

Impact of Model-Based Lithium-Ion Battery Control Strategy on Battery Sizing and Fuel Economy in Heavy-Duty HEVs

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ABSTRACT

Electrification and hybridization show great potential for improving fuel economy and reducing emission in heavy-duty vehicles. However, high battery cost is unavoidable due to the requirement for large batteries capable of providing high electric power for propulsion. The battery size and cost can be reduced with advanced battery control strategies ensuring safe and robust operation covering infrequent extreme conditions. In this paper, the impact of such a battery control strategy on battery sizing and fuel economy is investigated under various military and heavy-duty driving cycles. The control strategy uses estimated Li-ion concentration information in the electrodes to prevent battery over-charging and over-discharging under aggressive driving conditions. Excessive battery operation is moderated by adjusting allowable battery power limits through the feedback of electrode-averaged Li-ion concentration estimated by an extended Kalman filter (EKF). Battery terminal voltage is controlled within allowable operating limits while maximizing battery power availability with smaller batteries. HEV simulation shows trade-off between the battery sizing and the fuel economy both qualitatively and quantitatively. The results provide valuable information for battery sizing in a sense of balancing the battery cost and fuel economy in development of heavy-duty HEVs.

INTRODUCTION

Energy security and climate change concerns as well as upcoming regulation create strong impetus for developing efficient propulsion technologies. In the case of trucks, vehicle electrification and hybridization are promising approaches, more emphasized recently due to the proven potential for significant fuel economy improvement and the

advance of battery technologies. The vehicle electrification can be realized in forms of pure electric vehicles (EVs), hybrid electric vehicles (HEVs), and plug-in electric vehicles (PHEVs). Regardless of electrification types, larger batteries are required when the electrification level becomes higher. Recent improvement of Lithium-ion (Li-ion) batteries provides relatively high power density and high energy density [1] and benefits for reducing the total vehicle weight. However, durability of Li-ion batteries depends on the depth of cycles and peak charging/discharging current. Thus, preventing over-charging and over-discharging is critical for improving battery life and guaranteeing stable battery operations.

To ensure safe battery operations under wide variety of driving conditions, batteries tend to be oversized in real vehicle application. In the EV and the PHEV, the battery size is sufficiently large beyond the range so that the battery over-charging and over-discharging may not be problems. In contrast, in HEVs, especially heavy-duty or military HEVs, the battery pack cannot be significantly oversized due to the high cost. Thus, its size is determined close to the optimal that barely satisfies the power demand and to achieve the best fuel economy. Thus, minimizing the battery pack size without causing significant fuel economy deterioration and excessive battery operation is important in the HEV development.

Battery control strategy directly influences safe battery operations and overall vehicle performance regardless of HEV configurations: series HEV, parallel HEV, and power-split HEV. In series HEV configurations, the battery control is more sensitive to ensure safe operation since propulsion power entirely depends on electric power. Thus, a supervisory controller in the series HEV must manage the

battery sophisticatedly to achieve the desired performance as well as to prevent possible abnormal operations.

Most of the previous studies of simulation-based HEV design optimization and control design relied on equivalent circuit battery models because of the relatively simple structure and fast computation [2,3,4,5,6,7,8]. The battery responses predicted by equivalent circuit models in the previous studies are expressed as functions of battery initial state of charge (SOC) and applied current. However, the predicted responses in the equivalent circuit models cannot provide sufficient accuracy over various driving conditions due to the lack of observability of Li-ion concentration profiles along the solid particles.

Recently, an electrochemical model-based battery control strategy was proposed by Lee *et al.* [9]. The control strategy used the Li-ion concentration profile estimation and the feedback of the estimated profile to determine the battery allowable operating ranges. In the proposed control strategy, electrode-averaged Li-ion battery model [10], [11], [12], applying uneven discretization [9] was used for the control design with its good balance between computation time and prediction accuracy. The electrode-averaged model was derived from the full-order electrochemical models of the Li-ion battery developed by Fuller *et al.* [13] with the assumption that the Li-ion concentration in the electrolyte is constant along the electrode thickness direction. Each electrode is modeled with a spatially averaged single-particle. The averaged model is valid when the concentration distribution along the length of the electrodes and the separator can be assumed constant. Regardless of the limitation, the averaged model can provide Li-ion concentration profile information in the electrodes and can produce a state-space system with linear dynamics of spherical diffusion in the solid material and a nonlinear voltage output equation [11]. Thus, the averaged battery model is appropriate for the prediction of Li-ion concentration via an extended Kalman filter (EKF) with measured terminal voltage and applied current.

