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Estimation of State of Charge in Electric Vehicle using the Battery Digital Twin

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***Abstract*—The Electric Vehicle (EV) industry comprises several sub-domains currently dominating the research areas following the trends of green energy and sustainable development. One such sub-domain is Battery Management Systems (BMS). In the case of EVs, BMS includes the Sensory unit, State Estimation of the battery, Protection circuitry etc. The State of Charge (SOC) estimate of any battery gives users a metric to determine how long a battery would survive. Thus, accurate estimation of SOC becomes significant. The accurate measurement and implementation of SOC algorithms include several steps, from battery modelling to validation of algorithms and hardware implementation. Therefore, this paper proposes a thorough methodology for estimating SOC by simulating lithium-ion cell 21700 LGM50 using a battery's digital twin. This paper aims to explore the accuracy of Coulomb Counting (CC) and Extended Kalman Filter (EKF) with a rigorous discussion on true SOC. In addition to this, the convergence of EKF with unknown initial SOC is discussed. The wholesome methodology in this work can help in designing better BMS-related algorithms in future without initial hardware investment.**

***Index Terms*—BMS, SOC, Li-ion, PyBaMM, Coulomb Counting, True SOC, Extended Kalman Filter**

I. Introduction

Lot of research is being carried out in the last ten years to address issues like pollution, energy crisis, climate change etc. The current research area which is gaining importance is Electric vehicle (EV) as it comes under the Zero-Emission Vehicles (ZEV) thereby reducing pollution. In EV, the most important part is the battery. It is responsible for storing energy for the system. A system used to monitor, utilise and optimise the battery properly in the EV is the battery management system. The battery management System (BMS) is responsible for estimating the proper State of Charge (SOC), State of Health (SOH) and State of Power (SOP) of the battery and provide safety measures. It ensures that corrective actions are taken during abnormal conditions in the system. Hence testing this battery and the BMS under several conditions is very critical. Yet, no such quick analysis procedure can analyse it completely.

The procedure-oriented estimation of SOC involves several steps such as battery data acquisition for battery modelling, which in this paper is based on Hybrid Pulse Power Characterization (HPPC) test and constant current discharge test performed using LGM50 cell's digital twin on Python Battery Mathematical Modelling (PyBaMM) platform. Then, the data is deployed to estimate the RC parameters of the battery. Further, these parameters are given as input to filter-based algorithms. Then the validation of algorithms outputs the error and accuracy of SOC estimation. However, the estimated SOC must be compared with the true SOC to determine the error and accuracy. Thus, the true SOC must be acquired reasonably. The section II below explains how the existing research addresses SOC estimates in both a modular and integrated manner. The detailed implementation overview of all the steps above is presented in this paper sequentially in section III. In section IV, error comparison of implemented algorithms along with other results are discussed. Fig. 1 shows the block diagram of the system.

II. Literature Survey

Battery SOC is a crucial state estimation of any battery chemistries like Lithium ion, Lithium Iron Phosphate (LFP) and Nickel Manganese Cobalt (NMC). State of Charge estimation indicates to the EV user whether the battery can be used or should be charged and builds a foundation for other state estimates of a battery [1]. In recent research, the primary classification of SOC estimation algorithms is done based on if they are conventionally used, like current integration in Coulomb Counting (CC), Adaptive Filter based algorithms like Extended Kalman Filter (EKF), Machine Learning based algorithms, Non-Linear Observers, and upcoming Hybrid Algorithms [1].

