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Battery state estimation with a self-evolving electrochemical ageing model

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ABSTRACT

The parameters for most battery state estimation techniques are usually calibrated during the development stage before vehicle production. However different usages of battery lead to different ageing processes, and end up with different model parameters. As a result, an estimation algorithm based on pre-calibrated parameters may not generate accurate estimates. This paper presents a new advanced methodology to address this challenge. First, we employ a comprehensive electrochemical model for lead acid batteries that were developed recently. The battery model explicitly characterizes the electric and thermal behavior of the battery, as well as the evolution of major battery failure modes. Second, we apply a two-time-scale model-based estimation method, where the micro time-scale algorithm estimates battery SOC and SOH, and the macro time-scale algorithm tracks the changes of the battery being monitored and updates the parameters of the battery model accordingly. The algorithms at both time scales use particle filter, a sequential Monte-Carlo estimation technique. Several datasets based on real vehicle driving profiles are used to validate the proposed algorithms. The experiment results show that the proposed estimation scheme is effective, due to both the careful selection of battery model and the tailored filtering technique.

1. Introduction

Battery diagnosis, such as battery state of charge (SOC) estimation and state of health (SOH) estimation, is a core function of battery management system (BMS) in conventional internal combustion engine vehicles, hybrid electrical vehicles (HEV) and electric vehicles (EV) [1]. Here SOC is defined as the charging level of a battery in terms of percentage, and SOH is an indicator of battery ageing which is commonly determined by battery impedance or battery remaining capacity. In a conventional internal combustion engine vehicle, the primary function of the battery is to drive the starter motor, crank the engine, and start the vehicle. When the battery SOC or SOH is low, the vehicle won't start. Moreover, when the vehicle engine is active, the battery serves as the secondary electric power source additional to the alternator. It supplies electric power to the loads when the demand exceeds alternator's maximum output. When the vehicle is ignition-off, the battery is the only electric power source to operate electrical accessories such as the clock or the anti-theft system [2]. Therefore an accurate SOC estimation facilitates BMS to make appropriate decisions on battery charge control, which impacts both vehicle fuel efficiency and the life of electrical components in the vehicle including the battery itself. The SOH estimation allows the vehicle driver to be warned ahead of battery failure, as well as enabling BMS to prolong battery life.

Research on battery state estimation has attracted a lot of attention. General battery state estimation techniques fall into two categories, namely data driven (black-box) and empirical (physics-model-based). The former makes the estimation using direct mappings between battery states and one or more battery features, such as open circuit voltage for SOC, and battery internal resistance for SOH. The mappings are usually trained or calibrated at the development process. Regarding SOC estimation, such approaches include open-circuit voltage (OCV) mapping [3], neural network [4], support vector regression [5,6], impedance mapping [7,8] and "coup de fouet" mapping [9]. For SOH estimation, the cranking resistance mapping and cranking time mapping [1,10] fall into this category. The empirical/physics-model based approaches usually employ electrochemical battery models or equivalent circuit models to represent real batteries. Comparing to the black-box model, this model has certain physical meanings. Battery state estimation is accomplished by feeding the battery model with battery measurements such as current, voltage, and temperature.

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Coulomb counting [11] is the simplest and most popular method in this category. More sophisticated methods usually involve filtering techniques such as Kalman filter [12], extended Kalman filter [13–16], unscented Kalman filter [17], U-D factorization-based recursive least square [18], Bayesian estimation [19], H_∞ observer [20] and particle filters (PF) [21–26].

These two approaches can be combined. For example, a combination of OCV mapping and current integration can be employed for SOC estimation. In this scheme, the OCV is collected during ignition off when there is no or minimal electrical load on the battery. If the ignition off time is long enough, the battery can be considered as having reached the equilibrium state. Under this condition, OCV can be mapped to battery SOC using a lookup table, and used as the initial estimate SOC_0 in the following equation,

$$SOC_{Integration} = SOC_0 + \frac{\eta}{C_R}\int_{t_0}^{t} I d\tau \tag{1}$$

where C_R is the battery rated capacity, η is the charging or discharging efficiency, I is the battery current, and t_0 is the initial time.

However both approaches share a common weakness. The model parameters are usually calibrated during the development stage before vehicle deployment, e.g. the entries in the lookup table. For simplicity of description, we use model parameters to refer to the parameters in both approaches in the rest of this paper. Since batteries are highly nonlinear devices, the batteries used in the calibration process may have different model parameters from the batteries used in deployed customer vehicles. In addition, these parameters usually change as batteries age. To make the matter more challenging, different usages of battery can lead to different ageing processes which in return end up with different model parameters. As a result, an estimation algorithm based on pre-calibrated parameters may not generate accurate estimates of battery states.

In our previous work [27], an approach is proposed called collaborative vehicle health management (CVHM) to address this issue. The basic idea is an adaptive learning scheme that allows BMS to continuously and automatically calibrate the model parameters associated with the estimation algorithm at run time after vehicle deployment. The battery data used for the adaptive learning is collected from peer vehicles, and transferred to the host vehicle via wireless communication. The experiment results using this approach were promising.

