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A 2D-FILTER FOR BATTERY INCREMENTAL CAPACITY CURVE EXTRACTION

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ABSTRACT: A 2D filter is proposed for battery incremental capacity curve filtering in a cyclic aging test. The filter works in two directions, namely, from time to time and from batch (cycle) to batch. In details, a simple low-pass filter is applied in the batch direction, and a bias-corrected Gaussian filter is applied in the time direction. Experimental results show that the root-mean-square-error of the proposed method is 20% lower than the neural-network-based benchmarking algorithm. Over-fitting and under-fitting could also be resolved.

Keywords: 2D filter, incremental capacity analysis (ICA), Gaussian filter.

1. INTRODUCTION

The battery aging is inevitable during applications. This will lead to a decrease in capacity, increase in internal resistance, and in some extreme cases, safety problems [1]. Therefore, properly estimating the battery state of health is important for battery use, maintenance, and optimization.

Battery state of health can be obtained by estimating the battery capacity [2], calculating the battery resistance [3], extracting the features from the voltage curve [4], and data-driven methods [5]. However, the state of charge (SOC) is required when calculating the battery capacity, and the SOC estimation accuracy could be low if the battery degradation is uncertain [6]. Resistance can be influenced by factors such as SOC, state of health (SOH), temperature, and the amplitude and frequency of the excitation signal [3]. Decoupling them could be difficult. The features extracted from the voltage curve usually lacks electrochemical explanations [4], and data-driven methods require a considerable amount of data for training [5].

Using incremental capacity analysis (ICA) to estimate the SOH is an attractive alternative. First, this curve has electrochemical explanations [7]. Second, the features extracted from the IC curve could have a linear relationship with the battery SOH [8], while the battery itself is a highly nonlinear system. In general, the direct IC value can be calculated from (1) in a constant current process:

$$ic(k) = \frac{dQ}{dV} \approx \frac{\Delta Q}{\Delta V} = \frac{Q(k)-Q(k-N_I)}{V(k)-V(k-N_I)} \tag{1}$$

where Q stands for the capacity that could be calculated by Ah-counting method, and V is the measured battery terminal voltage.

It can be seen from Eq. (1) that the IC value is very sensitive to voltage measurement noise. Therefore, the filtering technique could directly influence the SOH estimate. As a response, different filters have been proposed. For instance, these filters include moving average filters (MA) [9], Gaussian moving average filters (GMA) [10], improved center least squares [11] and support vector machine [12]. It should be pointed out that the IC curves are usually treated as a measured signal, rather than a state underestimation in these methods. However, the IC value has a clear relationship with voltage. Second, the filtering result of the averaging-based filters (e.g., MA, GMA, or least-square based curve fitting tools) is biased if large quantization noise exists (explained in Section 3).

To overcome the drawback of the existing ICA filtering method, a 2D filter featured by a two-direction filtering strategy is proposed. In details, a simple low-pass filter is applied in the batch (cycle to cycle) direction, and a bias-corrected Gaussian filter is applied in the time direction. The effectiveness of the proposed filter is experimentally verified. It is also compared with a neural-network-based curve fitting tool.

2. EXPERIMENTAL & SIMULATION SETTINGS

The photo of our testing platform is shown in Figure 1-(a). The UPower battery testing system is utilized. Its measurement range is 0~5V for voltage, and -10~10A for current. The accuracy of the measurement is ±0.05%; the resolution of the measurement is 1mV and 1mA for voltage and current, respectively. The experiment is carried out in room temperature of about 25 ℃. An FST-2500 battery (rated capacity: 2500mAh) is selected for the cyclic aging test. The constant current-constant-voltage profile is used for charging, while the constant-current profile is used for discharging. The current rate is 0.2C in the constant current phase. The cut-off voltage is 4.2V for charging, 2.75V for discharging. The cut-off current in the constant voltage phase is 0.05C.

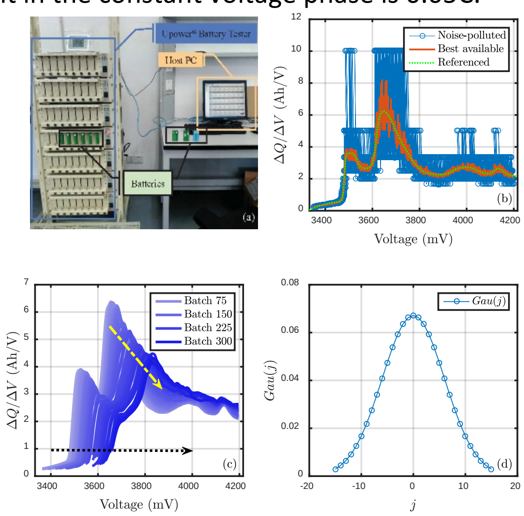

Figure 1. (a): Experimental platform; (b): Comparison between the noise-polluted, best available, and referenced IC curve; (c): Illustration of 2D filter, the yellow arrow stands for the batch-wise filtering; (d): Graphical illustration of a Gaussian window.

