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RESEARCH ARTICLE

Adaptive Integral Correction-Based State of Charge Estimation Strategy for Lithium-Ion Cells

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ABSTRACT Lithium-ion (Li-ion) battery systems are critical elements of future energy systems and electric vehicles. Accurate prediction of the state of charge (SoC) is necessary for the safe and reliable functioning of Li-ion battery systems. Achieving a precise SOC estimate is challenging due to the nonlinear characteristics and variations of model parameters caused over the cell lifetime. This paper introduces an adaptive estimation strategy that can compensate for the effect of cell degradation for achieving high accuracy SoC estimation. The proposed method uses an integral correction-based SoC estimation loop utilizing a Li-ion cell model. The effect of model parameter variation is corrected by introducing two additional correction factors, the cell model resistance, and capacity correction factor. These correction factors are employed to update the Li-ion cell model, resulting in an adaptive integral correction-based SoC estimation technique that can compensate for the influence of cyclic degradation-induced parameter change. The proposed method is validated through extensive simulations in the Matlab-Simulink environment, and its output is compared to the existing unscented Kalman filter-based SoC estimation method. The proposed estimation strategy can adapt to the cell circumstances and correct for model uncertainties. The results indicate that the proposed adaptive SoC estimation strategy provides more precise and accurate SoC estimates for the entire lifespan of the Li-ion cell.

INDEX TERMS Adaptive estimation, battery management systems, cell degradation, Kalman filter, lithium-ion cell, state of charge estimation, state of health.

I. INTRODUCTION

Lithium-ion batteries are extensively used in the electric vehicle and renewable energy industries. The high energy density and long life of Li-ion batteries make them a perfect choice in energy storage systems. Li-ion batteries help to store more energy and facilitate long-range electric vehicles and uninterrupted access to renewable energy systems [1], [2]. In addition to the advantages, these batteries can also cause dangerous explosions, if the Li-ion cells are operated beyond their safe operating limits [3], [4].

Battery management systems (BMS) are used along with Li-ion batteries to enhance their capacity utilization without going over the safety limits. By monitoring cell voltage, current, and temperature, BMS ensures the cell's safe and reliable operation. BMS's functions include SoC estimation, cell balancing, range estimation, power estimation, and communication with the main control unit [5]–[8].

For the smooth functioning Li-ion battery and for the reliable functioning of BMS, the remaining discharge capacity of the individual Li-ion cells has to be known. The state of charge (SoC) describes the remaining discharge capacity of a cell relative to its total discharge capacity. SoC is a decisive state in BMS, as most of its functionalities are dependent on the SoC of individual Li-ion cells. For the smooth functioning of BMS and to extract maximum energy from the battery pack, accurate SoC measurement is required. [9]. Since SoC is a cell's internal state, it is difficult to get a direct measurement. It is often estimated using direct or indirect methods [10]–[14].

Open circuit voltage (OCV), a key indicator of SoC, is one of the main direct measurement methods [15]–[18]. SoC-OCV relationships are recorded at the cell equilibrium condition, and OCV can be directly mapped to identify the

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cell SoC. Because Li-ion cells require a long rest time to reach equilibrium, direct OCV-based SoC estimate in practical situations is limited.

Coulomb counting (Ah Method) is another direct method used for SoC estimation [19]–[21]. The Ah-method counts the total charge-discharge ampere-hours (Ahs) relative to the total cell discharge capacity. This method works quite accurately, but the initial SoC must be known in advance. Also, the measurement noise and variation in total discharge capacity can cause SoC estimation errors. SoC-OCV relationships are often used to re-calibrate coulomb counting-based SoC estimation.

Electrochemical impedance spectroscopy(EIS) is another direct SoC measurement technique. It measures the impedance of the cell at a range of frequencies and the measured impedance is used for identifying the SoC of the cell [22]–[24]. EIS requires to apply sinusoidal voltage signals for extracting the impedance values and its applications are limited in online SoC estimation.

When dynamic load conditions are present, direct measurement of SoC will not be accurate and reliable. Model-based estimation methods are used for more accurate estimates of SoC during operation. Model-based methods employ cell models to describe the behavior of cells to estimate the SoC. Models such as the electrochemical model, equivalent circuit model, and data-driven models frequently appear in the literature [10]–[14], [25]–[27]. These models are used with direct SoC measurement methods to improve SoC estimation accuracy.

Model-based SoC estimation method uses a cell model and inputs the model with cell current and temperature. The model calculates the internal states and predicts the SoC. The main source of estimation error in model-based techniques are measurement noises and model parameter uncertainties. To correct the estimation error, the difference between the measured cell terminal voltage and model output value is applied to an algorithm or feedback observer to correct the estimated model states. Popular feedback algorithms or observers are PI-based, Kalman filter-based, sliding mode observers, etc. These model-based SoC estimation methods can provide accurate SoC estimation results with measurement noises and slight model uncertainties [28]–[39]. When Li-ion cells cycle and age, the cell parameters will get deviated from those in new cell conditions. This parameter variation causes higher model parameter uncertainties and makes the cell model inaccurate for the estimation of SoC.

In practice, it is necessary to update the cell model to match the current cell conditions in order to get higher SOC estimation accuracy. As the cell ages, the cell discharge capacity reduces and reaches its end of life. The reduction in cell capacity is represented using state of health (SoH). It is the relative measure of the cell's present total discharge capacity to its rated capacity. SoH estimation algorithms are used for identifying the capacity fade and to update the model to achieve better SoC estimation results [40]–[48].

Along with loss in cell capacity, the cell's internal resistance values also increase with the usage of the Li-ion cell. These model parameter variations in cell capacity and internal resistances increase with cell usage. These variations cause increased model errors and low estimation accuracy. In order to correct the model uncertainties induced by cycling and degradation, the model parameters must be updated to reflect cell conditions.

Adaptive SoC estimation methods which can suit the battery conditions have to be used in practical applications. In [49], [50] sliding mode observers and Lyapunov-based adaptive law is used for adjusting the model parameters, but does not account for actual variations in the cell capacity. References [51], [52] relays on the estimated SoC for calculating the present cell capacity, which can lead to an inaccurate SoC estimation. Most of the adaptive methods in the literature rely on the same cell measurements and estimated SoC for correcting the model parameters. Relying on the same estimated SoC for correcting the model errors can lead to higher estimation errors. The SoC can also be estimated accurately using data-driven neural network-based models. The usage patterns of battery systems in various applications will be different. The training of a data-driven model accommodating all these variations requires quite a large amount of data and resources, which makes it more complex and costly [53]–[56].

