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An online state of charge and input current co-estimation method for current sensor-free intelligent cells

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ABSTRACT

Recent research progress has witnessed the emergence of intelligent batteries integrating cell-level sensors and controllers for distributed and enhanced management. However, the highly integrated structure rises up multifold concerns over the rigorous thermal condition, and the trade-off between sensing quality and cost. Motivated by this, this paper pursuits the possibility of designing an intelligent battery with the function of state of charge (SOC) self-monitoring without using the current sensor. The essence is to propose a method converting the co-estimation of SOC and input current into a state-space model-based optimization problem, which is virtually solved in a moving horizon framework. Results suggest that the proposed method can realize accurate estimation of the SOC even if freeing the need of integrating a current sensor. The encouraging results are insightful for reducing the structural complexity and lowering down the cost of intelligence batteries.

Keywords: intelligent battery; state estimation; moving horizon estimation; current sensor

1. INTRODUCTION

Intelligent battery is an emerging technique allowing enhanced management and control of lithium-ion battery (LIB) [1]. With sensors and controllers integrated to the single cells, the intelligent battery enjoys multiple benefits, including the cell-level monitoring, dynamic configuration and self-management. However, the increase of components causes the unexpected thermal condition and the rising cost of LIB system. Moreover, low-cost sensors, especially for the current sensors, are easily disturbed in a heavy electromagnetic environment, resulting in low-quality measurements [2].

Without accurate measurements of current, many basic functions of the battery management system are disabled, e.g. state of charge (SOC) estimation. As the premise for battery balance and control, SOC estimation has been studied for decades [3-5]. Amongst the others, the model-based SOC estimators have viewed the most investigations attributed to the high accuracy and robustness. Based on specific model structures, real-time SOC observation techniques have been explored progressively in the literature, like Kalman Filter (KF) family [6, 7], particle filter [8, 9], sliding mode observer [10], etc. However, the accuracy of SOC estimation is limited as the parameters of the battery model varies with the temperature and SOC. Moreover, the model identification is easily impaired by the unexpected measurement disturbances [11]. Motivated by this, Wei et.al [12] proposed a recursive total least squares-based SOC observer with an online adapted battery model to improve the accuracy of the SOC estimation. A noise-tolerant model parameterization method is further proposed in [13] to improve the modelling accuracy. However, none of aforementioned methods can be implemented without current measurements.

This paper aims to bridge aforementioned research gap and proposes a novel current sensor-free method for co-estimating the SOC and input current. An equivalent circuit model (ECM) is built and parameterized to describe the electric dynamics of LIB. On this premise, the co-estimation of SOC and input current is transformed to a constrained optimization problem. The formulated optimization problem is further solved within a moving horizon framework to enhance the robustness. Experiments are performed to validate the proposed method. This endeavor sheds certain lights on the future design of intelligent batteries with lower configuration complexity, cost and higher tolerance to the low-quality measurement.

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The remainder of this paper is organized as follows. The proposed intelligent battery design and the battery modeling are presented in Section 2. The method for SOC and input current co-estimation is elaborated in Section 3. Results are discussed in Section 4, while the primary conclusions are drawn in Section 5.

2. INTELLIGENT BATTERY DESIGN AND MODELLING

2.1 Intelligent battery configuration

The design of an intelligent battery is shown schematically in Fig. 1, where a printed circuit board (PCB) integrating two switches, one voltage sensor and three temperature sensors is attached to a prismatic LIB cell. The active and bypass switch are controlled for system dynamic configuration, i.e., to either connect the cell to the system or disconnect the cell from the system. It is worth noting that in the present design, the current sensor is not included, but we still expect to achieve the accurate self-monitoring of the SOC. The cost of the intelligent battery can be largely reduced without current sensor, meanwhile, an input current and SOC co-estimator is proposed in this paper to realize the self-monitoring of SOC without current measurements.

