International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

Integration of Coulomb Counting Method in Battery Management System for Electric Vehicle

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***Abstract* : The coulomb counting (CC) approach is widely used in SOC estimation due to its simplicity and low calculation cost. However, in practical applications, the lack of error correction ability limits its accuracy due to the measured noise in the practical occasion. To address the issue, an improved CC (ICC) approach based on numerical iteration is proposed in this paper. In the proposed approach, a battery model based on a 2nd-order, RC circuit is first formulated to determine the SOC-OCV curve, R-OCV curve, and inner parameters. In the model, the slow dynamic and fast dynamic voltages are described separately, and are utilized for battery state assessment. Then, the SOC will be estimated by the CC approach at the unsteady state but through a numerical iteration approach at steady state. Consequently, the accumulative SOC error from the CC approach will be corrected when the numerical iteration approach is applied.**

INDEX TERMS: Improved coulomb counting (ICC), state of charge (SOC), accumulative error correction, numerical iteration, error accumulation rate.

I. INTRODUCTION:

To cut fossil energy consumption and mitigate the greenhouse effect, electric vehicle (EV) has been widely concerned. Battery system, as the energy provider in the EV, requires a battery management system (BMS) to ensure its safe operation [1]. Both over-charging and over-discharging will reduce the lifespan of the battery system or even lead to serious security accidents. Therefore, monitoring the state of charge (SOC), which is defined as the percentage of residual charge, has become one of the key tasks of the BMS. However, due to the complex electro-chemical behavior in a battery, estimating the exact SOC for a battery is extremely difficult in practice. Hence, the only available way is to perform an estimation of the SOC based on the measurable external parameters of the battery, such as current and voltage [2], [3]. The Coulomb Counting (CC) approach and open-circuit voltage (OCV) approach are the conventional methods to estimate SOC [4]. Ideally, CC approach could obtain relatively accurate SOC. However, in practice, there will be a large accumulated error due to the unavoidable measured noise and the lack of error correction ability. An enhanced CC approach has been proposed to improve the SOC accuracy, but the error is impossible to be eliminated fundamentally [5]. As to the OCV method, the relationship curve between SOC and battery OCV is usually applied for SOC estimation. Nevertheless, the OCV can be unavailable online due to the internal resistance and polarization phenomena of the battery

Model-based SOC estimation algorithms are another hot topic for SOC estimation [11]–[33]. In these algorithms, OCV is calculated based on the battery model, and then the SOC values obtained by OCV and CC are fused together using a weight coefficient. Compared with CC, error elimination ability is obtained. In general, model-based algorithms, such as EKF, UKF and H infinite filters [11], perform high accuracy and excellent stability if the battery model is ideal. However, model error can hardly be avoided in practice due to the complex chemical reaction in the battery and the noise [3], [12], even through numerous models have been proposed [13]–[24], such as the nth Thevenin model [13], multi-time scale model [14]–[16] and real-time updated model [17], [18]. To decrease the influence caused by model error, many information processing technologies are developed. The adaptive EKF can update the process and measured noise covariance in real-time [25]–[27]. The wavelet analysis technology has been employed to preprocess the measured data, which contain strong noise [28]. Algorithms using multiple filters and information fusion technologies have also been presented to improve the accuracy [29]–[33]. In these algorithms, more factors such as state of health (SOH) and models differences are considered. However, additional technologies result in the increase of calculation cost and implementation difficulty [9], [28]. In order to solve the contradiction between SOC accuracy and calculation cost, the ICC approach based on numerical iteration is proposed, where the battery model based on a 2nd-order RC circuit is built firstly with SOC-OCV curve, R-OCV curve and inner parameters identified offline. Then, the SOC is estimated by the CC approach in the unsteady state of the battery but by a numerical iteration approach in the steady state. Consequently, the accumulated SOC error from the CC approach can be corrected through the numerical iteration approach. Furthermore, a compensation coefficient is employed into CC approach to reduce the error accumulation rate. Hence, the proposed ICC approach could make full use of the advantage of conventional CC in the calculation rate and the numerical iteration approach in error correction.

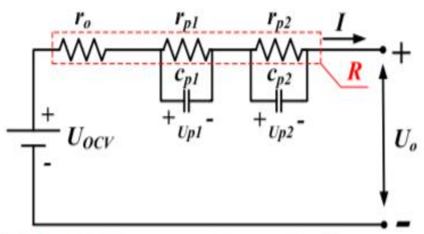

FIGURE 1. Schematic diagram of the 2nd-order RC model.