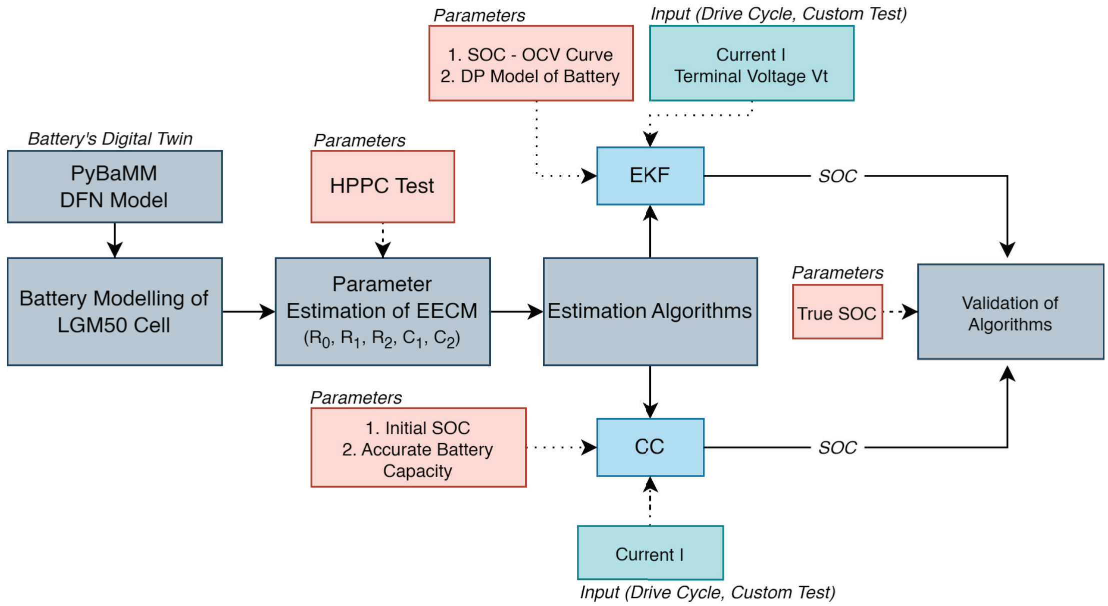

Fig. 1. Block diagram of the Methodology

Coulomb Counting or Ampere-Hr integral method is the easiest way to obtain battery SOC in which charging or discharging current is integrated over time. This method is helpful with the prerequisite of known initial battery capacity and discharging/charging coulomb efficiency. The technique has a drawback of accumulation error and requires precise current measurement with accurate initial SOC value [2], [3]. A review of the comparison of Kalman Filter (KF) family-based algorithms suggests the efficient development of each filter-based algorithm. It states EKF as the most preferred method to estimate battery SOC, working on the principle of linearisation of nonlinear functions [2]. The author has shown that EKF performs well with an error magnitude of less than 5% when implemented with Hardware-in-the-loop (HIL) [4], [5]. Results of [5] show the independence of EKF on initial SOC value, measurement and process noise.

The filter-based algorithms form the requirement of representation of the battery in the form of battery parameters to do the battery modelling. Datasets are available online. Recently developed platforms based on any battery's digital twin allow researchers to conduct tests and experiment independently. One such platform is PyBaMM, an open-source Python package that can solve standard electrochemical battery models. Considering electrical and electrochemical battery modelling as two categories, electrochemical models further subdivide into single particle models or the Doyle-Fuller-Newman model (DFN). The DFN model provides a deep understanding of the battery's physical parameters and can accurately predict battery ageing and experimental outputs [6].

After obtaining the experimental data, representing the battery as an electrical circuit is vital for filter-based algorithms. Two major approaches that are used for this are the identification of offline and online parameters. Offline parameter identification obtains the parameters as a function of SOC through experiments under specific working conditions; one such experiment is the HPPC test. It is responsible for the estimation of the dynamic characteristics of the battery, with the help of real-time measurement and updating the battery voltage by charging and discharging cycles over particular intervals [7], [8]. This test allows the calculation of parameters required to linearise the complex non-linear model of the battery, accelerating the simulation process. This data is then used for modelling the RC model that can mimic the battery during simulation and testing. These parameters are not constant for a battery as they keep changing due to the ageing of the battery [9]. One problem faced due to such offline parameters is that they rely on several experiments, which require long development cycles and increased costs. The amount of time and several experiments increase the error in the SOC estimation. On the other hand, online parameter estimation acquires the parameters related to the present battery state from the latest inputs, increasing the speed and accuracy of SOC estimation.

After the parameter estimation and algorithmic design, the accuracy of algorithms should be validated with accurate techniques and correct reference SOC. In the case of the validation part of the algorithm, various drive cycles are designed and used in various research works. The work in [10] proposes a Dynamic stress test (DST) to emulate the discharging of EV to validate proposed algorithms. The author in [4] validates the proposed EKF using multiple test conditions such as DST, Urban Dynamometer Driving Schedule (UDDS) and Federal Urban Driving Schedule (FUDS). In [5], UDDS and Highway Fuel Economy Test (HWFET) drive cycle emulate the city and highway driving conditions to compare CC and EKF algorithms with added sensory noise. Thus, different tests are used according to the application for validating estimation algorithms.