Estimation and use of the Li-ion concentration information in battery management are beneficial to develop sophisticated control design. Model-based battery control strategy used in this study can effectively prevent battery over-charging and over-discharging by adjusting allowable battery power limits in real-time [9]. However, the real-time adjustment may expense fuel economy benefit for safe battery operation from more frequent engine operation in the case that the battery size is relatively small. This paper investigates the impact of the model-based Li-ion battery control strategy on battery sizing and fuel economy in heavy-duty HEVs to provide insight for balancing battery size and vehicle fuel economy.

This paper is organized in the following way: First, a series HEV simulation framework with the model based battery

control strategy is presented. The electrode-averaged battery model is briefly shown. Then, the model-based battery control is described. HEV simulation results under various military and heavy duty driving cycles are presented, and the effectiveness of the model based control in ensuring safe battery operation and high fuel economy are investigated before presenting summary and conclusions.

SERIES HEV SIMULATION FRAMEWORK

Electrochemical model based battery control strategy is implemented into a series HEV simulation framework. The simulation framework enables the assessment of the battery control strategy under various driving cycles. Due to the high energy flow from the heavy weight, a heavy-duty series HEV equipped with a Li-ion battery is selected as a target vehicle to investigate the effect of the electrochemistry battery dynamics on control design with sufficient resolutions. Table 1 shows the specification of the selected vehicle.

Table 1. Heavy-duty Series-HEV Specification: Hybridized M-ATV

	Specification
Vehicle	Hybridized M-ATV
Weight	13,400 kg
Payload	1,814 kg (4000 lbs)
Frontal area	5.72 m ² (Width/Height: 2.49/2.70 m)
Engine	I6 Turbo-diesel engine: 275 kW
Generator	Permanent Magnet: 275 kW
Battery	Li-ion 6.0 kWh
Motors	Permanent Magnet: 380kW

Component sizes were initially determined to satisfy performance targets: maximum speed, gradeability, and acceleration. Rolling resistance, drag, and grade terms are taken into account in the vehicle power demand.

$$m_e \dot{v}_{veh} = F_{prop} - F_{RR} - F_{WR} - F_{GR}, \quad (1)$$

where F_{prop} is the propulsion force from the powertrain, F_{RR} is the rolling resistance force, F_{WR} is the wind resistance force, F_{GR} is the grade resistance force and all other external forces applied to the vehicle, m_e is the equivalent vehicle mass, and v_{veh} is the vehicle velocity. The simulation framework is constructed by combining engine model, motor/generator models, electrode-averaged battery model, vehicle dynamics model, supervisory control module, and model-based battery control module as shown in Fig. 1. The vehicle simulation model is a forward looking model, and the driver module determines control commands to follow desired velocity profiles. Based on the driving power demand, the supervisory controller distributes propulsion and braking