International Journal of Engineering Research & Technology (IJERT)
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II. METHODOLOGY:

MODEL AND OFF-LINE PARAMETER IDENTIFICATION OF LITHIUM-ION BATTERY A. BATTERY MODEL

The nth-order Thevenin model is widely used for SOC estimation because of its relatively high accuracy and computation efficiency compared with other models [1]. Increasing the order of the Thevenin model will improve the model accuracy further. However, higher order result in additional calculation cost [17]. In the paper, a 2nd-order RC model as shown in Fig. 1 is employed to estimate the dynamic characteristics of the battery. The voltage source UOCV represents the battery OCV. ro is the internal ohmic resistance. The parallel RC network consists of rp1 and cp1 is aimed to model the fast dynamic voltage of the battery. Similarly, the parallel RC network consists of rp2 and cp2 is aimed to model the slow dynamic performance. Up1 and Up2 represent the polarization voltages across the two RC networks, respectively. Uo and I are the terminal voltage and load current, respectively. The electrical behavior of the battery can be expressed as follows.

$$\begin{bmatrix} U_{p1}(k) \\ U_{p2}(k) \end{bmatrix} = \begin{bmatrix} e^{-\frac{T}{\tau_1}} & 0 \\ 0 & e^{-\frac{T}{\tau_2}} \end{bmatrix} \cdot \begin{bmatrix} U_{p1}(k-1) \\ U_{p2}(k-1) \end{bmatrix} + \begin{bmatrix} r_{p1} \cdot \left(1 - e^{-\frac{T}{\tau_1}}\right) \\ r_{p2} \cdot \left(1 - e^{-\frac{T}{\tau_2}}\right) \end{bmatrix} \cdot I(k)$$

$$U_o(k) = U_{ocv} - U_{p1}(k) - U_{p2}(k) - r_o \cdot I(k)$$

$$\begin{cases} \tau_1 = r_{p1} \cdot c_{p1} \\ \tau_2 = r_{p2} \cdot c_{p2} \end{cases}$$

where, k denotes the present step, k-1 denotes the previous step. T denotes the sampling period, QN denotes the maximum available capacity of the battery, and τ1 and τ2 are the time constants of the RC networks. The time constants denote the response rates of Up1 and Up2, respectively. A higher constant means a longer time for the polarization voltage to reach balance, for a given constant load current

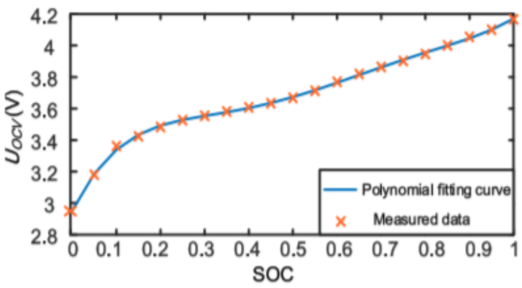

FIGURE 2. The offline identified SOC-OCV curve based on HPPC test.

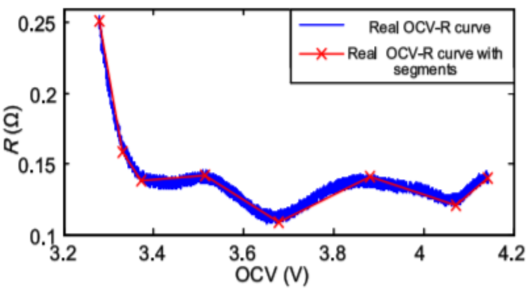

FIGURE 3. The offline identified OCV-R curve based on CCD test.

B. OFF-LINE PARAMETERS IDENTIFICATION To verify the performance of the proposed algorithm, an 18650 Li-ion battery with the nominal capacity of 3Ah and rated voltage of 3.6V was modeled. The parameter identification tests were performed on a rek-8511 programmable electronic load, where the measuring accuracy of voltage and current is 0.03%-0.05%. Then, the data were processed in Matlab. Different from the identification process in [2], the lumped resistance R, which is the sum of ro, rp1 and rp2, was identified independently. In practice, temperature and aging both have effect on battery performance. Hence, the tests were implemented under room temperature. Considering limited charging process in the test, the influence of aging on the battery performance is negligible.