III. Methodology and Design

The PyBaMM library is a battery mathematical modelling tool used for fast battery simulations [11]. CasADi is used heavily for nonlinear optimisation and algorithmic differentiation coupled with PyBaMM [12]. The DFN model, an electrochemical-based model for lithium-ion batteries, is used to predict the current and voltage response of the battery accurately [13]. The work proposed in the paper uses the test data for a single cylindrical LG M50 lithium-ion cell [14]. The cell's specifications are shown in Table I. The battery simulation is performed in PyBaMM and the test data is collected. The test data consists of constant current discharge test, HPPC test, drive cycles and Custom test. All these steps are explained in section III-A.

TABLE I
Specifications of LG M50 Cell

Specifications	Value
Nominal Capacity	5Ah
Nominal Voltage	3.6V
Maximum Charge Voltage	4.2V
Cut-off voltage	2.5V

A. LG M50 Cell Model

The Electrochemical model (ECM), Electrical Equivalent Circuit model (EECM) can be used for lithium-ion battery modelling. ECMs have high modelling complexity and high cost of computation due to the need to solve non-linear differential equations. Hence, ECMs are inappropriate for online SOC estimation [3]. EECMs better approximate the cell's behaviour with less computational cost than other models, such as physical models [1]. Double Polarized (DP) model has better accuracy and dynamic performance than other EECMs for modelling lithium-ion batteries [15]. The DP model is shown in Fig. 2.

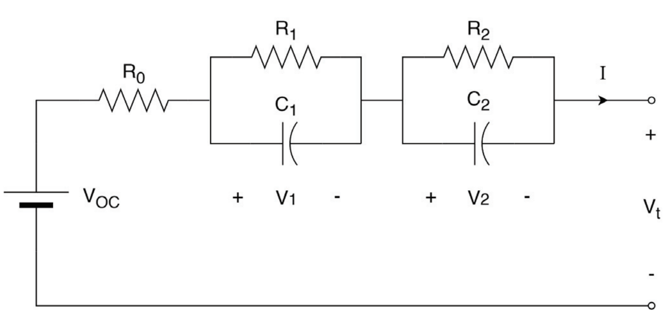

Fig. 2. DP Battery Model

The DP model consists of three elements: open circuit voltage, resistances R_0, R_1, R_2, and capacitances C_1 and C_2 to simulate the transient behaviour of the cell. All these parameters are functions of SOC and temperature [16]. Here, all tests are performed considering a cell is kept at room temperature of 25^o. Hence R_0, R_1, R_2, C_1 and C_2 are now functions of SOC only. The DP model equations are:

$$\dot{V_1} = -\frac{V_1}{R_1 C_1} + \frac{I}{C_1} \quad (1)$$

$$\dot{V_2} = -\frac{V_2}{R_2 C_2} + \frac{I}{C_2} \quad (2)$$

$$V_t = V_{OC} - V_1 - V_2 - IR_0 \quad (3)$$

Here $\dot{V_1}$ and $\dot{V_2}$ denote the derivative of voltage with respect to time.

B. Parameter estimation

Four types of tests are simulated in PyBaMM to find battery parameters and to get voltage and current data for the drive cycle and Custom test.

The first constant current discharge test is conducted to get the non-linear relation between SOC and open circuit voltage (OCV). The fully charged cell is discharged at a C/20 rate (C is the nominal capacity of the cell). The OCV values in the 4.2V – 2.5V obtained from the PyBaMM Model are then normalised to 100% – 0% scale as SOC. The SOC-OCV relationship is shown in Fig. 3.

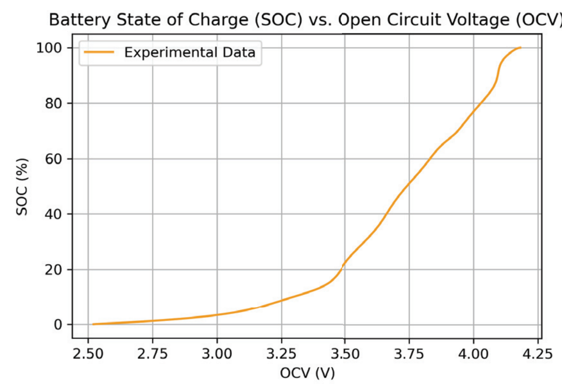

Fig. 3. SOC-OCV Relationship

This relationship between the SOC and OCV can be considered a high-precision method for SOC estimation [2]. The SOC can be found by interpolating the plot in Fig. 4 for a particular value of OCV.

