An RLS Based Battery Modeling Method to Compensate for Recovery Effect in Battery Balancing

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Abstract—In battery management systems, mismatched battery cells are expected to be equalized to the same voltage level to maintain the safety and reliability of the energy storage system. However, due to battery electrochemistry characteristics, voltage of the battery cell recovers after equalization, causing the final equalization result inaccurate. To compensate for the voltage recovery effect after balancing and to improve the accuracy of balancing process, this paper proposes a model-based prediction method. A 1st order battery model is established to imitate battery behaviors. Recursive-least-squares method is utilized to identify the parameters of the model to accurately fit the battery characteristic testing data. By deriving an accurate battery model, battery behavior can be better predicted. A simulation to equalize two battery cells is conducted to validate the voltage recovery prediction. The result shows that the recovery effect can be calculated in the model on a given balancing current. Therefore, it provides guidance to decide how much extended balance process is needed to compensate for the voltage recovery.

I. INTRODUCTION

In high power energy storage systems, battery cells are usually series-connected to achieve voltage or power expectations. However, individual cells have mismatch in capacity, voltage rate, and temperature characteristics due to the variation in manufacturing process and environment [1]. The inconsistencies of cells cause overcharge or depletion problems, which affects system performance and results in fire or explosion hazards. Therefore, battery equalization is necessary to redistribute energy between mismatched battery cells to ensure the safety and reliability of energy storage systems.

For battery equalization, balancing accuracy is a significant criterion to measure the performance of the balancing scheme. The ultimate goal of equalization is to equalize all battery cells to the same state-of-charge (SOC) [2]. However, SOC cannot be directly measured by physical sensors. Accurate real-time SOC estimation has difficulty being applied in practical battery equalization due to computation complexity. Therefore, many control schemes adopt voltage of battery cells as an indicator of the battery balancing state [3]–[6]. However, the relationship between voltage and SOC is nonlinear. There exists a plateau stage in the voltage curve, where minor difference in voltage results in much amplified difference in SOC [7]. Therefore, accurate voltage equalization is needed to ensure the consistency.

Battery cells are not ideal voltage sources. Battery parameters such as impedance and electromotive power result in battery cells deviation from ending voltage [8], as shown in Fig.1. On one hand, balancing accuracy cannot be ensured. On the other hand, the recovered voltage can break the tolerance of voltage difference which is set to finish balancing. Therefore, new equalization cycles are needed to allow battery cells to fall into the preset voltage tolerance range [6]. The entire balancing process is prolonged and the total balancing speed is slowed down. Meanwhile, the power loss increases considering the efficiency of the equalization circuit.

The voltage recovery process consists of two subintervals. From $t_a$ to $t_b$, a transient voltage variation is mainly caused by the equivalent impedance of the battery cell. From $t_b$ to $t_c$, a gradual variation depends on the diffusion. Both variations are linked with balancing current, and small balancing cur-
Current results in less voltage recovery. Therefore, some current converge balancing schemes are proposed to mitigate recovery effects. In [9], the balancing current is based on the voltage difference between battery cells. As battery cells are more balanced, the voltage difference converges, thus reducing the balancing current. The result shows the recovery voltage is not obvious after equalization stops. However, such a balancing strategy has limited balancing speed, as current converges to almost zero around the finishing point, which results in a much longer balancing time and more loss.

Another control strategy is to mitigate the recovered voltage with over equalization. However, the extent and duration of extended balancing are hard to identify. In [10] and [11], the battery equivalent circuit model is considered to predict the recovery effect. The equivalent impedance of battery cells is measured and battery characteristics are tested. However, both control schemes only consider the transient variation of the recovery voltage caused by $R_{eq}$. The gradual variation caused by diffusion still deviates from about 10% voltage mismatch compared to the initial voltage difference.

To further estimate the duration of extended balancing, more battery parameters are taken into consideration in this paper. A $1^{st}$ order battery model is established to estimate not only transient voltage variation, but also gradual variation as well. By accurately fitting the model parameter with battery behavior, the battery cell is more predictive in the balancing process. Simulation of balancing process can be conducted in advance to predict the voltage recovery effect, and to guide how long should over equalization extend. Therefore, the proposed method is more general to be deployed in different equalization topologies as long as the balancing current can be expressed in simulation.

II. BATTERY MODELING

A. Battery Model Selection

Conventional battery models can be divided into two categories, physics models and equivalent circuit models (ECM). Although physics models provide estimation with higher accuracy [12], the parameter identification process is time-consuming. Therefore, ECM is preferred for its easy application and low complexity.