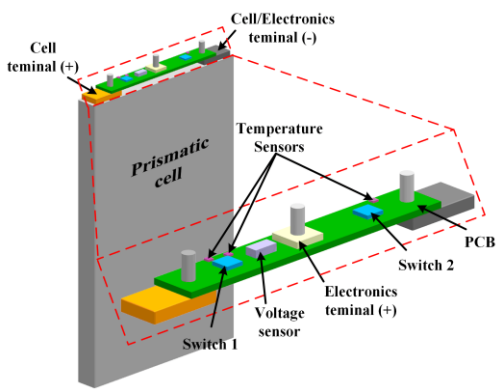

Fig. 1 Schematic illustration of the intelligent battery

2.2 Battery modeling and parameterization

The ECM has been widely used to simulate the electrical characteristic of the battery. The accuracy and complexity of the ECM increase with the number of RC pair. To achieve a tradeoff between the accuracy and complexity, the first-order RC model is selected in this paper. The structure of the first-order RC model is shown in in Fig.2. It consists a SOC-dependent open circuit voltage (OCV) source, an equivalent resistor R_o describing the electrical resistance of various cell components, and a resistor-capacitor network simulating the polarization effects like charge transfer, diffusion, and passivation layer effect on electrodes.

The mathematical expression of the model is given by:

$$C_p \frac{dV_p(t)}{dt} = I_L(t) - \frac{V_p(t)}{R_p} \tag{1.a}$$

$$V_t(t) = V_{OC}(t) + I_L(t) R_o + V_p(t) \tag{1.b}$$

$$\frac{dz(t)}{dt} = \frac{\eta I_L(t)}{3600 C_n} \tag{1.c}$$

where t represents the time, I_L is the load current (positive for charge), η is the coulombic efficiency, z denotes the SOC, C_n is the nominal capacity with the unit of ampere hours, V_p and V_t are the polarization and terminal voltage, and V_{OC} denotes the OCV.

V_{OC} is defined as a function of the SOC:

$$V_{OC} = f(z) = \sum_{i=0}^{m} c_i z^i \tag{2}$$

where m is the order of polynomial curve fitting (4 in this paper), c_i are the polynomial coefficients.

By defining $\boldsymbol{x}(k) = [V_p(k)\ z(k)]^T$, $y(k) = V_t(k)$. The discrete-time state-space function of the model can be derived based on Eq. (1.a-1.c):

$$\begin{aligned} \boldsymbol{x}(k) &= \boldsymbol{A}\boldsymbol{x}(k-1) + \boldsymbol{B} I_L(k-1) \\ y(k) &= f(z(k)) + V_p(k) + R_o I_L(k) \end{aligned} \tag{3}$$

$$\boldsymbol{A} = \begin{bmatrix} e^{-\frac{\Delta t}{R_p C_p}} & 0 \\ 0 & 1 \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \left(1 - e^{-\frac{\Delta t}{R_p C_p}}\right) R_p & \frac{\Delta t}{C_n} \end{bmatrix}^T \tag{4}$$

where Δt denotes the sample time.

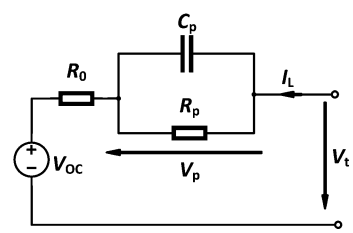

Fig. 2 Structure of the first order RC model

2.3 Parameter Identification

The parameters need to be identified in the first order RC model include the correlation between SOC and OCV, R_o, R_p and C_p. SOC-OCV test is imposed on a Lithium-ion battery with nominal capacity of 2.2 Ah. The coefficients of Eq. (2) are identified by polynomial fitting the experimental data of SOC and OCV as shown in Fig.3.

Then the hybrid pulse power characteristic (HPPC) test is imposed on the battery to identify R_o, R_p and C_p offline at different SOC interval. The parameters are set to be SOC-dependent by linear interpolating the identification results and the corresponding SOC.

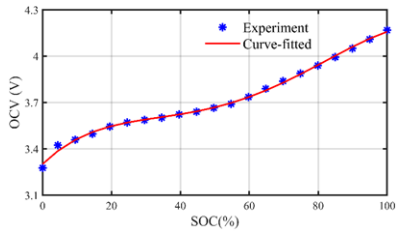

Fig. 3 Experimental and curve-fitted correlation between SOC and OCV

3. CO-ESTIMATE OF SOC AND INPUT CURRENT

With the model built in section 2, this section goes further to elaborate the method for co-estimating the SOC and input current. Traditional SOC estimation is invalid as the current is unmeasurable in the presented design. Instead, in this paper, the co-estimation task is reformulated as a constrained optimization problem given by:

$$\left\{\hat{\boldsymbol{\theta}}\right\}_{i=k-n}^{k} = \arg\min_{\left\{\hat{\boldsymbol{\theta}}\right\}_{i=k-n}^{k}} \left\|\boldsymbol{\alpha}\left(\hat{\boldsymbol{x}}_{k-n} - \bar{\boldsymbol{x}}_{k-n}\right)\right\|_2 + \sum_{i=k-n}^{k}\left|\hat{V}_t - V_t^m\right|$$

$$s.t.\quad \text{discrete-time state-space function} \quad (3)$$

$$\hat{\boldsymbol{\theta}}_{k-n} = \left[\hat{\boldsymbol{x}}_{k-n}^T \quad \hat{I}_L(k-n)\right]^T,$$

$$\hat{\boldsymbol{x}}_{k-n} = \left[\hat{V}_p(k-n) \quad \hat{z}(k-n)\right]^T, \quad (5)$$

$$\left\{\hat{\boldsymbol{\theta}}\right\}_{i=k-n}^{k} = \left[\hat{\boldsymbol{\theta}}_{k-n} \quad \hat{\boldsymbol{\theta}}_{k-n+1} \quad \dots \quad \hat{\boldsymbol{\theta}}_k\right],$$

$$\left\{\hat{\boldsymbol{x}}\right\}_{i=k-n}^{k} = \left[\hat{\boldsymbol{x}}_{k-n} \quad \hat{\boldsymbol{x}}_{k-n+1} \quad \dots \quad \hat{\boldsymbol{x}}_k\right],$$

$$\bar{\boldsymbol{x}}_{k-n} = \sum_{i=k-n}^{i=k}\hat{\boldsymbol{x}}_i \Big/ n, \boldsymbol{\alpha} = \begin{bmatrix}\alpha_1 & 0\\ 0 & \alpha_2\end{bmatrix}.$$

where the states of the battery (SOC and V_p) and I_L are the decision variables, the discrete-time state space functions given by Eq. (3) are the constraints, n is the length of the optimization horizon (determined as 3 in this paper), V_t^m is the measured terminal voltage, $\|\cdot\|_2$ represents the 2-norm, $\boldsymbol{\alpha}$ is the weight matrix.

As can be seen, the objective function in Eq. (5) is composed of two terms. The first term is used to restrict the variation range of the states in a short horizon as the states usually changes slowly in real application. The weight factors α_1 and α_2 an determined manually according to the variation characteristic of SOC and V_p, respectively. The second term is the main objective to minimize the mismatch between the measured terminal voltage and the terminal voltage estimated by the states and input current with function (3). The optimization problem characterized by Eq. (5) are solved at each iteration to estimate the SOC and load current online optimally.

4. RESULTS AND DISCUSSION

4.1 Experiment

To obtain the benchmark of the SOC, a calibration experiment is performed using the Arbin battery testing system. The federal urban drive schedule is imposed on the battery to validate the proposed method. The load current, terminal voltage and reference SOC are plotted in Fig.4. The reference SOC is determined with accurate SOC pre-setting and coulomb counting method with accurate current measurement enabled by the battery testing system. It is also worth noting that the current shown here is only used for benchmarking and reference SOC calibration, but not used by the proposed method.

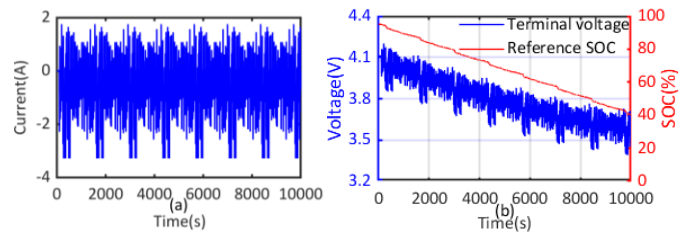

Fig. 4 Measured current, voltage and reference SOC: (a) Measured Current; (b) Measured voltage and reference SOC.

4.2 Validation of modelling accuracy

An accurate model is the prerequisite for the proposed method. Therefore, the modelling accuracy is validated firstly. Predicted and measured terminal voltage are plotted comparatively in fig.5 (a), while the modelling error is plotted in figure5 (b). As can be seen, the predicted terminal voltage matches the benchmarks well. And the modeling error was well confined in the range of 0.03 V for most of the time, except for the ending stage of the experiment. The deteriorated accuracy at the low SOC region, typically lower than 10%, is rotted in the high nonlinearity of battery dynamics which can not be easily simulated by the first order RC model. However, such low SOC regions are rarely reached in real application to protect the battery from over discharge.