This paper aims to provide a simple and adaptive technique for accurate estimation of SoC in Li-ion cells, considering parameter variations under practical conditions. The proposed adaptive methodology combines the equivalent circuit model and thermal model. To improve the SoC estimation accuracy, two additional control loops are used. These control loops update the model's resistances and cell capacities to match the cell conditions. The main contributions of this work are:-

- The article proposes a novel and simple methodology for adaptively estimating the state of charge of a Li-ion cell over its entire lifespan.
- The idea proposed in this paper which combines the cell's equivalent circuit model and the thermal model enables to correct the model errors in cell resistances and cell capacity caused due to the cell's cyclic degradation.
- The cell capacity correction control loop proposed in this work enables to compensate for the errors caused by the reduction in total discharge capacity and a model resistance correction control loop to compensate for the errors caused by the change in the internal resistance of the Li-ion cell.
- The proposed methodology is capable of estimating the state of charge with minimal error over the entire life of the Li-ion cell.

This paper is structured as follows: Section II discusses the Li-ion cell characteristics and cell model. Section III explains the working methodology and evolution of the proposed adaptive integral correction-based SoC estimation methodology. Section IV validates the proposed AIC-SE method using Matlab, and its results are compared with basic integral correction and UKF-based SoC estimation methods. Finally, the paper concludes in Section V.

II. LITHIUM-ION CELL MODEL

Cell models are the mathematical representations of the actual cell characteristics. The cell model tracks the terminal voltage of the Li-ion cell during operation. In estimating SoC, the cell model is a vital part of BMS. Since SoC estimation is highly dependent on model accuracy, a reliable model is essential in BMS. Despite the availability of many different models such as electrochemical models, neural network-based black-box models, and so on, equivalent circuit models are widely used in BMS applications. These equivalent circuit models use less computational burden and are simple to understand.

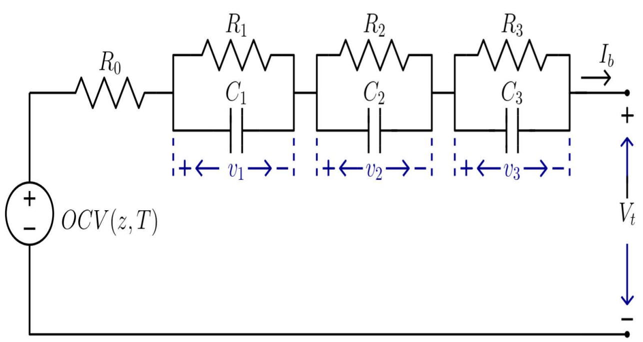

FIGURE 1. Equivalent circuit model of Li-ion cell.

The state of charge estimation accuracy is highly dependent on the accuracy of the cell model that we use in the estimation algorithm. An infinite number of RC branches is required to model Li-ion cell dynamics. To improve the accuracy of the SoC estimation, we have chosen a third-order equivalent circuit to model the Li-ion cell. An equivalent circuit model as shown in Fig. 1 is utilized in this work for SoC estimation [57]. The model consists of a voltage source $OCV(z, T)$ which is the open-circuit voltage of the Li-ion cell. OCV is a nonlinear function of the SoC and temperature. R_0 represents the ohmic resistance and RC_{1-3} branches are used for accurately representing the diffusion characteristics of the Li-ion cell. Q_c represents the cell charge capacity of the cell in Ah. All these model parameters are functions of SoC and temperature. The cell's internal states can be expressed using the following equations (1-4).

$$\dot{z} = \frac{-I_b}{Q_c \cdot 3600} \tag{1}$$

$$\dot{v_1} = \frac{v_1}{R_1C_1} - \frac{I_b}{C_1} \tag{2}$$

$$\dot{v_2} = \frac{v_2}{R_2C_2} - \frac{I_b}{C_2} \tag{3}$$

$$\dot{v_3} = \frac{v_3}{R_3C_3} - \frac{I_b}{C_3} \tag{4}$$

The voltages v_1, v_2, and v_3 represent the voltage polarization across each RC branch. z represents the SoC of the cell, and I_b is the cell current. Based on the model, the modeled terminal voltage, V_t of a lithium-ion cell can be expressed as follows:

$$V_t = OCV(z, T) - I_bR_0 - v_1 - v_2 - v_3 \tag{5}$$

Hybrid pulse power characterizing (HPPC) tests at various temperatures are commonly used for cell model parameter identification. Due to model inaccuracies, the cell model may differ slightly from actual cell behavior. Noise in the measurement can also cause small error from the actual value. These variations can affect the SoC estimation accuracy. In the literature, many methods such as the Kalman filter, extended Kalman filters, unscented Kalman filters, PI-based observers, sliding mode observers, and others have been used to compensate for these effects and have achieved satisfactory results. Our approach utilizes an integral correction method for compensating the initial model uncertainties and the effect of measurement noise.

III. SoC ESTIMATION METHODOLOGY

SoC estimation accuracies are highly dependent on the cell model accuracy. The SoC can be precisely estimated using observers or filters such as the Kalman filter along with an accurate cell model. But when the cell cycles and ages, the cell's internal parameters like cell capacity and internal resistances vary. As cell cycles,

- Internal resistance increases
- Cell capacity decreases
- Self-discharge increases

These variations in cell parameters make the cell model inaccurate and lead to a less accurate and uncertain SoC estimation. Since the safety and functionality of the Li-ion pack depend on the individual cell SoC, these erroneous estimates cannot be relied on to guarantee the proper performance of the battery pack. An adaptive SoC estimation method that can compensate for these model errors due to aging effects is proposed in this paper.

The proposed adaptive estimation method contains an integral correction-based SoC estimation algorithm (IC-SE) utilizing a third-order RC equivalent circuit model. If the model is accurate, the IC-SE method alone can predict SoC quite accurately. Two additional control loops are combined with the IC-SE method to compensate for model inaccuracy caused by cyclic degradation and aging.

A resistance correction loop is formed using the thermal model of the cell to compensate for the model resistance values. Also, another cell capacity correction loop is utilized to correct the errors caused by the variation in cell capacity. The IC-SE method combined with the parameter correction loops forms the adaptive integral correction-based estimation method (AIC-SE). The evolution of the proposed AIC-SE SoC estimation strategy is detailed below.

A. INTEGRAL CORRECTION SoC ESTIMATION METHOD

Open-circuit voltage and SoC of Li-ion cells are directly related. The cell OCV cannot be retrieved from the cell terminals while the cells are in operation. The internal voltage drops hinder directly measuring the OCV. Cells must reach an equilibrium condition for measuring OCV from cell terminals. Since direct measurement of OCV under loading conditions is difficult, it must be estimated using a cell model. But the measurement noises, model inconsistencies, and the initial condition errors have to be corrected for obtaining an accurate OCV.