1) IDENTIFICATION OF SOC-OCV CURVE:

The hybrid pulse power characterization (HPPC) test with one hour interval and 5% SOC each time was carried out [27]. Due to the employment of accuracy measuring equipment, the SOC could be calculated accurately based on measured data, and accuracy OCV could also be accurately measured after a long rest of the battery. The SOC-OCV relationship curve fitted by a 5-order polynomial is shown in Fig. 2.

$$U_{ocv} = 13.22SOC^5 - 39.38SOC^4 + 44SOC^3 - 22.32SOC^2 + 5.7SOC + 2.95 \quad (4)$$

2) DENTIFICATION OF R-OCV CURVE In the paper, the R-OCV curve will be utilized in the numerical iteration approach, which will be discussed in Section III. Hence, the identification accuracy of R is critical to identify the OCV.

$$R = r_o + r_{p1} + r_{p2} \quad (5)$$

Generally, the lumped resistance R defined in (5) can be calculated through the identification ofro,rp1 and rp2, respectively. However, the curve fitting errors of ro, rp1 and rp2 will decrease the accuracy of R. Therefore, the constant current discharg (CCD) test was carried out to obtain better accuracy. During the CCD test, the battery was discharged from 100% to 10% with the discharging current of 0.8A. Consequently, the discharging process would last more than three hours. As the Li-ion battery can reach its steady state after only a few minutes [14]–[16], the transient process into steady state can be neglected compared with the whole discharging process. After the dynamic voltage enters steady state, following equation could be expressed as:

$$U_{OCV}(k) - U_o(k) = R(k) \cdot I(k)$$

where, I(k) and Uo(k) are measured based on accurate measuring instrument. Hence, SOC(k) could be obtained through the CC approach. UOCV (k) could be calculated using the SOC-OCV curve discussed in previous Part. Then, R(k) could be solved through (6). The relationship between OCV and R is shown in Fig.3. Obviously, the OCV-R curve in Fig. 3 shows strong nonlinearity. Thus it requires extremely high order polynomial to fit the curve. To simplify, the OCV-R curve is decomposed into seven linear segments according to the inflection points in the OCV-R curve. The simplified curve is expressed as the following equations:

$$R(U_{OCV}) = \begin{cases} 0.268 \cdot U_{OCV} - 0.97, & U_{OCV} \in [4.073, 4.143] \\ -0.104 \cdot U_{OCV} + 0.544, & U_{OCV} \in [3.882, 4.073] \\ 0.157 \cdot U_{OCV} - 0.468, & U_{OCV} \in [3.677, 3.882] \\ 0.201 \cdot U_{OCV} + 0.8482, & U_{OCV} \in [3.513, 3.677] \\ 0.028 \cdot U_{OCV} - 0.44, & U_{OCV} \in [3.372, 3.513] \\ -0.501 \cdot U_{OCV} + 1.827, & U_{OCV} \in [3.332, 3.372] \\ -1.744 \cdot U_{OCV} + 5.97, & U_{OCV} \in [3.278, 3.332] \end{cases} \quad (7)$$

3) IDENTIFICATION OF INNER PARAMETERS: The other inner parameters are identified based on HPPC test as well. Cooperating with the voltage response expressions [2], [28], cp1, cp2ro,rp1 and rp2 can be obtained through curve fitting method.

$$c_{p1} = \left(-3.178SOC^4 + 8.528SOC^3 - 8.322SOC^2 + 3.311SOC - 2781\right) \cdot 10^4$$

$$c_{p2} = \left(-1.015SOC^4 + 1.126SOC^3 - 4.196SOC^2 + 2.937SOC + 1124\right) \cdot 10^5$$

$$r_o = 1.06SOC^5 - 3.17SOC^4 + 3.58SOC^3 - 1.84SOC^2 + 0.4SOC + 0.06$$

$$r_{p1} = -4.32SOC^5 + 13.24SOC^4 - 15.28SOC^3 + 8.21SOC^2 - 2.01SOC + 0.19$$

$$r_{p2} = -0.1SOC^5 - 0.05SOC^4 + 0.45SOC^3 - 0.35SOC^2 + 0.05SOC + 0.025$$

III. REAL-TIME STATE OF CHARGE ESTIMATION USING THE IMPROVED COULOMB COUNTING APPROACH A. STATE JUDGMENT STRATEGY FOR THE BATTERY