In ECM, the battery can often be expressed in the format including a series resistor $R_s$, several RC networks, and open-circuit voltage (OCV). These parameters are identified by fitting the system equation with the battery behavior measured from battery test. OCV can be measured by low-rate constant current discharge, or more accurately, pulsed current discharge after battery resting for a sufficiently long time. The time constant of RC networks can be identified by parameter identification methods.

According to the comparison in [13], $2^{nd}$ order models have the strongest power of battery behavior tracking and the least mean error. However, $1^{st}$ order model has an average error close to $2^{nd}$ order model. Considering its lower order and less computation burden, $1^{st}$ order model is more suitable for practical applications that guarantee accuracy without too much computation.

B. $1^{st}$-order Model Analysis

The model is plotted in Fig. 2. The equivalent resistance is to estimate the transient variation of the battery voltage, and the RC network is to estimate nonlinear variation such as diffusion. The transfer function of the model can be expressed as follows:

$$G(s) = \frac{U(s) - U_{OC}(s)}{I(s)} = -\left(\frac{R_s}{1 + R_p C_p s} + R_p\right)$$  \hspace{1cm} (1)

Considering the discrete data obtained from the battery characteristic test, eq. (1) can be mapped into Z domain using bilinear transformation [14]. Therefore, the Z domain format of transfer function is as follows,

$$G(z^{-1}) = \frac{a_2 + a_3 z^{-1}}{1 - a_1 z^{-1}}$$  \hspace{1cm} (2)

where

$$\begin{cases} a_1 = -\frac{T_s - 2R_p C_p}{T_s + 2R_p C_p} \\
        a_2 = -\frac{(R_s + R_p)T_s + 2R_s R_p C_p}{T_s + 2R_p C_p} \\
        a_3 = -\frac{(R_s + R_p)T_s - 2R_s R_p C_p}{T_s + 2R_p C_p} \end{cases}$$  \hspace{1cm} (3)

The parameters of the model can be derived by the coefficients of the above fractional polynomial, which can be expressed as,

$$\begin{cases} R_s = -\frac{a_2 - a_3}{1 + a_1} \\
        R_p = \frac{a_2 + a_3}{1 - a_1} + \frac{a_2 - a_3}{1 + a_1} \\
        C_p = \frac{T_s}{2 (1 - a_1) R_p} \end{cases}$$  \hspace{1cm} (4)

III. PARAMETER IDENTIFICATION METHOD

A. Static Parameter Identification

OCV curve can be derived via battery charging or discharging test. As only terminal voltage $U_T$ can be sampled in the actual test, the testing current should be small and constant (always $C/20$ or $C/30$) to minimize the effect of equivalent resistance and capacitance. Assuming a small
charging/discharging current leads to a minor change in cell temperature, the temperature is not considered while modeling. The testing starts at a fully charged battery state (as 100%SOC), with constant current discharge, until it reaches the discharge voltage limit (DVL). However, due to the recovery effect, the battery voltage may rise after resting. Therefore, the battery needs to be fully discharged before testing the charge curve. Similarly, the charge curve can be obtained after the battery cell sufficiently rests and starts from a fully discharged state (as 0%SOC) to the charge voltage limit (CVL).

SOC can be expressed as

$$SOC(t) = 1 - \frac{DOD(t)}{Q_{norm}}$$

$$DOD(t) = Q_0 - Q(t)$$

(5)

where DOD(t) represents the depth of discharge of the battery cell, $Q_{norm}$ represents the total capacity of battery cell and $Q_0$ represents the initial capacity of battery (usually starts from fully charged).

The two curves are misaligned at the same SOC, considering the different direction of $i$,

$$\begin{align*}
U_{OC(dis)} &= U_{T(dis)} + R_{eq(dis)}I_{dis} \\
U_{OC(chg)} &= U_{T(chg)} - R_{eq(chg)}I_{chg}
\end{align*}$$

(6)

Since the charge and discharge curves are fully experienced near 50%SOC, this point is used as a benchmark to calculate $R_{eq}$ of charge and discharge. Assuming $I_{dis} = I_{chg}$, and equivalent resistance slightly changes, at 50%SOC, $U_{OC(dis)} = U_{OC(chg)}$. $R_{eq(dis/chg)}$ can be derived as

$$R_{eq} = \frac{U_{T(chg)} - U_{T(dis)}}{2I_{dis/chg}}$$

(7)

As mentioned, discharge curves start from 100%SOC, but charge curve hardly reaches 100%SOC because of recovery.