HPPC is conducted to calculate DP model parameters as a function of SOC. A fully charged cell is discharged at 1C for 3 minutes and rested for 60 minutes. This step is repeated till the cell is fully discharged. The current and voltage profiles are shown in Fig. 4. The parameter extraction is done in MATLAB and numerical optimisation is performed [17].

UDDS drive cycle and a Custom test are conducted to evaluate the performance and accuracy of the SOC estimation algorithms. The current profile of UDDS is shown in Fig. 5.

The Custom test involves charging and discharging for various C rates and rest periods. The time intervals of charge

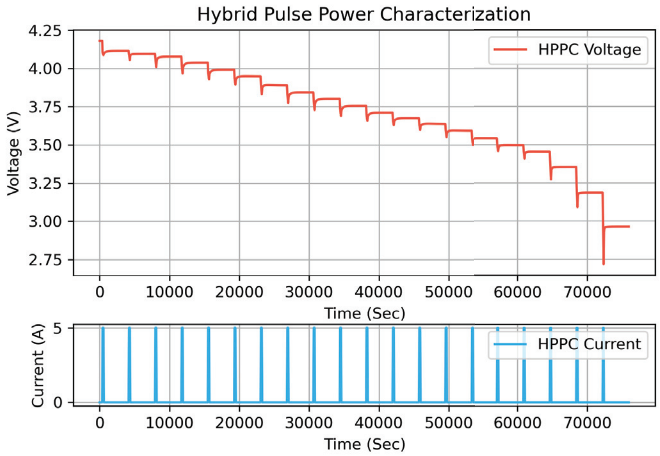

Fig. 4. HPPC Current and Voltage Profile

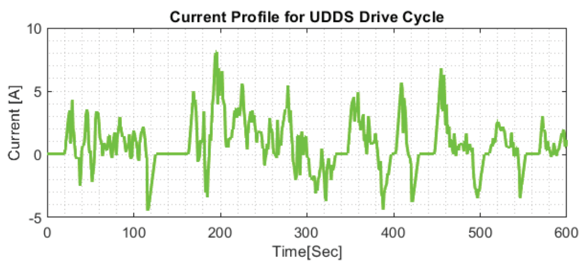

Fig. 5. UDDS Current Profile

and discharge can be customised according to the number of voltage points required for specific validation purposes to obtain better results. The Custom test helps evaluate algorithms' performance over a long time interval. The cell is discharged at 0.4C rate for 8 minutes, rested for 5 minutes, charged at 0.25C rate for 2 minutes, and rested for 5 minutes. This cycle is repeated four times, and then the cell is discharged at 0.4C for 15 minutes, rested for 60 minutes and then charged at 0.4C rate for 15 minutes. This whole cycle is repeated until the cell is fully discharged. The current profile for this Custom test is shown in Fig. 6.

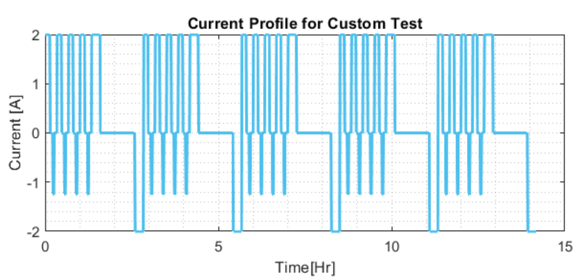

Fig. 6. Custom Test Current Profile

C. Coulomb Counting (CC)

The LG M50 cell is rated at 5Ah, so the cell can hold $5 * 3600 = 18000C$. By measuring the current, the consumed charge can be calculated. Then the SOC is found by dividing the used charge over the total charge the battery can store. After adding or subtracting that from the initial SOC, SOC as a function of current and time is calculated.

$$SOC(k) = SOC(k-1) - \frac{I \times \Delta t}{5 * 3600} \tag{4}$$

Where $SOC(k)$ denotes the SOC at k^{th} time interval and $SOC(0)$ represents the initial known SOC of the cell. And I is the measured current in time interval Δt in seconds.