The principle of conventional CC approach is shown in (13). Due to the measured noise in I(k), an increasing accumulative error will be introduced into the SOC.

$$SOC(k) = SOC(k-1) - \frac{\eta I(k) T}{Q_N}$$

Generally, if the battery model is precise, model-based SOC estimation approaches, such as EKF and UKF, perform well without accumulative error. However, the accuracy of the model will be reduced at the unsteady state of a battery and model-based SOC estimation approaches have heavy calculation [16], [19], [34]. Hence, in the proposed approach, CC approach is still employed at unsteady state, and numerical iteration based on battery model is proposed to correct the SOC value at steady state. Before the proposed approach is implemented, whether the battery has been steady should be assessed. As mentioned previously, at the steady state of a battery, the current flowing through the capacitors of the RC circuits in the model are negligible. That is to say, it can be assumed that the measured current I only goes through rp1 and rp2. Therefore, following criterion could be formulated:

$$\begin{cases} s_1(k) = \dfrac{U_{p1}(k)}{I(k) \cdot r_{p1}} = 1 \\ s_2(k) = \dfrac{U_{p2}(k)}{I(k) \cdot r_{p2}} = 1 \end{cases}$$

where, s1 and s2 are defined as the steady coefficients, reflecting the divergence degree of the dynamic voltages from steady state. In practice, the criterion can hardly be achieved due to the complex operation condition of EVs. To address the issue, a looser criterion is employed. This criterion denotes that if Up1 and Up2 approximate to the steady state in an adjacent time domain, their mean values will also close to the steady state. Namely, the battery is in quasi-steady state. The restrictions for the mean values are aimed to eliminate the misjudgment caused by the oscillation in I(k).

$$\begin{cases} \{s_1(k-i) \in [0.95, 1.05] \mid i = [1, 2, \cdots, n]\} \\ \{s_2(k-i) \in [0.95, 1.05] \mid i = [1, 2, \cdots, n]\} \\ \dfrac{\sum_{i=1}^{10} s_1(k-i)}{n} \in [0.95, 1.05] \\ \dfrac{\sum_{i=1}^{10} s_2(k-i)}{n} \in [0.95, 1.05] \end{cases}$$

B. OCV ESTIMATION USING NUMERICAL ITERATION A simple iteration algorithm is employed for OCV estimation and then the SOC could be estimated directly through SOCOCV curve. Corresponding principle can be illustrated by (16)-(19).

$$x = \Phi(x)$$

$$x_{l+1} = \Phi(x_l)$$

$$x^* = \lim_{l \to \infty} x_{l+1} = \lim_{l \to \infty} \Phi(x_{l+1}) = \Phi\left(\lim_{l \to \infty} x_{l+1}\right) = \Phi(x^*)$$

$$x_{l+1} = x_l + \varepsilon$$

The equation to be solved needs to be deformed into (16) firstly, where 8(x) is named as iterative function. Further, corresponding iteration structure can be discretized as (17), where xl is the solution of the lth iteration and will be taken as the input variable of the next iteration. If xl+1 satisfies equation (18) after infinite iterations, it is treated as x ∗ , named the fixed point of 8(x), which is the approximate solution of x. In practice, infinite iteration is unnecessary, and xl satisfying equation is sufficient. ε is a pretty small value, which is set according to the required accuracy. Assuming that the battery is in steady state at k, following iteration function can be obtained

$$U_{OCV}\ (k) = U_o\ (k) + R\ (U_{OCV}\ (k)) \cdot I\ (k)$$

Corresponding iteration structure is shown in (21). UOCV l is the solution of the lth iteration, and UOCV l+1 is the solution of the (l+1)th iteration. With iteration going on, UOCV l+1 will converge to a certain value, which is the solution of UOCV (k). It is notable that, the initial value of UOCV 1 should be within the OCV range of the battery

$$U_{OCV\_l+1} = U_o\ (k) + R\ (U_{OCV\_l}) \cdot I\ (k)$$

C. COMPENSATION COEFICIENT TO PREVENT ERROR ACCUMULATION IN CC APPROACH

Assuming that numeral iteration happens at ki . Then, the accumulative SOC error Ei during each time interval can be calculated by following equation