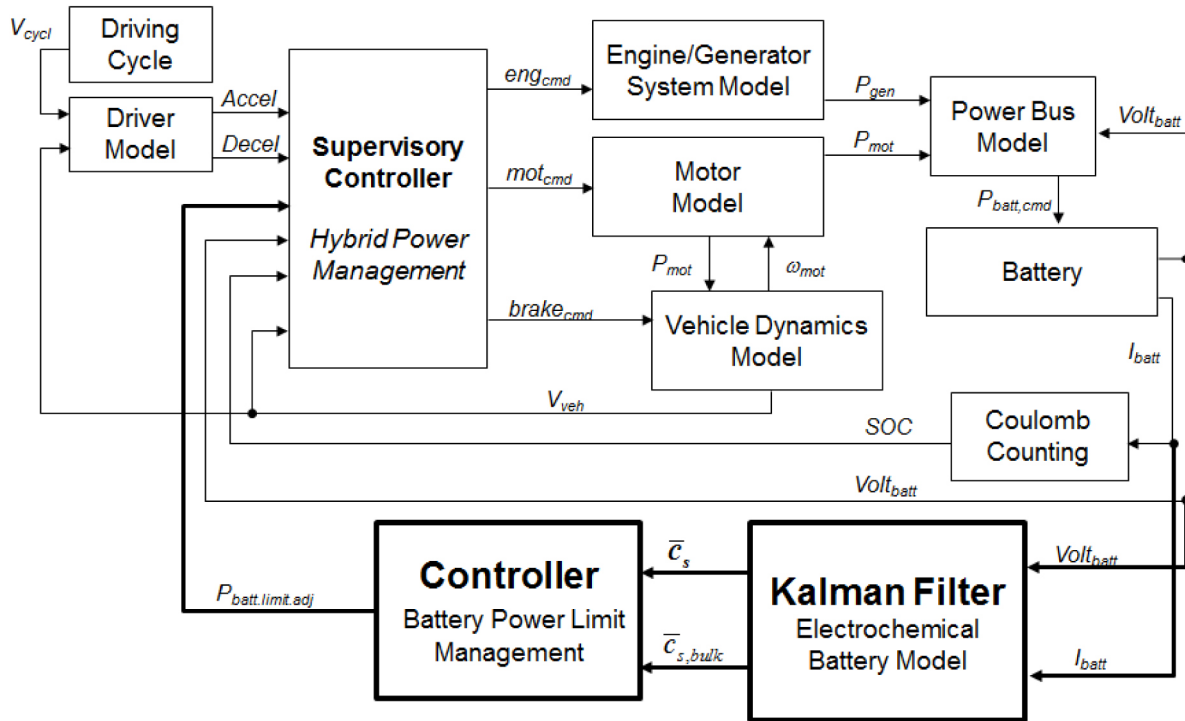


Figure 1. Series HEV Simulation framework in SIMULINK with a forward-looking approach

power to the engine and the motor respectively. The electric power demand from the battery is then determined as,

$$P_{batt} = -P_{egn} + P_{mot} + P_{accs}, \quad (2)$$

where P_{batt} is the battery output power, P_{mot} is the motor output power, P_{egn} is the engine output power, and P_{accs} is electric accessory power. The required P_{batt} determines the current input to the battery, $I_{inp, batt}$, using the battery terminal voltage, V_{batt} , and the terminal voltage is calculated from a higher order electrode-averaged electrochemistry battery model.

In a real vehicle, battery voltage and current are generally measured, thus, they are fed into the EKF to estimate the Li-ion concentration profiles. Battery allowable operating limits are adjusted utilizing the estimated Li-ion concentration information in real-time.

PROPULSION COMPONENT MODELS

In the vehicle simulation framework, propulsion components, such as the engine and the motor/generator, are constructed using map-based models with the consideration of transients by first order dynamics models. The reduced model complexity allows fast computational time while maintaining sufficient fidelity.

A map-based engine model is appropriate to reduce the computation time with the assumption that vehicle dynamics

is much slower than engine dynamics and the engine is fully warmed up. The engine operating point is controlled to follow the best brake specific fuel consumption (*bsfc*) line at a given power demand. When engine power demand P_{eng} is given, engine speed ω_e and engine torque T_e is determined by $T_e = P_{eng} / \omega_e$. To realize feed-forward control of the engine, the fuel amount to produce the engine torque is determined by inverting the torque function $T_e = f_{eng, T}(\omega_e, \dot{m}_f)$ and expressed as a function of engine speed and engine torque.

$$\dot{m}_f = f_{eng, T}^{-1}(\omega_e, T_e) = f_{eng, fuel}(\omega_e, T_e). \quad (3)$$

Total fuel consumption is calculated by integrating fuel consumption rate over the entire driving cycle. Engine speed is calculated based on

$$\dot{\omega}_{eng} = \frac{T_{eng} - T_{gen}}{J_{eff, eng}}, \quad (4)$$

where ω_{eng} is the engine speed, T_{gen} is the generator torque, $J_{eff, eng}$ is the combined effective rotational inertia of the engine and the generator.

The electric motor and generator are modelled by a map-based model since the motor torque dynamics are much faster than vehicle dynamics. The efficiency of the electric machine is assumed to be a function of the operating speed ω_{veh} and

torque T_{elec} (or power P_{elec}). The efficiency is generally measured through experiments. In the simulation work, quasi-steady state nonlinear efficiency maps are used to compute the output power expressed as:

$$P_{mech} = P_{elec} \cdot \eta_{em} \quad (\text{discharging}) \quad (5a)$$

$$P_{elec} = P_{mech} / \eta_{em} \quad (\text{charging}) \quad (5b)$$

where $\eta_{em} = \eta_{em}(\omega_{elec}, T_{elec})$, or $\eta_{em} = \eta_{em}(\omega_{elec}, P_{elec})$ is the electric motor efficiency, and the motor torque is expressed by $T_{mot} = P_{mot} / \omega_{mot}$.