The measurement of the second half of the discharge curve more accurately reflects the relationship between OCV and SOC from 50%SOC to 100%SOC. Similarly, the first half of the charge curve reflects the relationship better from 0%SOC to 50%SOC. Therefore, the final OCV can be a combination of both half-curves,

$$U_{OC} = \begin{cases} 
U_{T(chg)} - R_{eq}I_{chg}, & SOC \in (0\%, 50\%) \\
U_{T(dis)} - R_{eq}I_{dis}, & SOC \in (50\%, 100\%)
\end{cases}$$

(8)

which is shown in Fig.3.

B. Dynamic parameter identification

The least-squares (LS) method is the most straightforward method which is of popular use in offline or online parameter identification. To reduce the space of data storage, the recursive-least-squares (RLS) method is more often used to repeatedly iterate the intermediate variable.

The battery model can be expressed as

$$U - U_{OC} = a_1z^{-1}(U - U_{OC}) + a_2I + a_3z^{-1}I$$

(9)

which can be transformed into the differential equation,

$$U[k] - U_{OC}[k] = a_1U[k - 1] - a_1U_{OC}[k - 1] + a_2I + a_3I[k - 1]$$

(10)

Considering the sampling frequency is rather high, OCV changes slightly between two data points. The matrix format equation can be expressed as

$$U[k] = \phi[k] \cdot \theta[k]$$

(11)

where

$$\phi[k] = [1, U[k - 1], I[k], I[k - 1]]$$

$$\theta[k] = [(1 - a_1)U_{OC}[k], a_1, a_2, a_3]^T$$

(12)

By using RLS method [13], the estimation of parameters updated as

$$\hat{\theta}[k] = \hat{\theta}[k - 1] + L[k](y[k] - \phi^T[k]\hat{\theta}[k - 1])$$

(13)

where

$$L[k] = P[k]\phi[k]$$

$$= P[k - 1]\phi[k](1 + \phi^T[k]P[k - 1]\phi[k])^{-1}$$

(14)

$$P[k] = (1 - L[k]\phi^T[k])P[k - 1]$$

After iteration, the error between the estimated value and the actual measured value converges gradually. Notice that dynamic parameters vary with SOC, the identification process should be applied with different testing data under different SOC. Finally, a parameter look-up table can be obtained. For more accurate modeling, the temperature is also a dimension that affects the parameter. To obtain the dynamic characteristics of batteries, pulse current is applied to activate battery cell. Although the pulse current is large sometimes (up to 4C), the time applied to battery cell is short. Therefore, not much heat is generated and temperature factor is not considered to simplify the model.
the different direction of represents the initial capacity of battery (usually starts from limit (CVL).

Therefore, the battery needs to be fully discharged before the discharge voltage limit (DVL). However, due to the

The measurement of the second half of the discharge curve of both half-curves, SOC. Therefore, the final OCV can be a combination of both.

The voltage variation with SOC in charge and discharge period. The OCV-SOC curve is obtained from combining halves of each test curve.

IV. RESULTS

A. Static Battery Test

Panasonic 18650PF Li-ion Battery is utilized to validate the proposed method. Test data are collected both from experiment and public online datasets. Static test data are collected from electrochemical workstation VMP-300 at room temperature. The test curve is plotted in Fig.4. The test battery starts at full capacity. The first stage is 250mA constant current (CC) discharge. After about 11 hours, the terminal voltage reaches DVL = 3.0V. However, the battery is not fully discharged. A constant voltage (CV) hold period is added to continue discharge with smaller current. After 1 hour CV discharge, the discharge current is detected to converge to 0, and the battery is considered to be fully discharged. There exists a charge difference ∆Qdis compared with the ending point of the CC period, which is shown in Fig.4. Then the battery sufficiently rests for 2 hours, and the voltage slightly recovers and maintains at about 3.06V. The charging test is similar to discharging, including a 250mA CC charge period to CVL = 4.2V and a CV hold period. Finally, the battery cell rests for 2 hours and prepares for the next test cycle.

When the battery is sufficiently discharged, the remaining charge Qmin is considered as a reference of zero capacity. And when the battery is sufficiently charged, Qmax is considered as a reference of full capacity. Therefore, the total capacity Qnorm and DOD of every point of time can be calculated as,

\[
\begin{align*}
Q_{\text{norm}} &= Q_{\text{max}} - Q_{\text{min}} \\
DOD(t) &= Q_{\text{max}} - Q(t)
\end{align*}
\]  

According to Eq.5, SOC can therefore be obtained. The voltage variation with SOC is plotted in Fig.5. Using the method in Section III, the OCV-SOC curve can be generated.

