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Online state of charge and model parameter co-estimation based on a novel multi-timescale estimator for vanadium redox flow battery

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HIGHLIGHTS

- Battery model parameters and SOC co-estimation is investigated.
- The model parameters and OCV are decoupled and estimated independently.
- Multiple timescales are adopted to improve precision and stability.
- SOC is online estimated without using the open-circuit cell.
- The method is robust to aging levels, flow rates, and battery chemistries.

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ABSTRACT

A key function of battery management system (BMS) is to provide accurate information of the state of charge (SOC) in real time, and this depends directly on the precise model parameterization. In this paper, a novel multi-timescale estimator is proposed to estimate the model parameters and SOC for vanadium redox flow battery (VRB) in real time. The model parameters and OCV are decoupled and estimated independently, effectively avoiding the possibility of cross interference between them. The analysis of model sensitivity, stability, and precision suggests the necessity of adopting different timescales for each estimator independently. Experiments are conducted to assess the performance of the proposed method. Results reveal that the model parameters are online adapted accurately thus the periodical calibration on them can be avoided. The online estimated terminal voltage and SOC are both benchmarked with the reference values. The proposed multi-timescale estimator has the merits of fast convergence, high precision, and good robustness against the initialization uncertainty, aging states, flow rates, and also battery chemistries.

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1. Introduction

Battery storage has been an essential technique for the renewables penetration, transportation electrification, and smart grid establishment. Driven by the urgent demand, battery technology has been growing rapidly toward high performance and low cost. Among different flavors of battery chemistries, the all-vanadium redox flow battery (VRB) proposed by Skyllas-Kazacos [1,2] and co-workers has shown great potential due to the unique merits including elimination of cross contamination, independent capacity and output power design, tolerance to deep discharge, high energy efficiency and long life cycle [3,4].

Extensive studies have been conducted aimed at the improvement of cell performance, mainly in the field of electrode modification, membrane enhancement, and electrolyte solution update [5–7]. Some important issues of the VRB technology in real application have yet to be adequately addressed however. The state of charge (SOC), as one important state to be monitored in battery management system (BMS), is essential to assess the battery condition and to avoid overcharge and/or over-discharge. Measurement of electrolyte conductivity and spectrophotometric properties were proposed by Skyllas-Kazacos and Kazacos [8] to determine battery SOC under lab testing conditions. The two half-cell solution potentials were further calibrated for SOC monitoring by Corcuera and Skyllas-Kazacos [9]. These methods monitor the SOC of each half-cell and aim at detecting any imbalance between the two individual half-cell electrolytes that would lead to capacity loss. In real

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application, the overall SOC of cell is also vital considering its implication on the short- and long-term energy management. Regarding online SOC determination, open circuit voltage (OCV) measurement is straightforward and has been widely used in commercial products [10]. This method, however, relies on the assumption that the two half-cell solutions are balanced and at the same state of charge. Additional open-circuit cells and sensors are also needed to be installed thus adding more complexity to the battery configuration. Furthermore, the open-circuit cell approach can only be used with flow batteries where the electrolytes are stored in external reservoirs and pumped through a cell stack where the charge-discharge reactions take place. Coulomb counting (CC) is a simple technique and implementable on low-cost micro controllers, but suffers from troubles like uncertainty in initial state, high sensitivity to measurement noise, as well as error accumulation over time.

In recent works [11–21], SOC was estimated in real time for lithium-ion batteries by the equivalent circuit models (ECMs) based observers. This category of methods is fundamentally achieved with two steps. First, an accurate model is established to reproduce the transient behavior of battery. Till now, only a few publications can be found concerning ECMs applied to the VRB although they have already been frequently attempted on Li-ion batteries. Wei and Xiong et al. [22–24] presented a simple circuit model with a simple thermal model included. Zhang et al. [25] discussed a comprehensive ECM by taking the transient process, shunt current and vanadium iron diffusion into account. Mohamed et al. [26] modeled the dynamics of VRB including activation polarization and concentration polarization with a second-order ECM. In the second step, the adaptive filters, such as extended Kalman filter (EKF) [11–13], unscented Kalman filter (UKF) [13,14], particle filter (PF) [15–17], and some other extensions [18–21], are applied to observe the SOC in a close loop approach. Such ECM-based observers effectively overcome the shortcomings of SOC–OCV mapping and CC technique. However, one common defect is that the model parameters are either prescribed by theoretical values or identified offline and left without adaption. As the battery parameters change continuously with working conditions and self-aging, the lack of adaption of them will deteriorate the estimation accuracy significantly. The online identification of model parameters has been focused recently, albeit limited, to improve the precision of SOC estimation. The model parameters and SOC/OCV are integrated together for joint estimation [26–28] or dual estimation [29–32]. However, the integration can cause cross interference between the model parameters and SOC/OCV and thus substantially compromise the regression stability. The joint estimation can also cause large-scale matrices calculation and accordingly bring more parameterization effort.