The maximum torque output limits are determined with the consideration of both electrical and mechanical sides,

$$T_{max,mot} = T_{peak,mot} - HI \times [T_{peak,mot}(\omega_{mot}) - T_{cont,mot}(\omega_{mot})] \quad (6)$$

where $T_{peak,mot}$ and $T_{cont,mot}$ are the peak and the continuous torques respectively, HI is the heat index that adjust the available torque between the peak and continuous torques depending on operating condition. The HI is computed by

$$\frac{dHI}{dt} = \frac{const}{\tau_{max,mot}} \left(\left| \frac{T_{mot}}{T_{cont,mot}} \right| - 1 \right) \quad (7)$$

where $\tau_{max,mot}$ is a time constant of the motor.

CONTROL ORIENTED ELECTROCHEMICAL BATTERY MODEL

The electrode-averaged Li-ion battery model provides relatively fast computation and captures Li-ion diffusion dynamics, thus enabling the estimation of Li-ion concentration profiles along the electrode solid particle radius. In the averaged electrochemistry model, Li-ion concentration change in the solid particles along the electrode is neglected, and the concentration in the electrolyte is assumed constant. Although the simplification may reduce the prediction accuracy under high charging and discharging conditions, important diffusion dynamics in the solid particle are captured. In this paper, the electrode-averaged model proposed by Di Domenico *et al.* [10],[11],[12] is modified to improve the computation speed and the prediction accuracy by using uneven discretization [9], while constructing a set of ordinary differential equations (ODE). Figure 2 shows the conceptual illustration of the battery model reduction from the full-order model, which is represented as a macroscopic (x-direction) cell model, with coupled microscopic solid diffusion model (r-direction), to the electrode-averaged model.

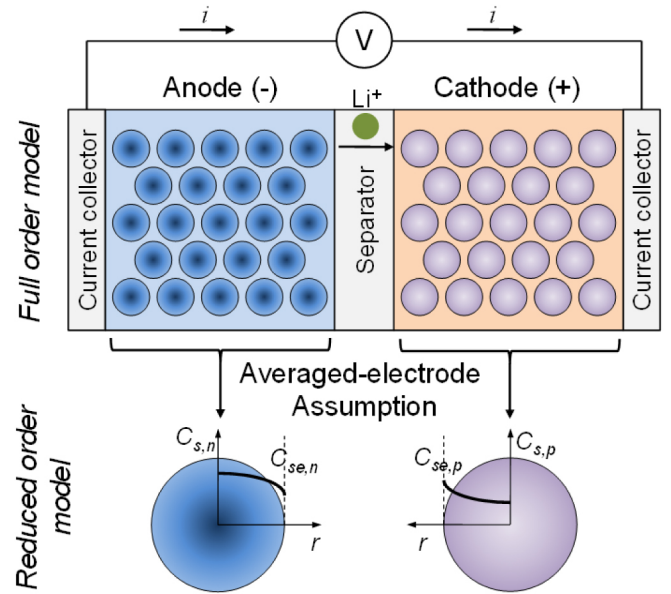


Figure 2. Illustration of Li-ion battery model reduction from the macroscopic (x-direction) cell model with coupled microscopic solid diffusion model (r-direction) to the electro-averaged cell model with coupled microscopic solid diffusion model (r-direction)

The averaged-electrode battery model is derived from the complete set of equations describing the Li-ion battery system with solid and electrolyte concentrations (c_s , c_e) and solid and electrolyte potentials (ϕ_s , ϕ_e) by Fuller *et al.* [13]. In the electrode-averaged model, set $\vec{\nabla}_x \phi_e = const.$, $\vec{\nabla}_x \phi_s = const.$, and $\vec{\nabla}_x c_e = const.$, then, the governing equations are collapsed to the diffusion dynamics equation in the electrode solid,

$$\frac{\partial c_s}{\partial t} = \vec{\nabla}_r (D_s \vec{\nabla}_r c_s), \quad (8)$$

where D_s is the effective diffusion coefficient of Li-ion in the electrodes, and the boundary conditions of eqn. (8) are:

$$\left. \frac{\partial c_s}{\partial r} \right|_{r=0} = 0 \quad (9a)$$

$$\left. \frac{\partial c_s}{\partial r} \right|_{r=R_s} = -\frac{\bar{j}^{Li}}{F a_s D_s} \quad (9b)$$

In an averaged electrochemistry model represented by one solid particle for each electrode (anode and cathode), the Butler-Volmer current j^{Li} is assumed constant $\bar{j}^{Li}$ regardless