In the simulations, we assume our voltage measurement contains a system noise of [-3, 3] mV and a quantization noise of 5mV. A system noise of [-3, 3] mA and a quantization noise of 1mA are also added to the current measurement. These signals are termed as "*noise-polluted*" signals. The battery voltage/current measured by our experimental platform, on the other hand, are termed as "*best available*" measurements. In the following discussions, we use Eq. (1) with $N_I = 360$ to calculate the IC curve for the noise-polluted and the best available cases. The referenced IC curve is obtained by fitting the best available result with a three-layer back-propagation neural network with 10 hidden neurons (denoted as 1-10-1 neural network). An illustration of these three IC values is provided in Figure 1-(b). Based on the fact that the battery charging is usually carried out in a relatively stable environment with constant currents, the IC curve will be extracted using only the data collected in the constant current charging phase.

3. METHODOLOGY

3.1 Concepts, symbols, and terminologies.

The key feature of the 2D filter is that the filtering is carried out in two directions, as shown in Figure 1-(c), where a batch is defined as a charging-discharging cycle. The subscript s is selected to denote the batch number. In batch s sampling time k, the noise-polluted voltage ($V_s(k)$) and current ($I_s(k)$) can be obtained. Therefore, the noise-polluted IC value can be directly calculated following (1), and $ic_s(k)$ is utilized to denote this direct IC value.

Due to the battery aging, the charging time of each cycle could be different. However, a 2D filter requires the signal under filtering having the same length. In this concern, the IC value is modeled as a lookup function of the voltage with a resolution of 1mV, denoted as $z(V)$. This follows the fact that the voltage operating range of a battery (denoted as $(\underline{V}:\overline{V})$) remains the same during the cyclic aging test.

3.2 The 2D filtering algorithm

Due to the limited paper length, we first summarize the proposed algorithm in Table 1 and then explain each equation step by step.

The first step of the proposed 2D filter is to provide a batch-wise initialization for $\hat{z}_0$. The initialization could be done by obtaining a referenced IC curve in the lab or set $\hat{z}_0(\underline{V}:\overline{V}) = \Omega > 0$. Then, in Eq. (2), the IC curve extracted from the previous batch is used to initialize the IC filtering result of the current batch. This step provides low-pass batch-wise filtering. It should be noted that the IC curve usually changes slowly in the batch direction, as shown in Figure 1-(c). In addition to the batch-wise initialization, the initial battery voltage in each batch, $\hat{V}_s(1)$, should also be specified.

For each sampling time k in the batch s, an observer is required for battery voltage filtering, because the resolution of the voltage measurement (5mV) is lower than the resolution of the IC-voltage look-up table (1mV). A Luenberger observer shown in Eq. (3) and (4) is applied in this paper, where L_1 is the gain of the Luenberger observer, and $[\cdot]$ is the rounding function.

Table 1. Proposed 2D filter.

Method
Initialize $\hat{z}_0$

for $s = 1, 2, \ldots$

$$\hat{z}_s(\underline{V} : \overline{V}) \leftarrow \hat{z}_{s-1}(\underline{V} : \overline{V}) \quad (2)$$

Initialize $\hat{V}_s(1) = V_s(1)$

for $k = 2, 3, \ldots$

$$\hat{V}_s^-(k) = \hat{V}_s(k-1) + \frac{\Delta Q}{\hat{z}_s\left(\left[\hat{V}_s(k-1)\right]\right)} \quad (3)$$

$$\hat{V}_s(k) = \hat{V}_s^-(k) + L_1\left(V_s(k) - \hat{V}_s^-(k)\right) \quad (4)$$

for $j = -N_p : N_p$

$$\hat{z}_s\left(\left[\hat{V}_s(k) + j\right]\right) = \hat{z}_s\left(\left[\hat{V}_s(k) + j\right]\right) + \frac{L_2 \cdot Gau(j)}{ic_s(k)} \cdot \left(ic_s(k) - \hat{z}_s\left(\left[\hat{V}_s(k) + j\right]\right)\right) \quad (5)$$

end for

end for

end for

Next, a Gaussian type moving average updater is developed, as described in (5). In this equation, $Gau(\cdot)$ is the value of the Gaussian window, whose length is $2 \cdot N_p + 1$. An illustration of the Gaussian window with $N_p = 15$ is provided in Figure 1-(d). L_2 is the feedback gain of the updater. The $ic_s(k)$ in the denominator is designed to compensate the bias introduced by $1/\Delta V$. In details, when taking lots of measurements for noise-polluted ΔV, the true value can be approximated by the following equation:

$$E\{\Delta V\} = \alpha\lfloor \Delta V \rfloor + (1-\alpha)\lceil \Delta V \rceil \quad (6)$$

where $\lfloor \cdot \rfloor$ is the round-down function, $\lceil \cdot \rceil$ is the round-up function, and α is the frequency that the measurement result after quantization is $\lfloor \Delta V \rfloor$. However, when calculating the direct IC value, we need to inverse the ΔV, and we have:

$$E\left\{\frac{\Delta Q}{\Delta V}\right\} = \frac{\Delta Q}{\alpha\lfloor \Delta V \rfloor + (1-\alpha)\lceil \Delta V \rceil} \neq \frac{\alpha \cdot \Delta Q}{\lfloor \Delta V \rfloor} + \frac{(1-\alpha) \cdot \Delta Q}{\lceil \Delta V \rceil} \quad (7)$$

The right-hand side of (7) is the weighted summation of direct calculated noise-polluted IC value. The inequality means the mathematical expectation of $\left(ic_s(k) - \hat{z}_s\left(\left[\hat{V}_s(k)\right]\right)\right)$ in (5) a is not zero, and a state estimator whose gain is $L_2 \cdot Gau(j)$ is biased. However, when $1/ic_s(k)$ is added to the observer, we have:

$$\begin{aligned} E\left\{\frac{\Delta Q}{\Delta V \cdot ic_s(k)}\right\} &= \frac{\Delta Q}{\Delta V} \cdot \left(\frac{\alpha\lfloor \Delta V \rfloor}{\Delta Q} + \frac{(1-\alpha)\lceil \Delta V \rceil}{\Delta Q}\right) \\ &= \frac{\Delta Q}{\alpha\lfloor \Delta V \rfloor + (1-\alpha)\lceil \Delta V \rceil} \cdot \left(\frac{\alpha\lfloor \Delta V \rfloor}{\Delta Q} + \frac{(1-\alpha)\lceil \Delta V \rceil}{\Delta Q}\right) \\ &= \frac{\alpha \cdot \Delta Q}{\lfloor \Delta V \rfloor} \cdot \frac{\lfloor \Delta V \rfloor}{\Delta Q} + \frac{(1-\alpha) \cdot \Delta Q}{\lceil \Delta V \rceil} \cdot \frac{\lceil \Delta V \rceil}{\Delta Q} = 1 \end{aligned} \quad (8)$$

This implies that the proposed observer is unbiased.

It should be noted that the above derivation ignores the influence of the current measurement noise, because the ΔQ is in the numerator in (1), and the side effect of the noise is relatively small compared with that of ΔV, which is in the denominator.

3.3 Benchmarking algorithm

In the benchmarking algorithm, a 1-10-1 size back propagational neural network is used to fit the relationship between the noise-polluted voltage the noise-polluted direct IC value.

4. EXPERIMENTAL RESULT

In the experiment, $N_p = 25$, $\hat{z}_0(\underline{V} : \overline{V}) = \Omega = 2$, and $L_1 = L_2 = 0.03$ are selected. The results of the proposed and the benchmarking algorithms are shown in Figure 2, Figure 3, and Table 2. From Figure 2-(a), the filtered IC value can converge within 20 batches. From Figure 2-(b)~(d), the proposed filter can track the referenced result accurately, even if the shape of the IC curve could change significantly over time. Quantitively, the root-mean-square-error (RMSE) of the proposed method is reduced by more than 20% compared with the benchmarking algorithms. From Figure 3, the IC value of the benchmarking algorithm is slightly higher than the referenced value. The reason is that the neural network fitting is optimized using the sum squared error function. In other words, the benchmark algorithm tends to average the noise-polluted signal. As indicated in (7), the averaged result is biased. Further, from Figure 3-(a), the proposed method can avoid the over-fitting (3400s) and under-fitting problem (4100s) of the benchmarking algorithm.

5. CONCLUSIONS

In this paper, a 2D filter is proposed to extract the battery incremental capacity curve from the noise-polluted measurements. A low-pass filter in the batch-direction and a Gaussian filter in the time-direction are combined. The novelties of the proposed method arise from two aspects: first, the 2D filter could use the batch-wise information to enhance the quality of the filtering further. Second, the bias introduced by the quantization noise could be corrected through the proposed time-wise filter. Experimental results show that the batch-wise filter could converge within 20 batches, and the root-mean-square-error of the proposed algorithm is 20% lower than that of the benchmarking algorithm. This filtering technique paves the way to the study of the battery aging. In the future, the case when batteries are not fully charged or discharged will be studied.