B. Dynamic Battery Test

Due to equipment limitations, battery dynamics tests use readily available online data sets (Panasonic 18650PF Li-ion Battery Dataset [15]). The dataset is tested using the same type of battery used in the experiment. An Urban Dynamometer Driving Schedule (UDDS) test profile is applied, consists of

Fig. 4. Voltage and capacity variation of a battery cell in static test. The discharge and charge test both consists of CC, CV hold and Rest period.

Fig. 5. The voltage variation with SOC in charge and discharge period. The OCV-SOC curve is obtained from combining halves of each test curve.

Fig. 6. The simulation result of obtained battery model. (a) Predicted and measured voltage under UDDS test profile. (b) A detailed scale of variation in measured and predicted voltage.
random pulse current varying from 0 to $4C$. To simplify the case, some discrete SOC is selected as breakpoints to form the look-up table (from 100% to 0% in a step of 10%SOC). The parameters are identified utilizing the RLS method under the following SOC fitting the UDDS test profile. For SOC between breakpoints, the parameter is linear interpolated to ensure smooth variation. The estimation of voltage variation with parameters is compared with measured data in the dataset in Fig.6(a). And a detailed scale of voltage variation is shown in Fig.6(b). The relative error is plotted in Fig.7, which shows an average error below 2% in most estimations. The error is large as SOC approaches 100 or 0, because there are no SOC reference points at either endpoint to generate the look-up table.

C. Voltage Recovery Prediction

After obtaining the battery parameter table, assuming that the parameters will not change significantly in the balancing process, battery behavior can be predicted in simulation. According to OCV-SOC curve in Fig.5, the initial SOC can be obtained from the initial OCV of the battery. The SOC variation can be calculated by the Coulomb counting method expressed as

$$SOC[k] = SOC[k - 1] + \frac{\eta[k]i[k]\Delta t}{Q}$$

(16)

where the efficiency $\eta[k]$ is assumed to be 1. For equalization units with constant current equalization, the balancing current is preset, so it is easier to calculate the SOC variation. For the equalization structure with changing current, the current can be obtained from the battery management system (BMS) current monitor. However, in that case, the sampling period will be longer, and errors accumulate. Therefore, a more accurate SOC estimation method should be applied.

The look-up table can be stored in the controller in advance, and the prediction can be made only by providing the voltage and current information of the battery cells. Therefore, the calculation burden is small, and it is suitable for real-time estimation. Meanwhile, the prediction of voltage recovery degree does not need to stop the balancing process, but the current is assumed to be 0 in the program to predict the voltage recovery, which can run synchronously with the balancing process to guide for the balancing time.

Fig.8 shows an example of simulation where two battery
cells with initial SOC of about 80% and 50% are equalized in simulation with a balancing current of 2A. According to the OCV-SOC curve, the initial voltage of the cells is 3.95V and 3.66V, respectively. In the simulation, equalization is assumed to stopped at 30 minutes to 200 minutes after balancing starts and predict the final mismatch of two equalized battery cells. The voltage difference on balancing for different balancing durations is plotted in Fig.8(a). For instance, when the balancing time $T_{bal}$ is set as 100 minutes, the detailed behavior of the two battery cells is plotted in Fig.8(b). The simulation indicates that the voltage of $Cell_A$ recovers about $\Delta V_{CellA} = 116mV$ and $Cell_B$ recovers about $\Delta V_{CellB} = 113mV$. And the final voltage mismatch of the two battery cells is 76mV.

The total balancing time can be adjusted in simulation to the best stop point to compensate for the voltage recovery. By adjusting the total balancing time, the recovered voltage slightly changes and a fully balanced point can be found in simulation. For instance, in the given case, a total balancing time of $T_{perfect} = 8100s$ (135 minutes) should be applied to the cells, including an extended balancing process for about 100 minutes. Fig.9 shows the two battery cells achieve perfect balance with almost no voltage difference. This prediction can guide equalization in practical application.

V. CONCLUSION

In this paper, an RLS-based modeling method to predict and compensate battery voltage recovery effect is proposed. A 1st order battery model is established and derived. Parameters of the battery model are identified with RLS method to reduce computation burden and to accelerate model training. The obtained model can fit the measured battery test data with beneath 3% error. The model is utilized to simulate battery behaviors in the balancing process. On providing the knowledge of balancing current and voltage, the battery behavior can be predicted through model parameters with low computation burden. Meanwhile, the prediction of voltage recovery can be synchronously obtained by assuming the current input next time is 0 in the program. The predicted extent of voltage recovery can provide guidance to control design in balancing practice.

REFERENCES