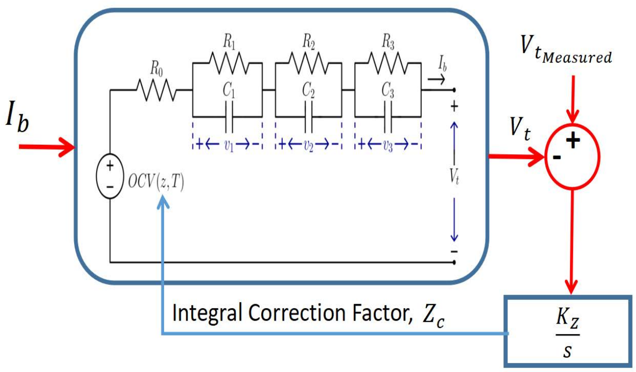

FIGURE 2. Integral correction-based SoC correction method.

A third-order RC equivalent circuit model with an integral correction loop is used to estimate the SoC of the Li-ion cell. The RC model shown in Fig. 1 is used to estimate the terminal voltage of the Li-ion cell. The error in the estimated terminal voltage to actual measured terminal voltage is given to an integrator to calculate the correction factor. In order to correct the error in the estimated SoC, this correction factor is added to the cell model's SoC. Fig. 2 shows the block diagram representation of the integral correction method.

Z_c, the integral correction factor can be expressed as,

$$Z_c = K_Z \int (V_{t_{Measured}} - V_t)dt \tag{6}$$

$V_{t_{Measured}}$ and V_t are the measured and estimated terminal voltage of the cell. K_Z is the loop gain of integral correction loop. Z_c is added to (1)compensate the model uncertainties, measurement noises, and initial SoC error.

The estimated SoC (z) can be obtained by integrating (1) and adding the integral correction factor Z_c. The SoC, z of a cell can be ex[ressed as,

$$z = \frac{\int -I_b dt}{Q_c \cdot 3600} + Z_c \tag{7}$$

The integral correction based SoC estimation method can provide accurate SoC estimates if the cell models is accurate.

B. ADAPTIVE INTEGRAL CORRECTION-BASED SoC ESTIMATION

The integral correction method can only compensate for minor model uncertainties. When the cell cycles and ages, the amount of active lithium in the electrodes reduces. As the result cell resistance increases, and the cell's total discharge capacity reduces. This causes a significant deviation in cell parameters from the fresh cell, and the model behavior deviates from reality. As the estimation accuracy is limited to the model accuracy, these deviations cause unacceptable errors in the estimated SoC.

In order to compensate for these model parameter uncertainties caused by the cyclic degradation and aging process, two additional control loops are added along with the integral correction method to form an adaptive estimation method.

1) MODEL RESISTANCE CORRECTION

It is necessary to compensate for the variations in model parameters caused by cyclic degradation of Li-ion cells in order to achieve high SoC estimation accuracy. The cell resistance increases and deviates from the model parameters during the degradation process. To compensate for the increase in internal resistance, a correction factor is introduced. This model resistance correction term is found using the thermal model of the Li-ion cell [58]. The internal resistances of the Li-ion cells contribute to the power loss in the cell during operation. Using the thermal model, the temperature of the Li-ion cell can be estimated. Fig. 3 shows the thermal model of the Li-ion cell [58].

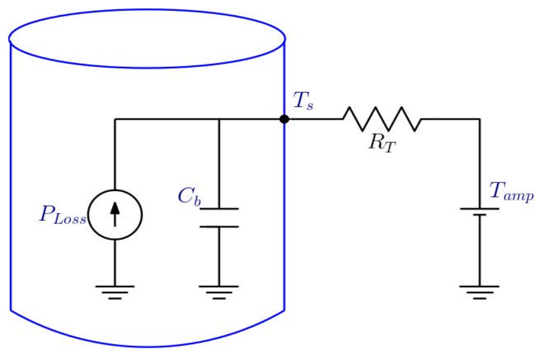

FIGURE 3. Thermal model of Li-ion cell.

T_s and T_{Amp} represent the cell surface and ambient temperatures, respectively. C_b is the heat capacity of the cell, and R_T is the thermal resistance from the cell surface to surroundings, which are assumed to be constant for a cell in an assembled battery pack. The total power dissipated in the Li-ion cell, P_{Loss}, can be expressed as,

$$P_{Loss} = {I_b}^2 R_0 + \frac{{v_1}^2}{R_1} + \frac{{v_2}^2}{R_2} + \frac{{v_3}^2}{R_3} \tag{8}$$

The thermal model of a Li-ion cell can be represented as,

$$\frac{dT_s}{dt} = \frac{P_{Loss}}{C_b} - \frac{T_s - T_{Amb}}{C_b R_T} \tag{9}$$

The thermal model of the Li-ion cell can be used to estimate the surface temperature of the cell.

$$T_S = \int (\frac{P_{Loss}}{C_b} - \frac{T_s - T_{Amb}}{C_b R_T})dt \tag{10}$$

The variation between the estimated temperature and measured temperature can be considered either because of the thermal model parameter variations or due to the mismatch in the power loss in the Li-ion cell. Since there will not be any change in the mechanical configuration after the assembly, the thermal model parameters C_b and R_T are assumed to be constant for a cell in an assembled battery pack. The power loss in the Li-ion cell can be expressed as,

$$P_{Loss} = I_b{}^2 R_0 + I_1{}^2 R_1 + I_2{}^2 R_2 + I_3{}^2 R_3 \tag{11}$$

where I_1, I_2, I_3 are the currents through resistances R_1, R_2, R_3 respectively. From (11) it can be seen that the power loss inside the Li-ion cell is directly related to the internal resistances. As the cell cycles and degrades, the cell's internal resistance increases. Any deviation seen between estimated cell surface temperature and the actual measurement is regarded as an error in calculated power loss. A higher measured temperature than the estimated cell temperature indicates an increase in internal resistance, so the equivalent model resistances must be updated accordingly.

In order to update the equivalent circuit model resistances, a resistance correction loop is added to the integral correction-based SoC estimation method. The resistance correction loops will reduce the model inaccuracies by modifying the equivalent circuit parameters by using the correction factor M_R. Fig. 4 shows the control block diagram of the resistance correction loop. The resistance correction factor, M_R can be calculated as,

$$M_R = K_R \int (T_{S_{Measured}} - T_S)dt \tag{12}$$

where, K_R is the loop gain of the resistance correction loop and $T_{S_{Measured}}$ is the measured cell surface temperature. The resistance correction factor, M_R is identified using an integral controller to minimize the cell temperature estimation error.