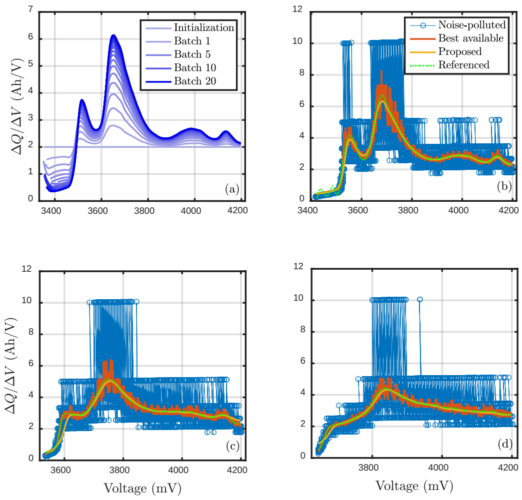

Figure 2. (a): The proposed filtering of the first 20 batches; (b): The filtering result of batch 100; (c): The filtering result of batch 200; (d): The filtering result of batch 300.

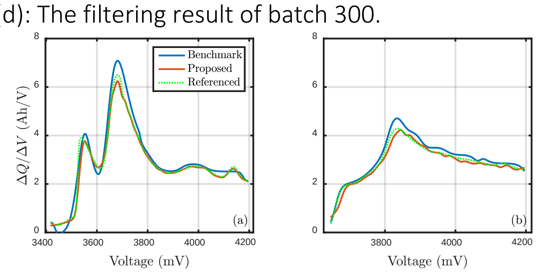

Figure 3. (a): The filtering result of batch 100; (b): The filtering result of batch 300.

Table 2. RMSE of the proposed and benchmarking algorithms

Batch	100	200	300
Benchmark	0.28	0.27	0.18
Proposed	0.18	0.21	0.13

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REFERENCES

[1] R. Xiong, Y. Zhang, J. Wang, H. He, S. Peng, M. Pecht, Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles, IEEE Transactions on Vehicular Technology, (2018).

[2] Z. Wei, K.J. Tseng, N. Wai, T.M. Lim, M. Skyllas-Kazacos, Adaptive estimation of the state of charge and capacity with online identified battery model for vanadium redox flow battery, Journal of Power Sources, 332 (2016) 389-398.

[3] X. Tang, Y. Wang, C. Zou, K. Yao, Y. Xia, F. Gao, A novel framework for Lithium-ion battery modeling considering uncertainties of temperature and aging, Energy Conversion and Management, 180 (2019) 162-170.

[4] D. Yang, X. Zhang, R. Pan, Y. Wang, Z. Chen, A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve, Journal of Power Sources, 384 (2018) 387-395.

[5] Y. Li, C. Zou, M. Berecibar, E. Nanini-Maury, J.C.-W. Chan, P. van den Bossche, J. Van Mierlo, N. Omar, Random forest regression for online capacity estimation of lithium-ion batteries, Applied Energy, 232 (2018) 197-210.

[6] X. Tang, Y. Wang, Z. Chen, A method for state-of-charge estimation of LiFePO4 batteries based on a dual-circuit state observer, Journal of Power Sources, 296 (2015) 23-29.

[7] Y. Jiang, J. Jiang, C. Zhang, W. Zhang, Y. Gao, Q. Guo, Recognition of battery aging variations for LiFePO4 batteries in 2nd use applications combining incremental capacity analysis and statistical approaches, Journal of Power Sources, 360 (2017) 180-188.

[8] X. Tang, C. Zou, K. Yao, G. Chen, B. Liu, Z. He, F. Gao, A fast estimation algorithm for lithium-ion battery state of health, Journal of Power Sources, 396 (2018) 453-458.

[9] I. Bloom, A.N. Jansen, D.P. Abraham, J. Knuth, S.A. Jones, V.S. Battaglia, G.L. Henriksen, Differential voltage analyses of high-power, lithium-ion cells: 1. Technique and application, Journal of Power Sources, 139 (2005) 295-303.

[10] Y. Li, M. Abdel-Monem, R. Gopalakrishnan, M. Berecibar, E. Nanini-Maury, N. Omar, P. van den Bossche, J. Van Mierlo, A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter, Journal of Power Sources, 373 (2018) 40-53.

[11] L. Wang, C. Pan, L. Liu, Y. Cheng, X. Zhao, On-board state of health estimation of LiFePO4 battery pack through differential voltage analysis, Applied Energy, 168 (2016) 465-472.

[12] C. Weng, Y. Cui, J. Sun, H. Peng, On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression, Journal of Power Sources, 235 (2013) 36-44.

