Enhanced Online Parameter Identification Coupled with Discrete Wavelet Transform for Accurate Estimation of the SOC of Lithium-ion Battery Amid the Presence of Measurement Noise

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Abstract

Precise identification of battery parameters plays a crucial role in the accuracy of state-of-charge (SOC) computation algorithms. Moreover, measurement noise in charging and discharging voltages from battery management system (BMS) communication can impact SOC estimation accuracy. This study implements a signal processing method that filters out noise and extracts meaningful information from the sensor data. A modified formulation of the forgetting factor recursive least squares (MFFRLS) coupled with discrete wavelet transform (DWT) is implemented. The proposed method is utilized to estimate the state-of-charge (SOC) through the extended Kalman filter (EKF). The proposed MFFRLS coupled with the denoising method effectively and accurately estimates SOC.

Ⅰ. Introduction

The electric vehicle (EV) market has seen an abrupt increase with governments making enormous efforts to assist EVs due to their eco-friendliness, zero emissions, and energy conservation. Lithium-ion batteries are nonlinear electrochemical systems, which makes the estimation of their states problematic. Also, measurement noise in BMS communication can have implications for information technology. Traditional methods including open circuit voltage (OCV), Coulomb counting, machine learning, and battery model-based approaches have been explored for SOC estimation [1]. SOC estimation is susceptible to erroneous instantaneous noise sensing in the BMS. This is primarily attributed to the inevitable discrepancies between low-precision measurement sensors, electromagnetic interference, and random noise from unfavorable conditions. In addition, the battery parameters identified by the analytical offline method cannot accurately reflect the influence of real-time fluctuations that may occur during battery operation. Information technology is critical in developing and implementing signal-processing algorithms within the BMS. Based on the abovementioned concerns that arise in model-based battery SOC estimation, we propose an improved accurate online parameter identification method using MFFRLS and DWT de-noising of charging/discharge signals.

Ⅱ. Method

DWT offers information on the frequency and position of the signal being analyzed and it is constantly employed to address and treat more complex issues. The DWT is defined in Eq. (1). where * is the complex associate and ψ(t) represents the source wavelet function. The scale parameter $j (j \in R)$ controls the wavelet's length and oscillation frequency.

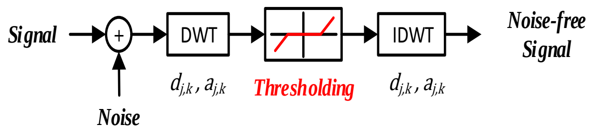

Fig.1 Schematic of the wavelet denoising technique.

$$\mathrm{DWT}(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-k2^j}{2^j}\right)dt \qquad (1)$$

The DWT is frequently used to reduce noise from signals [2]. This is proven by the fact that noise energy is disseminated across most wavelet coefficients with small wavelet magnitudes, whereas signal energy is usually distributed among a limited number of large wavelet coefficients. The denoising procedure is shown in Fig.1. To obtain a noisy signal, a band-limited electrical noise with a signal power of 0.2 is combined with the original signal to obtain a noisy simulation discharging/charging voltage (DCV) signal with a signal-to-noise ratio (SNR) of 25 dB. The noisy simulated DCV signal was decomposed using a dB4 wavelet for an iterative decomposition of five layers, and the noise was then reduced using four hard-threshold denoising methods based on the minimaxi, rigrsure, heursure, sqtwolong rules. In Fig.2, the outcomes of the denoising procedures were compared. As shown in Fig.2 (b), the rigsure adaptive threshold selection rule with the highest SNR of 36.20 dB provided the best noise suppression for the noise-riding DCV.