This paper presents an update to our previous work. First, a comprehensive electrochemical model is employed that was developed recently [28] for lead acid batteries to replace the polynomial regression ageing model used in our previous paper [29]. The new model explicitly characterizes the electrical and thermal behavior of the battery, as well as the evolution of major battery failure modes in vehicle applications. Second, a two-time-scale model-based estimation method has been developed, where the micro time-scale algorithm estimates battery SOC and SOH, and the macro time-scale algorithm tracks changes of the battery being monitored and updates battery model parameters accordingly. The algorithms at both time scales use particle filter, a sequential Monte-Carlo estimation technique. The experiment results show that the proposed estimation scheme is effective, due to both careful selection of the battery model and the tailored filtering techniques.

This paper contains a description of the battery ageing model in Section 2. A brief introduction of particle filter method is given in Section 3. The proposed estimation scheme is presented in Section 4. The experiment results are presented in Section 5 and several datasets based on real vehicle driving profiles are used to validate the proposed algorithms. Finally, discussions on the experiment results and future work are presented in Section 6.

2. Comprehensive electrochemical battery model

The battery ageing process involves long-term complex chemical reactions. To accurately describe the ageing process, a comprehensive electrochemical model was developed, and validated using data collected from real batteries. We will only briefly describe the ageing model here. For more detailed derivation of this model, the readers are referred to [30].

The model takes battery load current and ambient temperature as inputs, and generates battery terminal voltage, SOC, capacity, internal resistance, battery internal temperature, and acid stratification information. Seven sub-models shown in Fig. 1 are employed. These sub-models interact with each other to characterize the ageing process of the battery.

The first of the seven sub-models is the static electric model, which calculates the battery terminal voltage based on the modified Shepherd equation [29,30],

$$U_d(t) = U_{0d} - g_d DoD(t) + (T(t) - 25)\beta_d + \rho_d(t)\frac{I(t)}{C_N} + \rho_d(t)M_d\frac{I(t)}{C_N}\frac{DoD(t)}{SOH(t) - DoD(t)}, \quad \forall I(t) < 0 \tag{2a}$$

$$U_c(t) = U_{0c} - g_c DoD(t) + (T(t) - 25)\beta_c + \rho_c(t)\frac{I(t)}{C_N} + \rho_c(t)M_c\frac{I(t)}{C_N}\frac{SOC(t)}{C_c - SOC(t)}, \quad \forall I(t) > 0 \tag{2b}$$

where $DoD(t) = 1 - SOC(t)$, $I(t)$ is the battery current, $T(t)$ is the battery internal temperature calculated from the thermal model, $\rho_d(t)$ and $\rho_c(t)$ are aggregated internal resistance ($\Omega \cdot Ah$) obtained from the corrosion and cycling model, C_N is the rated battery capacity, and $U_d(t)$ and $U_c(t)$ are the battery cell voltage under discharging and charging respectively. Others parameters such as open-circuit voltages for the fully charged battery U_{0d} and U_{0c}, electrolyte proportionality constants g_d and g_c, open-circuit voltage temperature coefficients β_d and β_c, charge-transfer overvoltage coefficients M_d and M_c, are calibrated parameters. Also calculated in the static electric model is the electric potential of the positive electrode which is used for the calculation of the anodic corrosion. Note that the aggregated internal resistance, $\rho_d(t)$ or $\rho_c(t)$, is a parameter that closely related to battery charge acceptance. It is different from the cranking resistance that is usually used in the literature, such as [1].

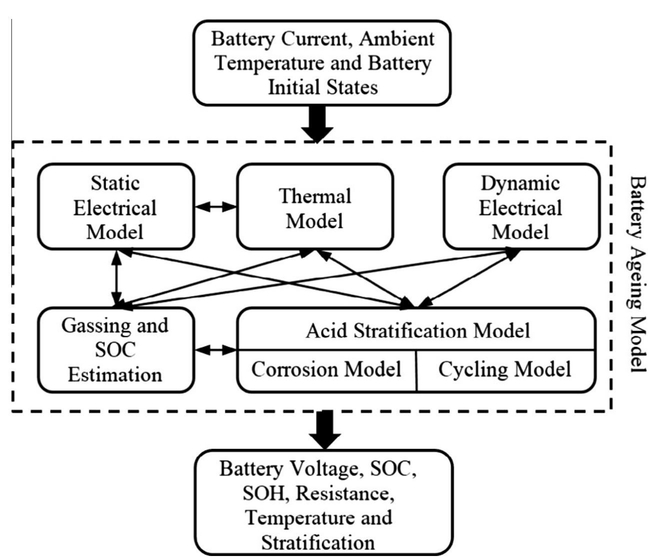

Fig. 1. The schematics of the battery ageing model.