

Fig.3

III. CONCLUSIONS

This paper proposes an optimal control-based energy management strategy for HEVs, which intends to minimze both fuel consumption and battery capacity degradation. Based on the previous analysis, there is a trade off between these two objectives. However, it is possible, according to the simulation results, to reduce the battery capacity loss by a relatively large percentage without giving up much fuel economy. This methodology will be teseted with various operating condition so that an implementable control strategy can be developed.

ACKNOWLEDGMENT

We gratefully acknowledge the financial support of Honda R&D.

REFERENCE:

F. Todeschini, S. Onori, G. Rizzoni, "An experimentally validated capacity degradation model for Li-ion batteries in PHEVs applications", 8th IFAC International Symposium on Fault Detection, Supervision and Safety of Technical Processes, Mexico, August , 2012.

L. Serrao, S. Onori, Y. Guezennec, G. Rizzoni, "*Model Based Strategy for Estimation of the Residual Life of Automotive Batteries*", 7th IFAC International Symposium on Fault Detection, Supervision and Safety of Technical Processes, Barcelona, June 30-July 3, 2009.

S. Onori, P. Spagnol, V. Marano, Y. Guezennec, G. Rizzoni, "A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications", *International Journal of Power Electronics*, Vol. 4, No. 3, pp. 302-319,2012

G. Suri, and S. Onori, "Experimental characterization of severity factor map for optimal energy management in HEVs," in preparation Journal of Power Sources, 2014

L. Serrao, S. Onori, A. Sciarretta, Y. Guezennec, and G. Rizzoni, "Optimal energy management of hybrid electric vehicles including battery aging,"in Proc. ACC, Jul. 2011, pp. 2125–2130

J. Wang, P. Liu, J. Hicks Garner, E. Sherman, S. Soukiazian, M. Verbrugge, H. Tataria, J. Musser, P. Finamore, "Cycle life model for graphite LiFePO4 cells," J. Power Sources 196(2011) 3942-3948.