$$E_i = SOC\ (k_i) - SOC\ (k_i - 1) \quad i = 1, 2, 3 \ldots$$

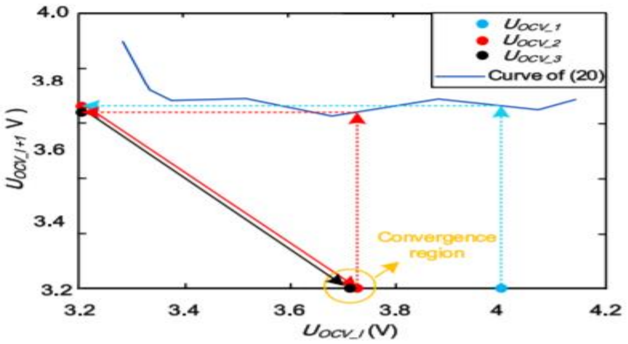

FIGURE 4. Convergence process of numerical iteration.

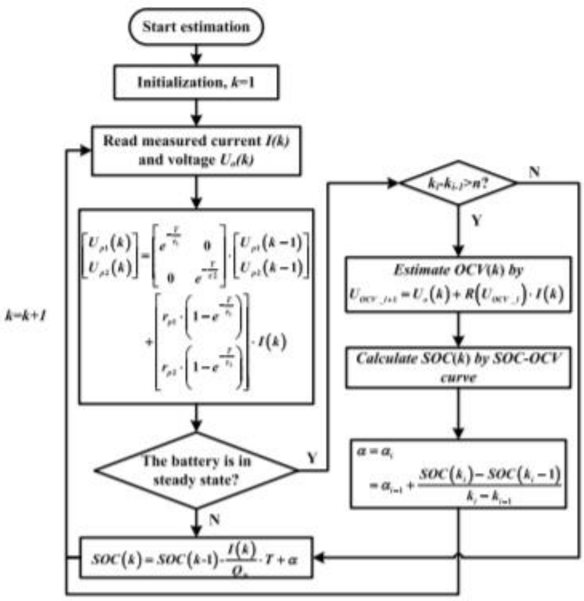

FIGURE 5. Flow chart of the proposed ICC approach.

where, SOC(ki) is the precise SOC estimated by numerical iteration. SOC(ki −1) is the last SOC value got by CC, which contains the SOC error accumulated during [ki−1 +1, ki −1]. Therefore, the error accumulation rate α can be estimated by following equation.

$$\alpha_i = \alpha_{i-1} + \frac{SOC\ (k_i) - SOC\ (k_i - 1)}{t_{k_i} - t_{k_{i-1}}} \tag{23}$$

$$SOC\ (k) = SOC\ (k-1) - \frac{I\ (k)}{Q_N} \cdot T + \alpha_i \tag{24}$$

DESIGN OF ALGORITHMS USED: Algorithms used for SOC and SOH Estimation are:

1. coulomb counting,OCV
2. kalman filter
3. Internal Resistance and Impedance Measurement Method.
4. Neural Network
5. Support Vector Machine
6. Sliding Mode Observer
7. Fault Diagnostic Methods
8. fuzzy logic
9. incremental capacity analysis (ICA) method ,
10. Gaussian process regression method,
11. Bayesian network,
12. particle filter method,
13. Thevenin model.

State of charge (SOC) is a relative measure of the amount of energy stored in a battery, defined as the ratio between the amount of charge extractable from the cell at a specific point in time and the total capacity. Accurate state-of-charge estimation is important because battery management systems (BMSs) use the SOC estimate to inform the user of the expected usage until the next recharge, keep the battery within the safe operating window, implement control strategies, and ultimately improve battery life.

Traditional approaches to state-of-charge estimation, such as open-circuit voltage (OCV) measurement and current integration (coulomb counting), can be reasonably accurate for cell chemistries with a significant OCV variation throughout the SOC range, as long as the current measurement is accurate. However, estimating the state of charge for battery chemistries that exhibit a flat OCV-SOC discharge signature, such as lithium iron phosphate (LFP), is challenging. Kalman filtering is a promising alternative approach that circumvents these challenges with a slightly higher computational effort. Such observers typically include a nonlinear battery model, which uses the current and voltage measured from the cell as inputs, as well as a recursive algorithm that calculates the internal states of the system, including state of charge.