In this study, a novel multi-timescale estimator is proposed to online adapt the model parameters and estimate battery SOC simultaneously. The proposed method is data-driven type and is free from the constraint of using additional open-circuit cells for OCV determination. Unlike other traditional methods, the OCV and model parameters are identified with three independent estimators to avoid the cross interference, while SOC is estimated by the look-up table of SOC versus OCV. As another merit, the SOC estimator is implementable without exact information on the cell capacity, which is indispensable in most of the existing ECM-based observers. Theoretical analysis on sensitivity, stability and precision are executed to explore the performances of each independent estimator. Based on this, different timescales are applied to enhance each estimator and to release computational burden.

The rest of the paper is organized as follows. Section 2 presents the OCV estimator and associated sensitivity analysis. Section 3 discusses the identification of model parameters and proposes the multi-timescale estimator based on the analysis of model precision and stability. Section 4 describes the experimental setup and details while the verification is presented in Section 5.

2. Independent OCV estimator

2.1. Battery modeling

To simplify the battery model configuration to the greatest extent while keep sufficient precision, the first-order RC model which has been used for Li-ion and NiMH battery is adopted in this paper. It has to be mentioned, however, that the method proposed here is applicable to a broad range of higher-order battery models.

The structure of the applied first-order ECM is shown in Fig. 1. The voltage source represents the OCV which is SOC and temperature dependent. R_s, R_p, and C_p are the model parameters to be identified. Specifically, R_s is the internal resistance that describes effect of current excitation within the cell stack and is a function of temperature, SOC and aging state. The parallel resistor capacitor (RC) network is used to represent any transient dynamics involved in the electrochemical process of VRB. The constant phase element (CPE) and Warburg impedance term which provide more detailed description of the dynamic process is omitted in this study aiming at reducing model complexity and enhancing numerical stability. However, it will be verified in the following sections that the applied model is still with high precision if appropriately parameterized despite the simplification.

2.2. OCV estimation

In this section, an independent OCV estimator is introduced. The electrical behavior of the first-order ECM can be expressed by the following state equations:

$$C_p \frac{dV_p}{dt} + \frac{V_p}{R_p} = I_L \tag{1}$$

$$V_t = V_{OC} - V_p - I_L R_s \tag{2}$$

where I_L denotes the load current which is defined as positive for discharge and negative for charge throughout the paper, V_{OC} denotes the OCV, V_p denotes the polarization voltage across the RC network, while V_t is the terminal voltage. Eq. (1) can be rewritten in the discrete-time form as:

$$V_p(t) = e^{-\frac{nt_s}{R_pC_p}} V_p(t - nt_s) + \left(1 - e^{-\frac{t_s}{R_pC_p}}\right) R_p \sum_{j=1}^{n} e^{-\frac{(j-1)t_s}{R_pC_p}} I_L(t - jt_s) \tag{3}$$

where t_s is the sampling time of onboard data, n denotes the user-defined sampling interval used to update the OCV. Thus, the timescale of OCV estimator can be calculated as $\Delta t_1 = nt_s$. At any time step, the below relationship holds according to Eq. (2):

$$V_p(t - nt_s) = V_{OC}(t - nt_s) - V_t(t - nt_s) - I_L(t - nt_s) R_s \tag{4}$$

Substituting Eq. (4) into Eq. (3) yields:

$$\begin{aligned} V_{OC}(t) = {} & e^{-\frac{nt_s}{R_pC_p}} V_{OC}(t - nt_s) + V_t(t) + I_L(t) R_s \\ & - e^{-\frac{nt_s}{R_pC_p}} [V_t(t - nt_s) + I_L(t - nt_s) R_s] \\ & + \left(1 - e^{-\frac{t_s}{R_pC_p}}\right) R_p \sum_{j=1}^{n} e^{-\frac{(j-1)t_s}{R_pC_p}} I_L(t - jt_s) \end{aligned} \tag{5}$$

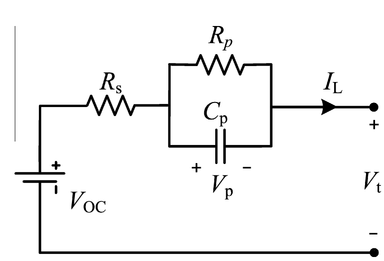

Fig. 1. Schematic diagram of the first order ECM.

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