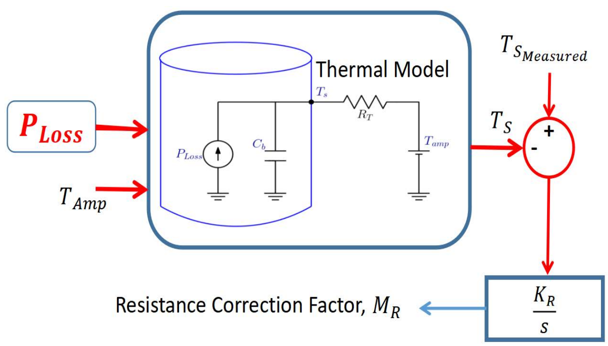

FIGURE 4. Block diagram representation of resistance correction loop.

Updated model resistances can be expressed as,

$$R_i = R_{i_{initial}} \cdot M_R \tag{13}$$

where $R_{i_{initial}}$ ($i = 0 - 3$) represents the model resistance values for a new cell. The resistance correction factor, M_R is multiplied with initial cell model resistance parameters to compensate for the cyclic degradation effects on internal resistances.

2) CELL CAPACITY CORRECTION

The total discharge capacity, Q_c, of the Li-ion cell decreases as the cell cycles and ages, due to the loss of active Lithium in the electrodes. Since Q_c is part of the cell model, the changes in cell capacity reflect in SoC estimation accuracy. As cell capacity changes, the errors in the SoC estimation also increase. To estimate capacity fade, and to update the model cell capacity, state-of-health estimation algorithms are commonly used. This paper presents a new method for correcting cell capacity and improving the accuracy of SoC estimation.

The SoC estimation algorithm has to account for the model uncertainties like model resistance and cell capacity deviations from the actual values. The integral correction loop corrects the model error by adding the integral correction factor to the model SoC. If the cell model were accurate, the correction effort taken by the integral correcting loop will be less.

The inaccuracy in model resistance can be corrected using the thermal model-based resistance correction loop. So the correction effort produced by the integral SoC correction loop is mostly used to compensate for deviations in cell capacity. A higher value of the correction factor means a higher level of capacity deviation from the actual value. If cell capacity is different from the cell model, the amplitude of oscillations in the integral correction factor from its mean value will increase, as shown in Fig. 5(a). The deviation of the integral SoC correction term from its mean value is treated as a measure of capacity deviation and can be utilized for correcting the model's cell capacity.

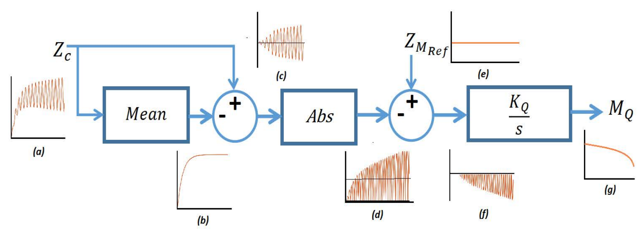

FIGURE 5. Block diagram representation of the capacity correction loop, (a) symbolic representation the integral correction factor, (b) mean value of integral correction factor, (c) deviation of integral correction factor from its means value($\hat{Z_c}$), (d) absolute deviation of Z_c from its mean value, (e) $Z_{M_{Ref}}$, (f) deviation of $\hat{Z_c}$ from $Z_{M_{Ref}}$, (g) cell capacity correction factor M_Q.

Fig. 5 shows the control block diagram representation of the capacity correction loop. The correction loop finds the mean value of the integral correction factor in each cycle and calculates the absolute deviation of Z_c from its mean value. This deviation, $\hat{Z}_c$ is taken as the measure of capacity change. When the deviation in Z_c is more than a threshold value $Z_{M_{Ref}}$, it is passed to the integrator to find the capacity correction factor, M_Q. K_Q is the loop gain of the capacity correction loop.

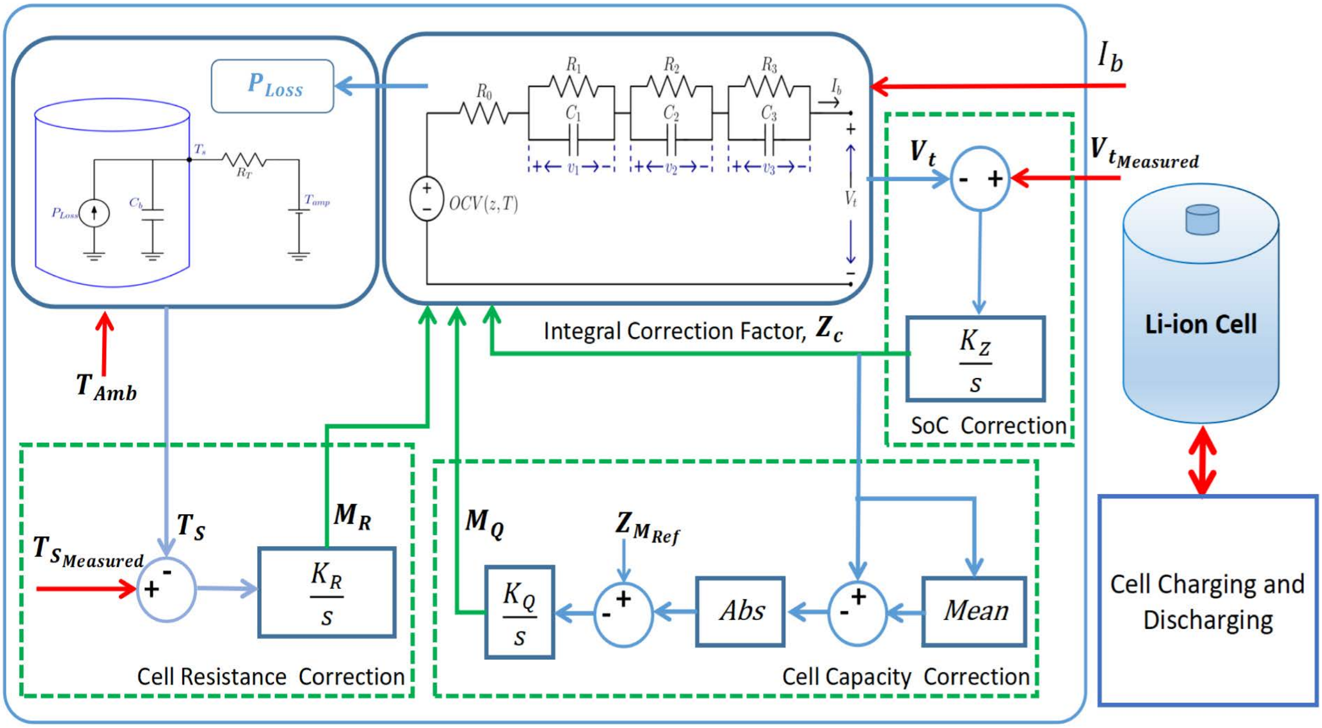

FIGURE 6. Block diagram representation of adaptive integral correction based SoC estimation method.