D. Extended Kalman Filter (EKF)

Kalman Filter (KF) estimates the states of dynamic systems considering the measurement and process noise. EKF is an extended version of the Kalman filter which linearises the non-linear behaviour of the measurement related to the process [18].

The non-linear state space model of the battery is as follows:

$$x_{k+1} = A_k x_k + B_k u_k$$
$$y_k = C_k x_k + D_k u_k$$

Where x_{k+1} is the state vector at time k+1, with states as $x = [SOC, V_1, V_2]$, input $u_k = i_k$ and output $y_k = V_t$. The A, B, C, D matrices are :

$$\text{A=} \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{R_2 C_2}} \end{bmatrix}, \text{ B = } \begin{bmatrix} -\frac{\Delta t}{Q} \\ R_1(1 - e^{-\frac{\Delta t}{R_1 C_1}}) \\ R_2(1 - e^{-\frac{\Delta t}{R_2 C_2}}) \end{bmatrix},$$

$$\text{C = } \begin{bmatrix} \frac{\partial V_{OC}}{\partial SOC} & -1 & -1 \end{bmatrix}, \text{ D = } R_0$$

The symbol $\wedge$ represents an estimate, $|k$ represents a predicted estimate and $|k+1$ represents an updated estimate.

Prediction:

1.Predict the states:

$$\hat{x}_{k+1|k} = A_k \hat{x}_{k|k} + B_k u_k$$

2.Predict the error covariance :

$$P_{k+1|k} = A P_{k|k} A^T + Q_k$$

Where P is the covariance of the measurement error and Q is the covariance of the process.

Correction:

1.Compute Kalman Gain

$$K_{k+1} = P_{k+1|k} C^T (C P_{k+1|k} C^T + R_{k+1})^{-1}$$

2.Update the estimate with measurement y_k

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(y_{k+1} - C\hat{x}_{k+1|k})$$

3.Update the error covariance

$$P_{k+1|k+1} = (1 - K_{k+1} C) P_{k+1|k}$$

As the relation between OCV vs SOC is non-linear, the only non-linear matrix among the state space Equations is the C matrix.

During each iteration, state matrix x is updated and the SOC is predicted as it is the first element of the matrix x.

E. True SOC

True SOC or Reference SOC is a SOC value of a battery that is considered to validate any SOC estimation algorithm. SOC-OCV relationship is regarded as an accurate method of SOC estimation, as discussed in section III-B. True SOC becomes challenging because open circuit voltage can't be continuously measured. In most of the literature, true SOC is not appropriately addressed while calculating the error of the SOC estimation algorithm. So, it becomes necessary to acquire the reference SOC reasonably.

Conventionally, CC can be used as reference SOC for short interval tests, accurately knowing the cell's capacity. But CC itself has the disadvantage of accumulation error in the long-time test. Further, SOC using OCV is also an excellent measure of true SOC, but the cell must rest for 1-2 hours to get a steady state OCV value [19]. In this paper, PyBaMM's DFN model continuously calculates the open circuit voltage for a given drive cycle and Custom test. These OCV points are linearly interpolated on Fig. 3 to get the true SOC. Hence true SOC is obtained, which can be used to calculate the error and compare the estimation algorithms.

IV. Results and Discussion

The performance of algorithms is evaluated using a short-time test and a long-time test.

A. Short-time Test (UDDS)

For the short-time test, UDDS is performed. The SOC estimated using CC, and EKF are shown in Fig. 7 and the error plot is shown in Fig. 8. This test is conducted assuming the initial SOC is known.