However, estimating the SOC for modern battery chemistries that have flat OCVSOC discharge signatures requires a different approach. Extended Kalman filtering (EKF) is one such approach that has been shown to provide accurate results for a reasonable computational effort.

1. Coulomb Counting Method.

The Coulomb counting method is associated with monitoring the input and the output current continuously. Since capacity is the integral of current with respect to time, by measuring the input and the output current, change in capacity or capacity degradation of a battery can be measuredeasily.Inthismethod,SoHiscalculatedbydividingm easured capacity (after discharging the battery to 0% SoC

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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value) to its ratedcapacity.Itisanextensivelyusedmethodbyresearchersfor itssimplicity.But,theaccuracyofthismethodisnotveryhigh. Therefore, to improve its accuracy, for example, Ng et al. proposed a smart coulomb counting method to estimate both SoC and SoH accurately. Similarly, an adaptive neurofuzzy inference system (ANFIS) was modeled in the paper [51]. It considered the cell's nonlinear characteristics to get the relationship between SoC and open circuit voltage (OCV) at different temperatures. During the estimation of SoC, at some random OCV and temperature ,modelingofcellcharacteristicswasdonebyANFIS.Theassess mentwas done on the cell level instead of the pack level for better precision.

The coulomb counting method, also known as ampere hour counting and current integration, is the most common technique for calculating the SOC. This method employs battery current readings mathematically integrated over the usage period to calculate SOC values given by

$$SOC = SOC(t_0) + \frac{1}{C_{\text{rated}}} \int_{t_0}^{t_0+\tau} (I_b - I_{\text{loss}})\, dt$$

where SOC(t0) is the initial SOC, C_{rated} is the rated capacity, I_b is the battery current, and I_{loss} is the current consumed by the loss reactions. The coulomb counting method then calculates the remaining capacity simply by accumulating the charge transferred in or out of the battery.

Advantages and disadvantages of various methods for state-of-health estimation of Li-ion battery

Method/model	Advantages	Disadvantages
Coulomb counting	• Less complex • Easy implementation	• Time consuming
Electrochemical impedance spectroscopy	• Lower computational cost	• Applicable for specific charging conditions/current pattern only
Neural network	• Match with other techniques, suitable for different battery applications	• Needs lot of training data as it depends on historic data set
Support vector machine	• This method is suitable in both nonlinear and high dimensional model	• It a complex method in terms of computation
Kalman filter	• Fast and highly accurate method • Accurate estimation can be done • No initial data of SoC/SoH is required • Easy filter of data (noise, etc.)	• Method is complex as it requires large amount of calculations
Thevenin model	• Simple and easy to implement	• Capacity fading cannot be predicted
Fractional order	• Accurate in dynamic load condition	• Weak in self-updating the model parameter
Sliding mode observe	• Simple control structure and robust tracking performance, under uncertain environments • High accuracy can be achieved	• Slow time observer for SoH
Fuzzy logic	• Applicable for complex and nonlinear system	• High amount of computation is required

The accuracy of this method resorts primarily to a precise measurement of the battery current and accurate estimation of the initial SOC. With a preknown capacity, which might be memorized or initially estimated by the operating conditions, the SOC of a battery can be calculated by integrating the charging and discharging currents over the operating periods. However, the releasable charge is always less than the stored charge in the charging and discharging cycle. In other words, there are losses during charging and discharging. These losses, in addition with the self discharging, cause accumulating errors. For more precise SOC estimation, these factors should be taken into account. In addition, the SOC should be recalibrated on a regular basis and the declination of the releasable capacity should be considered for more precise estimation.

Enhanced Coulomb Counting Algorithm: In order to overcome the shortcomings of the coulomb counting method and to improve its estimation accuracy, an enhanced coulomb counting algorithm has been proposed for estimating the SOC and SOH parameters of Li-ion batteries. The initial SOC is obtained from the loaded voltages (charging and discharging) or the open circuit voltages. The losses are compensated by considering the charging and discharging efficiencies. With dynamic recalibration on the maximum releasable capacity of an operating battery, the SOH of the battery is evaluated at the same time. This in turn leads to a more precise SOC estimation.