The capacity correction factor, M_Q can be calculated as,

$$M_Q = K_Q \int (\hat{Z}_c - Z_{M_{Ref}})dt \tag{14}$$

M_Q is multiplied with the initial cell capacity to modify the model discharge capacity. The updated model discharge capacity can be expressed as,

$$Q_c = Q_{c_{initial}} \cdot M_Q \tag{15}$$

where $Q_{c_{initial}}$ represents the discharge capacity value for a new cell. M_R is the cell resistance correction factor.

3) ADAPTIVE INTEGRAL CORRECTION-BASED SoC ESTIMATION

To compensate for the model uncertainties caused by the cyclic degradation, the resistance correction loop, and cell capacity correction loop are employed along with the integral correction-based SoC estimation method. This new adaptive integral correction-based SoC estimation method can compensate for the aging effects of the Li-ion cells and can provide better SoC estimation accuracy. Fig. 6 shows the complete block diagram representation of the proposed adaptive integral correction-based SoC estimation technique.

The complete algorithm of the proposed adaptive integral correction-based SoC estimation strategy is given in Algorithm 1. The equivalent circuit model resistance is updated using the resistance correction factor, and the cell capacity is updated using the capacity correction factor.

Algorithm 1 Adaptive Integral Correction Based SoC Estimation Algorithm

1: **Initialize:** Cell model parameters
2: **Measure:** $V_{t_{Measured}}$, I_b,,$T_{S_{Measured}}$, and T_{Amb}
SoC estimation
3: Estimate cell terminal voltage using equivalent circuit model, V_t :
$V_t = OCV(z, T) - I_b R_0 - v_1 - v_2 - v_3$
4: Calculate the SoC correction factor, Z_c:
$Z_c = K_Z \int (V_{t_{Measured}} - V_t)dt$
5: Estimate the SoC of the Li-ion cell, z:
$z = \frac{\int -I_b dt}{Q_c \cdot 3600} + Z_c$
6: **Return:** SoC = z
Model Correction: Cell resistance correction
7: Estimate cell surface temperature, T_S using thermal model of Li-ion cell:
$T_S = \int (\frac{P_{Loss}}{C_b} - \frac{T_s - T_{Amb}}{C_b R_T})dt$
8: Calculate the resistance correction factor:
$M_R = K_R \int (T_{S_{Measured}} - T_S)dt$
9: **Update:** Cell equivalent circuit model resisters:
$R_i = R_{i_{initial}} \cdot M_R$; For $i = 0 - 3$
Model Correction: Cell capacity correction
10: If $(\hat{Z}_c > Z_{M_{Ref}})$: calculate the resistance correction factor,
$M_Q = K_Q \int (\hat{Z}_c - Z_{M_{Ref}})dt$
11: **Update:** Cell capacity of Li-ion cell model:
$Q_c = Q_{c_{initial}} \cdot M_Q$
12: **Goto Step 2**

The updated model values are used for accurately estimating the SoC using the integral correction-based SoC estimator.

IV. RESULTS AND DISCUSSION

To demonstrate the proposed method the test setup can be arranged as shown in Fig. 7. The proposed adaptive integral correction-based estimation methodology requires the knowledge of cell current, cell terminal voltage, cell surface temperature, and ambient temperature for the estimation of SoC. Test setup also contains controlled charging and loading arrangements to charge and discharge the Li-ion cell.

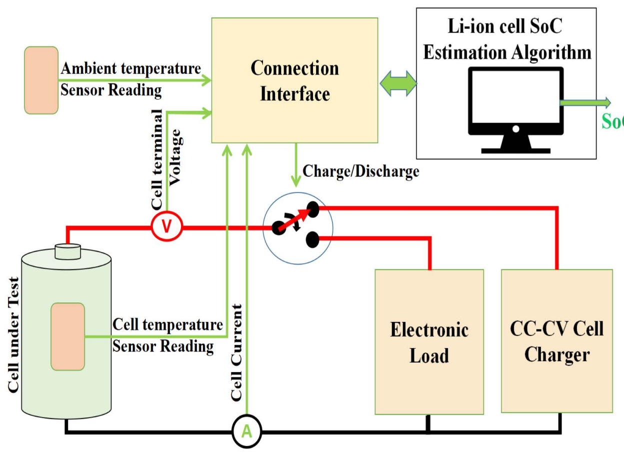

FIGURE 7. Test setup for demonstration.

The charging and discharging modes are decided based on the state of charge of the Li-ion cell. The cell is operated between 20% and 90% of SoC so that the cell will never be overcharged or discharged. When the cell SoC reaches 90%, charging stops, and discharging starts at an average C-rate of 1C. Discharging mode stops when the SoC reaches 20%, and the cell is charged in CCCV mode at a C-rate of 0.5C. The CC-CV method limits the output voltage to a fully charged level and prevents the cells from overcharging.

TABLE 1. Li-ion cell specifications.

Cell Specifications	Quantity
Rated discharge capacity	31 Ah
Cell Voltage	3.7 V
Cell chemistry	NMC
Cell dimensions	$0.215 \times 0.0084 \times 0.22\ m^3$
Cell heat capacity	$2.04 \times 10^6\ J/m^3/K$
Heat exchange coefficient	$5\ W/m^2/K$

The test setup is arranged in a Matlab-Simulink environment for the demonstration of the proposed methodology. Matlab Li-ion cell model is used for replicating the Li-ion cell dynamics and effects of cyclic degradation effects. A Matlab model of NMC Li-ion cell with 31Ah capacity [57] is utilized for validating the proposed method.Matlab model-based validation aids in gaining access to the internal states of the Li-ion cell and comparing them to their estimated value. Cell specifications are listed in Table 1. As the effect of cell degradation after 300 cycles, an increase of 25%, 20%, 30% and 30% of the cell's first, second, and third polarization resistances and terminal resistance is applied in the cell model. The model is set to lose 25% of its initial total discharge capacity after 300 cycles. In order to introduce measurement noise to the system, white noise is added to the cell current and terminal voltage. Noise power for cell current and terminal voltage is chosen as 2.5×10^{-3} and 0.05×10^{-3}, respectively.

Extensive simulation studies have been conducted using Matlab Simulink to evaluate the effectiveness of the proposed integral correction-based SoC estimation method (IC-SE) and adaptive integral correction-based SoC estimation method (AIC-SE).