In this study, a dual-resistor-capacitor lithium-ion battery model was examined. In the forgetting factor recursive least square (FFRLS) algorithm, the weights of the combined new and old data are allocated by the forgetting factor (λ) which generally assumes a constant value of 0.98 and degenerates to recursive least square (RLS) when λ=1. The FFRLS encounters difficulties due to data oversaturation; therefore, this research developed MFFRLS, which adaptively modifies λ, which is associated with and influenced by

(a) (b)

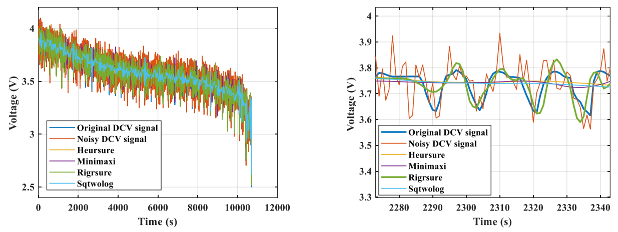

Fig.2 Denoising of DCV signals; (a) The comparison of four different hard thresholding denoising rules of noise riding DCV; (b) Zoomed view.

the prediction error. Using MFFRLS, the λ approaches an appropriate number that only influences the inaccuracy of the immediate future, allowing the identification parameter to be swiftly traced to its real value and progressively approach its ideal value. To achieve the aforementioned goal, the robust forgetting factor proposed is obtained using Eq. (2).

$$\begin{aligned} \lambda(k) &= \lambda_{\min} + (1-\lambda_{\min}).h^{\xi(k)} \\ \xi(k) &= round\left(\left(e(k)/e_{base}\right)^2\right) \end{aligned} \tag{2}$$

where λmin is the least value of λ. h is the sensitivity coefficient and ebase, is the allowed error reference. The round(n) indicates the digit adjoining n whose disparity choice is between 0.98 and 1.

Ⅲ. Result and discussions

The proposed method was tested using data from dynamic tests. The battery parameters were identified using the proposed MFFRLS approach, and the efficiency of the combined denoising procedure and MFFRLS was validated by the SOC estimate accuracy after the application of wavelet decomposition to

(a) (b)

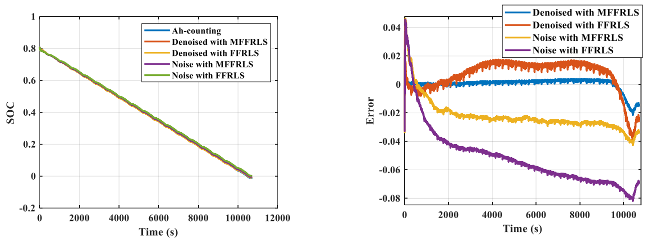

Fig.3 Estimated results and errors from US06 data. (a) Estimated SOC. (b) The SOC estimation error comparison.

(a) (b)

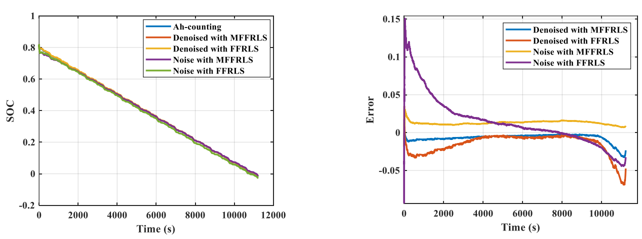

Fig.4 Estimated results and errors from BJDST data. (a) Estimated SOC (b) The SOC estimation error comparison

decompose the original signal and the noise-riding DCV signal. Ampere-hour counting was utilized to compare all SOC estimations. The experimental battery had an initial SOC of 0.8. The SOC estimation results and the corresponding error levels are shown in Fig.3 and Fig.4. The results show that both denoising and improved parameter identification offer the best SOC estimation with the lowest error for all four working profiles. The convergence of the SOC estimation results obtained using the denoising procedure in conjunction with the proposed MFFRLS was superior to that of the FFRLS with denoised DCV signals. Even though the denoising method tends to reduce the estimation errors with incorrect information regarding the applied experimental voltage, the incorporation of the MFFRLS parameter identification algorithm can further improve the error.

IV. Conclusion

For high accuracy in lithium-ion battery SOC estimation, a denoising method employing DWT was applied. This method aims to eliminate unforeseen measurement noise in the DCV signal during communication in the battery management system. In addition, his study proposes a MFFRLS algorithm, which is an extension of the FFRLS method of parameter identification which also has a significant influence on the SOC estimation algorithm. The experimental results demonstrated that denoising using the proposed algorithm can maintain the SOC estimation error within 1%, with few fluctuations, to approximately 2% under the two tested working profiles.

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