Technical Principle

The releasable capacity (Creleasable), of an operating battery is the released capacity when it is completely discharged. Accordingly, the SOC is defined as the percentage of the releasable capacity relative to the battery rated capacity (Crated), given by the manufacturer.

$$SOC = \frac{C_{\text{releasable}}}{C_{\text{rated}}}\ 100\%$$

A fully charged battery has the maximal releasable capacity (Cmax), which can be different from the rated capacity. In general, Cmax is to some extent different from Crated for a newly used battery and will decline with the used time. It can be used for evaluating the SOH of a battery.

$$SOH = \frac{C_{\max}}{C_{\text{rated}}}\ 100\%$$

When a battery is discharging, the depth of discharge (DOD) can be expressed as the percentage of the capacity that has been discharged relative to Crated,

$$DOD = \frac{C_{\text{released}}}{C_{\text{rated}}}\ 100\%$$

where Creleased is the capacity discharged by any amount of current. With a measured charging and discharging current (Ib), the difference of the DOD in an operating period (Ʈ) can be calculated by

$$\Delta DOD = \frac{-\int_{t_0}^{t_0+\tau} I_b(t)\, dt}{C_{\text{rated}}}\ 100\%$$

where Ib is positive for charging and negative for discharging. As time elapsed, the DOD is accumulated.
DOD(t) = DOD(t0) + ΔDOD

To improve the accuracy of estimation, the operating efficiency denoted as ŋ is considered and the DOD expression becomes,

DOD(t) = DOD(t0) + ηΔDOD

with ŋ equal to ŋc during charging stage and equal to ŋd during discharging stage. Without considering the operating efficiency and the battery aging, the SOC can be expressed as

SOC(t) = 100% – DOD(t)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

Considering the SOH, the SOC is estimated as SOC(t) = SOH(t) – DOD(t) .

Figure 1 shows the flowchart of the enhanced coulomb counting algorithm. At the start, the historic data of the used battery is retrieved from the associated memory. Without any information for a newly used battery, the SOH is assumed to be healthy and has a value of 100%, and the SOC is initially estimated by testing either the open circuit voltage, or the loaded voltage depending on the starting conditions. The estimation process is based on monitoring the battery voltage (Vb) and Ib. The battery operation mode can be known from the amount and the direction of the operating current. The DOD is adding up the drained charge in the discharging mode and counting down with the accumulated charge into the battery for the charging mode. After a correction with the charging and discharging efficiency, a more accurate estimation can be achieved. The SOC can be then estimated by subtracting the DOD quantity from the SOH one. When the battery is open circuited with zero current, the SOC is directly obtained from the relationship between the OCV and SOC. It is noted that the SOH can be reevaluated when the battery is either exhausted or fully charged, and the battery operating current and voltage are specified by manufacturers. The battery is exhausted when the loaded voltage (Vb) becomes less than the lower limit (Vmin) during the discharging. In this case, the battery can no longer be used and should be recharged. At the same time, a recalibration to the SOH can be made by reevaluating the SOH value by the accumulative DOD at the exhausted state. On the other hand, the used battery is fully charged if (Vb) reaches the upper limit (Vmax) and (Ib) declines to the lower limit (Imin) during charging. A new SOH is obtained by accumulating the sum of the total charge put into the battery and is then equal to SOC. In practice, the fully charged and exhausted states occur occasionally. The accuracy of the SOH evaluation can be improved when the battery is frequently fully charged and discharged. finally simple calculation and the uncomplicated hardware requirements, the enhanced coulomb counting algorithm can be easily implemented in all portable devices, as well as electric vehicles. In addition, the estimation error can be reduced to 1% at the operating cycle next to the reevaluation of the SOH.