RC equivalent circuit and thermal models are formulated to match the Matlab Li-ion cell behavior. The equivalent circuit model parameters of the Li-ion cell are shown in Fig. 9. All cell parameters are a function of SoC and temperature. The total discharge capacity of the model is 31Ah. The thermal model parameters are $C_b = 810 J/°C$ and $R_T = 2\ W/°C$.

The proposed IC-SE method was validated by subjecting the cell to many charge-discharge cycles and estimating the SoC. The initial SoC of the cell was 50%, and the ambient temperature was 20°C. The model was initialized to 60% SoC at the beginning of the estimation. Because the cell is new and not subjected to cyclic degradation, the cell model characteristics should match the actual cell.

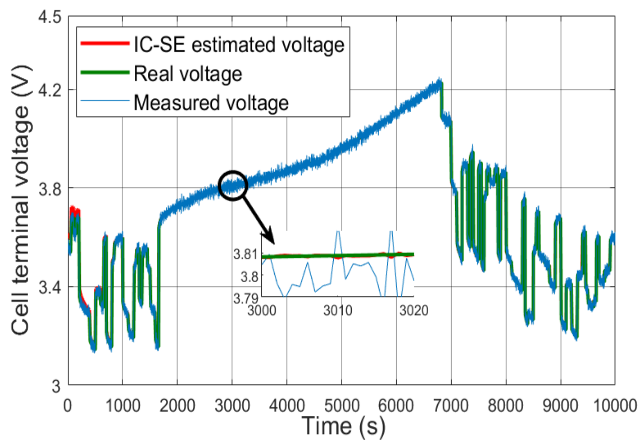

FIGURE 8. Modeled terminal voltage of Li-ion cell for the first cycle by IC-SE.

The IC-SE estimation method predicts the cell terminal voltage and compares it with the measured terminal voltage. The IC-SE estimation algorithm corrects this error through the integral feedback loop. Noise in voltage measurements is assumed to be Gaussian white noise. Since the mean value of white noise is zero, the integral feedback loop can remove the effect of these noise signals from the estimation. The actual, measured, and estimated terminal voltage of the Li-ion cell using the IC-SE method is shown in Fig. 8. The cell model of the IC-SE algorithm was initialized 60% SoC, where the actual cell was at 50%. The results demonstrate that the

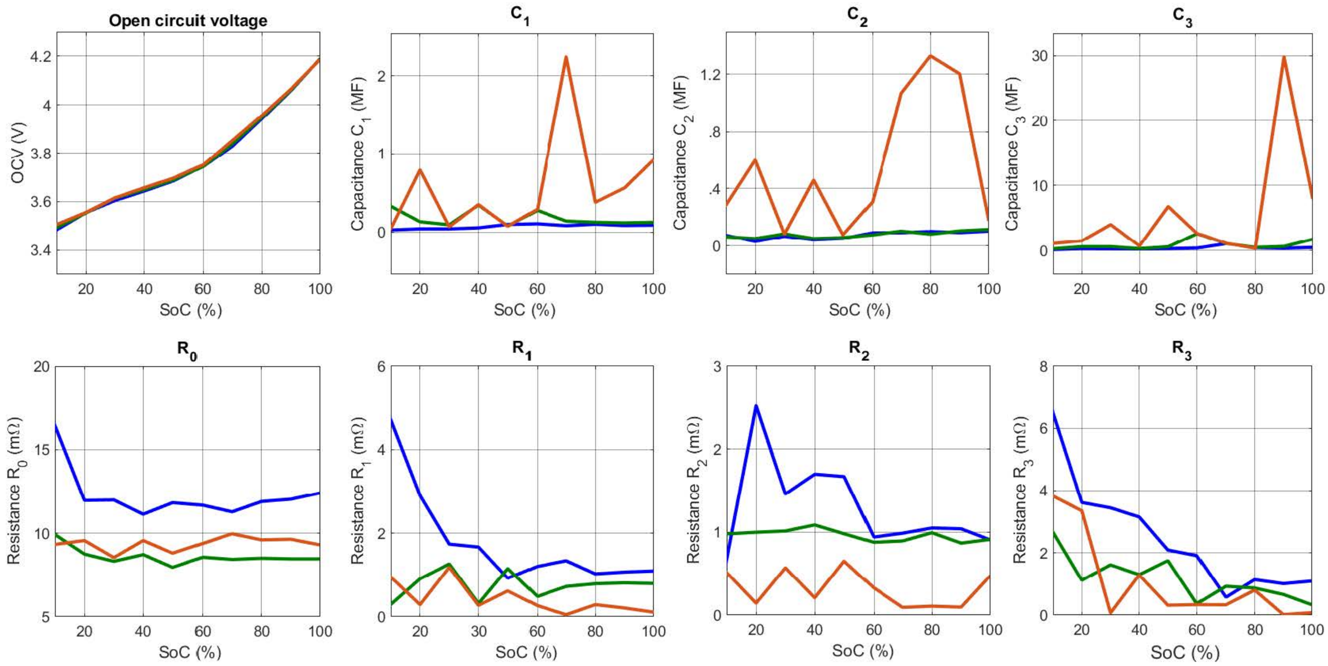

FIGURE 9. The equivalent circuit parameters identified by cell characterization at three different temperatures. Figure shows open circuit voltage, three diffusion capacitance, cell internal ohmic resistance and three diffusion resistances plotted against SoC. blue, green, red lines indicates the parameter values at temperatures 5°C, 25°C and 40°C respectively.

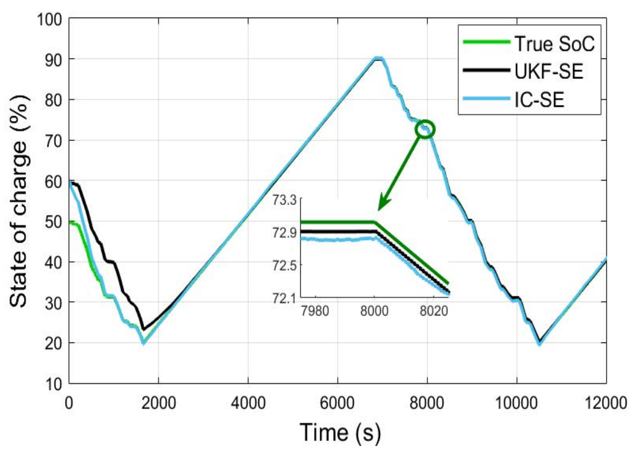

FIGURE 10. Comparison of SoC estimation results for first cycle of the Li-ion cell by IC-SE and UKF-SE.