The mean absolute error (MAE) and the root mean squared error (RMSE) of the model are 5.5 mV and 6.8 mV, respectively, which quantitatively indicates a high accurate model.

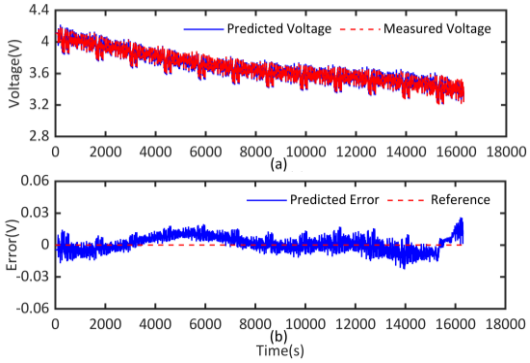

Fig. 5 Modelling results: (a) predicted voltage and measured voltage; (b) modelling error

4.3 Validation of SOC/input current co-estimation

The SOC estimation results are plotted in Fig.6. It is shown that the estimated SOC converges to the reference with errors constrained within 3% for entire experiment. The proposed method took 1000 s to converge to the reference value within 2% error bounds from the 5% initialization error. The MAE and RMSE of the SOC estimation are 0.98% and 1.3%, respectively. Despite the estimation error of the proposed method is higher than the traditional model-based method, the estimation accuracy of the proposed method is acceptable from a practical perspective. Moreover, the proposed method is not dependent on the load current measurement, which is a desirable characteristic when utilized in intelligent cells.

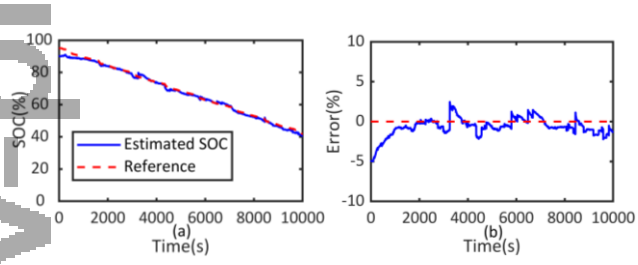

Fig. 6 SOC estimation results: (a)Estimated SOC vs. reference SOC; (b) Estimation error.

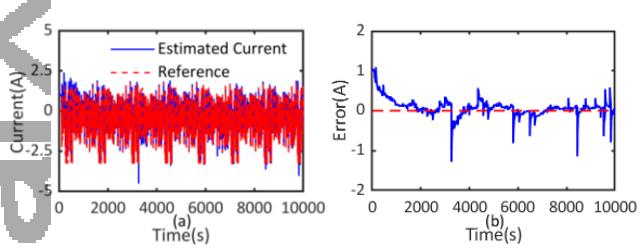

Fig. 7 Load current estimation results: (a)Estimated load current vs. measured load current; (b) Estimation error

The estimation results of the load current are plotted in Fig.7. The current estimation errors reach to -1.5 A maximumly but are significantly small during steady-state conditions. The MAE of the estimation is 0.1478 A, which is acceptable as the Hall-effect sensor itself exhibits a large error in a complicate electromagnetic environment.

CONCLUSION

This paper proposes a novel model-based method to online estimate the SOC and input current for a broad range of current sensor-free intelligent batteries. The method is rooted in the reformulation and solution of a state space-constrained optimization problem. The primary conclusions are drawn as follows:

1) The MAE of the proposed method for SOC estimation is less than 1% without the need of current measurement.

2) The input current can be estimated accurately with the MAE of 0.1478 A (corresponding to a signal-to-noise ratio of 5.91%), which is acceptable from the real application point of view.

The proposed method presents much scope for the design of current sensor-free intelligent batteries to cut the design cost while reserve sufficient accuracy for self-state monitoring. As a model-based method, the performance of the proposed method is significantly affected by the battery degradation. To diminish the adverse effect of the battery degradation, we plan to develop a capacity correction mechanism utilizing the estimates of input current and SOC in our future work.

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