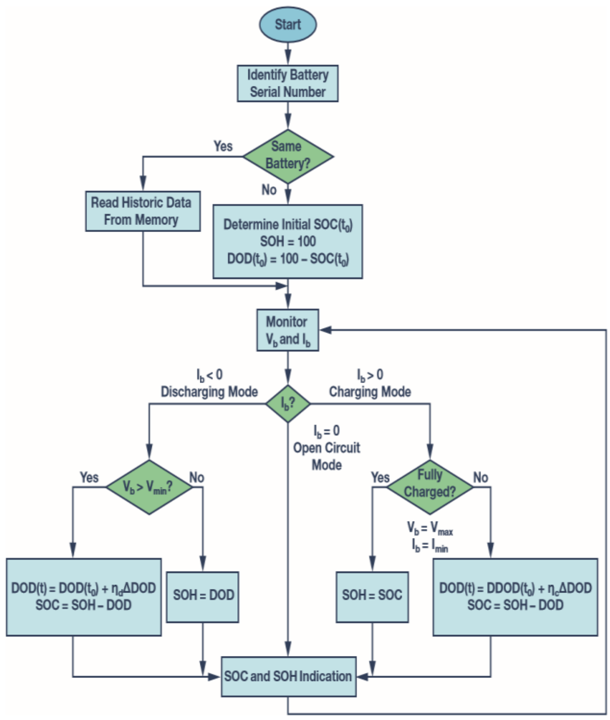
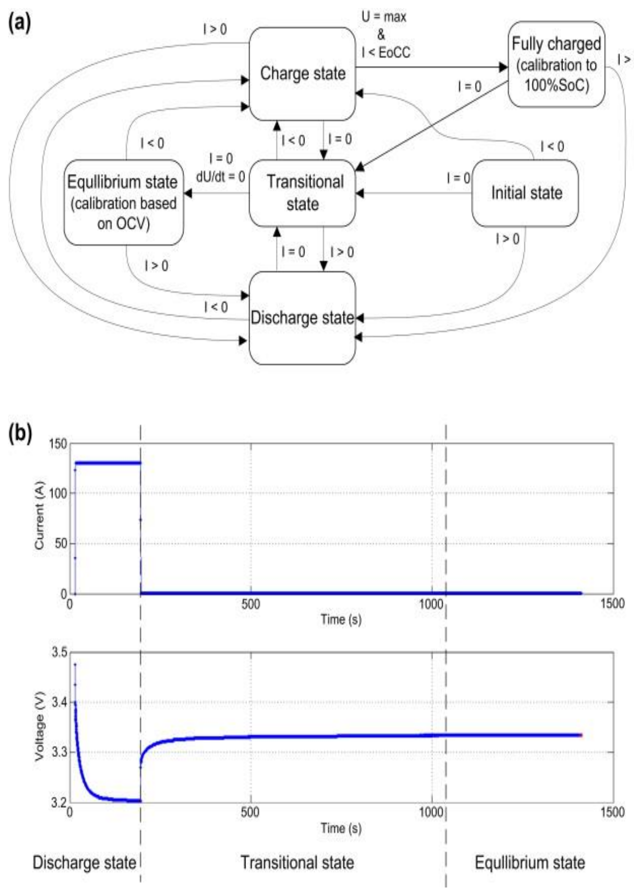
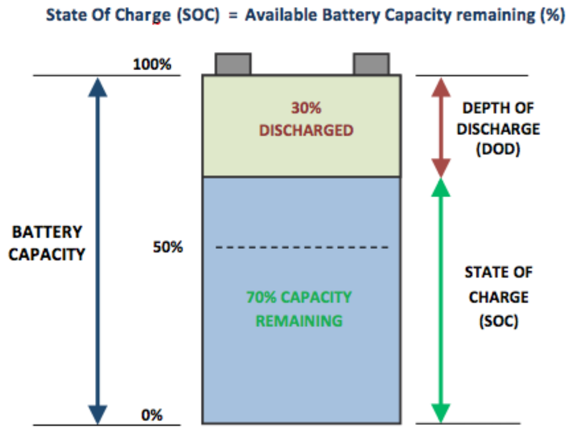


Figure: Flowchart of the enhanced coulomb counting algorithm.

Charging and discharging methods of coulomb counting:





V. CONCLUSION

In the paper, an ICC approach with real-time error correction ability is proposed. The SOC is estimated online by the CC approach at unsteady state, leading a much higher estimation rate. At steady state, numerical iteration approach can accurately eliminate the accumulated SOC error of CC approach, leading a much higher accuracy than traditional CC approach. The numerical iteration approach is based on a 2ndorder RC circuit model, where its parameters were identified offline during HPPC and CCD tests. Hence, the proposed approach could combine the advantages of CC approach and model-based approach together. Furthermore, a compensation coefficient α is employed into the CC approach to reduce the error accumulation rate. Experimental results suggest that the SOC error of ICC is effectively limited within 1% and its calculation cost is 94% lower than that of EKF. Therefore, it provides beneficial guidance for the real-time SOC estimation in EVs.

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