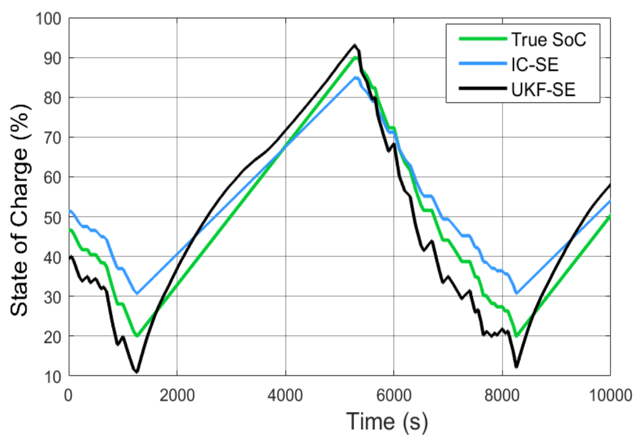

FIGURE 11. Comparison of SoC estimation results after 300 charge-discharge cycles of the Li-ion cell by IC-SE and UKF-SE.

IC-SE method can predict the actual terminal voltage while accounting for initial SoC errors and measurement noise.

A UKF-based estimation algorithm is run alongside the IC-SE method to compare performance. The SoC estimation results for IC-SE and UKF-SE are shown in Fig. 10. The results show that, during fresh cell conditions, both IC-SE and UKF-SE provide very good estimation results. The UKF-SE method corrects the initial SoC error taking around 3000s, where IC-SE takes only 1000s. The UKF-SE is able to track SoC with 0.5% error and IC-SE tracks SoC with less than 0.7% error.

When the cell cycles and degrades, the model parameters deviate from the actual cell parameters. Since SoC estimation relies on the cell model, these model errors can contribute to high SoC estimation errors. Fig. 11 shows the performance of IC-SE and UKF-SE for the same cell after 300 charge-discharge cycles. In degraded conditions, IC-SE is able to limit the errors between -11% to 8%, whereas UKF-SE has error levels between -5% to 11%. The IC-SE and UKF-SE have estimated SoC RMS errors of 6% and 5%. SoC estimation results after 300 cycles have a significant error in estimated SoC. Most of the time, both IC-SE and UKF-SE fail

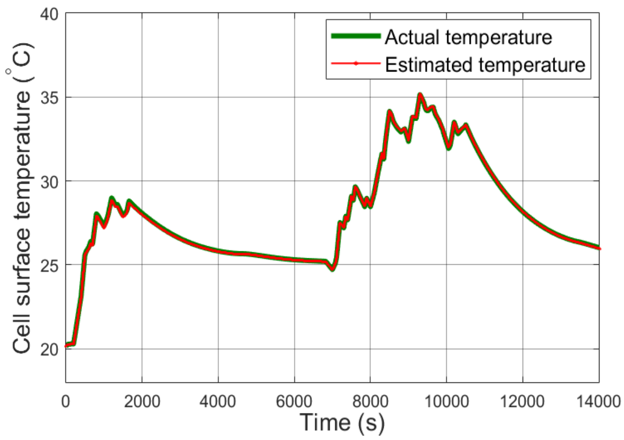

FIGURE 12. Li-cell surface temperature and cell temperature estimated by the temperature observer.

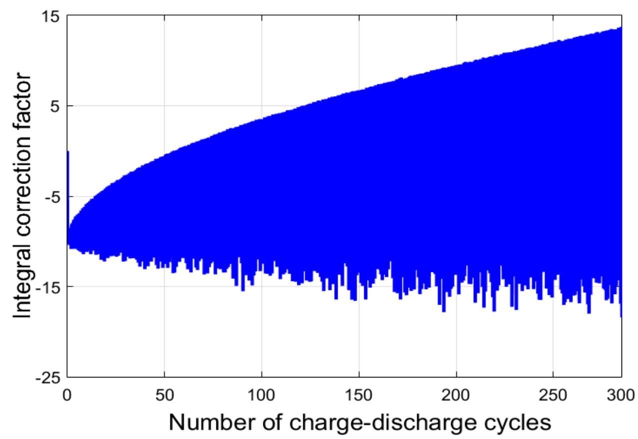

FIGURE 14. Integral correction factor changes for a degrading cell from its first cycle to 300th cycle.

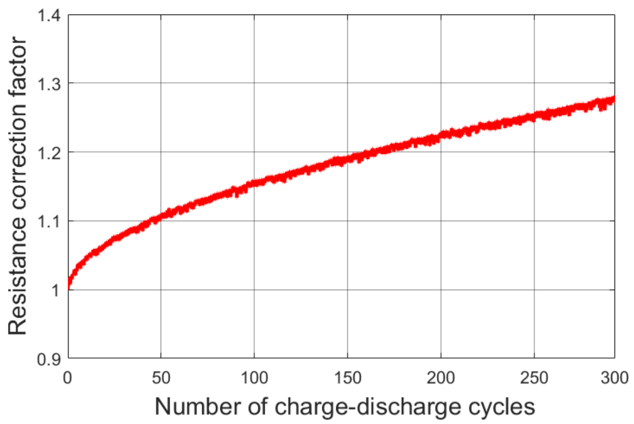

FIGURE 13. Evolution of resistance correction factor when cell cycled upto 300 cycles.

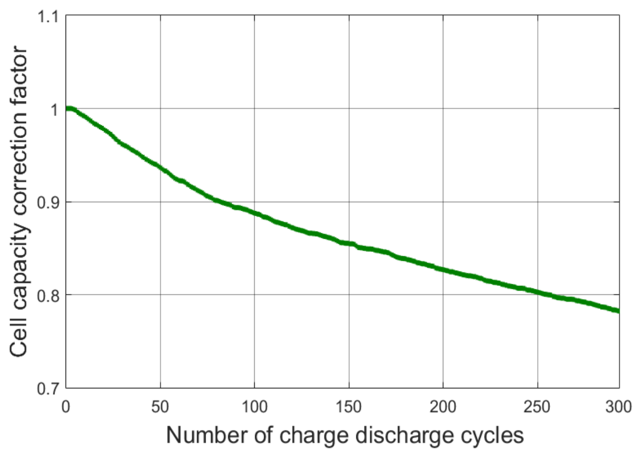

FIGURE 15. Evolution of cell capacity factor when cell cycled upto 300 cycles.

in tracking the actual SoC. The SoC estimation errors have reached an unreliable level.

To improve the accuracy of SoC estimation, model parameters have to be updated to match the degrading cell. Resistance correction loop and cell capacity correction loop are added to IC-SE to form an adaptive integral correction SoC estimator. AIC-SE has the ability to change to suit changing conditions using the parameter correction loops.

Fig. 12 shows the estimated and actual temperature at the cell surface. The temperature estimator is able to track the Li-ion cell surface temperature by correcting the model resistance values by using the resistance correction factor. Fig. 13 shows the evolution of the resistance correction factor from 0-300 cycles. The resistance correction factor, M_R is multiplied with initial model resistance values for modifying the model parameters. The resistance correction factor starts at 1 and reaches around 1.3 by the end of the 300th cycle.

To compensate for the capacity loss during the cyclic degradation process, the cell capacity correction loop is used. As the actual cell parameters deviate from the model parameters, the control effort introduced by the IC-SE integral correction loop increases. The deviation of the integral correction factor for a degrading cell is shown in Fig. 14 for the IC-SE method. It can be seen that the amplitude of oscillations in integral correction factor is increasing with number of charge-discharge cycles. The deviation from integral correction factor from its average value over that cycle is utilized for correcting the cell capacity variation. When the deviation from mean Z_c is given to the capacity correction loop to calculate the capacity correction factor. Fig.15 shows the evolution of cell capacity correction factor. As the cell degrades, the cell capacity correction factor decreases. This correction factor is used for updating the model cell capacity.

Resistance correction loop and capacity correction loop is combined with IC-SE method to form an adaptive integral correction SoC estimation method. This AIC-SE method is applied for estimating SoC along with IC-SE and UKF-SE methods. Fig. 16 shows the AIC-SE estimated and actual terminal voltage of the cell after 300 charge-discharge cycles. The results show that the proposed AIC-SE algorithm is able to capture the cell dynamics quite accurately even after 300 cycles. The resistance and capacity correction loops in the algorithm help the model parameters to change and suit the cell conditions.

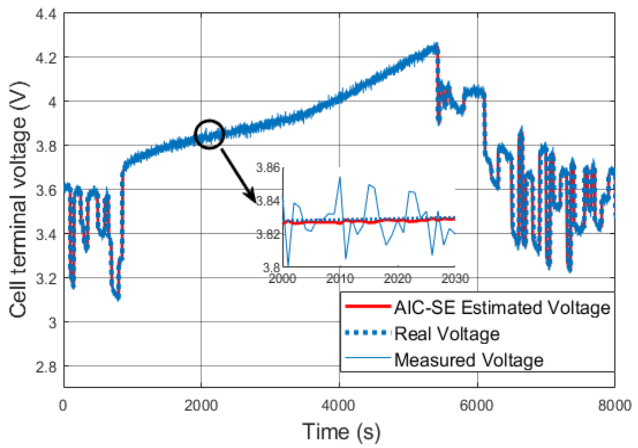

FIGURE 16. Modeled terminal voltage of Li-ion cell for the 300th cycle by AIC-SE.

The SoC estimation results for the proposed AIC-SE method, as well as UKF-SE and IC-SE, for the 300th charge-discharge cycle of the Li-ion cell, are shown in Fig. 17. The proposed AIC-SE method is able to track the SoC of the cell with RMS errors limited to less than 0.25% for the entire charge-discharge cycles. The maximum error in the estimated SoC is also limited to −0.4% to 0.8%.

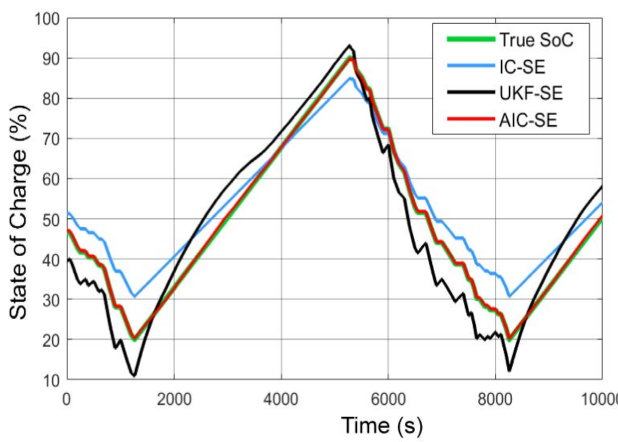

FIGURE 17. SoC estimation results for AIC-SE, IC-SE and UKF-SE for 300th cycle.

Table 2 lists the performance comparison of proposed AIC-SE with UKF-SE, IC-SE, data-driven methods, and co-estimation method from the literature. It can be seen that the proposed adaptive integral correction method provides excellent SoC estimation accuracy for degrading cells. The performance of data-driven-based SoC estimation methods is highly dependent on the amount and quality of training data. Reference [51] use the estimated SoC to calculate the present cell capacity, which limits the maximum error only to 1%. In sliding mode-based SoC estimation [49], the estimation error is 2%. The maximum SoC estimation error in the proposed adaptive estimation method is only 0.8%, whereas in existing methods it is greater than 1%. In the proposed method the RMS SoC estimation error is only 0.3%, whereas in existing methods RMS error is greater than 0.5%.

TABLE 2. SoC estimation performance comparison.

Estimation method	RMS SoC estimation error (%)	Maximum SoC estimation error(%)
AIS-SE	0.3%	0.8%
IC-SE	6%	11%
UKF-SE	5%	11%
Data-driven [56]	1.68%	5%
Data-driven [54]	0.55%	1.4%
[51]	0.5%	1.1%
Data-driven [59]	0.9%	3.5%
Data-driven [60]	0.9%	2%

V. CONCLUSION

In this paper, an adaptive integral correction-based estimation method is proposed for estimating the SoC of lithium-ion cells while accounting for model parameter uncertainties caused by cyclic degradation. The proposed method uses a third-order equivalent circuit model with an integral correction-based SoC estimation and a simple thermal model of the Li-ion cell for temperature estimation. The effect of parameter variation is corrected by introducing two additional correction factors, resistance correction factor and capacity correction factor. These correction factors update the equivalent circuit model to form an adaptive integral correction-based SoC estimation technique that can compensate for the effect of parameter variation caused by cyclic degradation. Simulation results verify the capability of the proposed AIC-SE method. Under the aging condition, where the unscented Kalman filter and simple integral correction method fail to estimate accurately, the proposed adaptive integral correction-based SoC estimation method predicts the SoC of the Li-ion cell with great accuracy. In comparison with UKF, which has an error of 11%, the proposed AIC-SE method has a significant improvement in estimation accuracy. In AIC-SE method, the maximum SoC estimation error observed was around ±0.8%, and the RMS error was less than 0.3%. Future works may focus on the applications of AIC-SE algorithm in distributed BMS systems, and also to calculate the SoH of Li-ion batteries.

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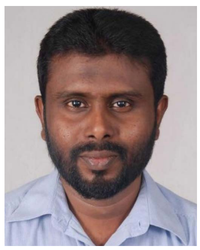

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