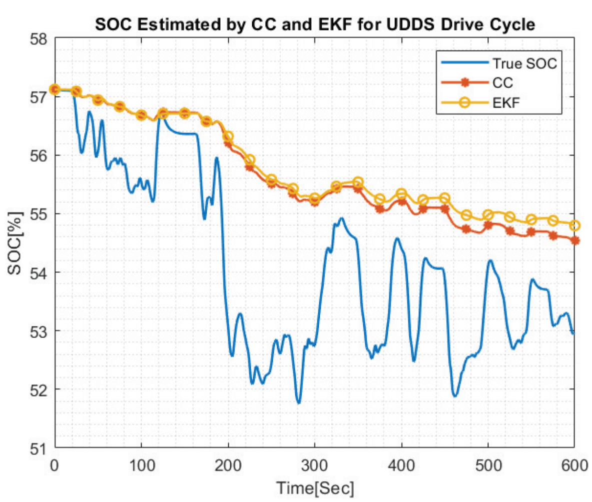

Fig. 7. SOC comparison for UDDS

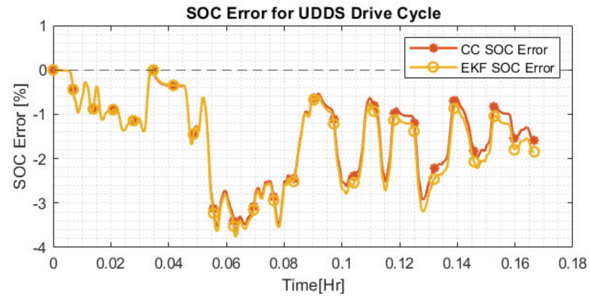

Fig. 8. Error graph for UDDS

CC performs slightly better than EKF in this short-time 600 seconds UDDS test with Root Mean Square Error (RMSE) of 1.8535% and Mean Average Error (MAE) of -1.6839% as shown in Table II. This supports the claim in section III-E that CC can approximate true SOC in hardware-based systems provided accurate current measurements, precise cell capacity and known initial SOC. The MAE is negative because the SOC estimated by CC is more than the true SOC most of the time.

TABLE II
Error Comparison for UDDS

	CC	EKF
RMSE (%)	1.7736	1.8824
MAE (%)	-1.4991	-1.6028
Max. Error (%)	3.6499	3.7631

B. Long-time Test (Custom Test)

For the long-time test, the Custom test is performed for about 14 hours. This test is conducted assuming the initial SOC is known. The SOC estimated using CC and EKF is shown in Fig. 9 and the error plot is shown in Fig. 10. EKF performs better than SOC in this long-time test with an RMSE of 1.29%, as shown in Table III.

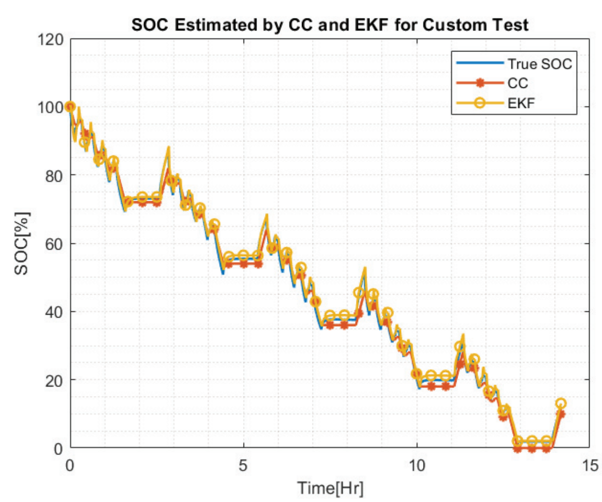

Fig. 9. SOC comparison for Custom Test

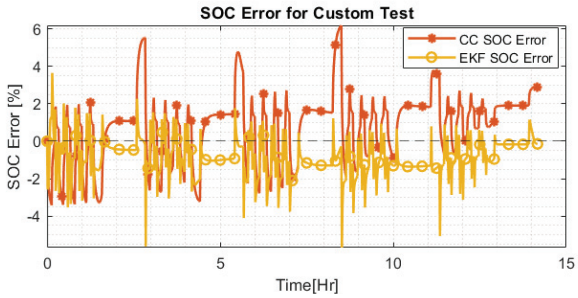

Fig. 10. Error graph for Custom Test

Though CC performs better than EKF in the short-time test, as shown in section IV-A, in the long run, it performs poorly due to the accumulation of errors, as mentioned in section II.

TABLE III
ERROR COMPARISON FOR CUSTOM TEST

	CC	EKF
RMSE (%)	1.9950	1.2957
MAE (%)	0.8287	-0.8697
Max. Error (%)	6.1982	5.6876

C. Custom Test with unknown initial SOC

CC requires a good guess of the initial SOC. CC is just an integration, so it does not converge to the true SOC value. But EKF provides a robust solution for the estimation of SOC. Even if the initial SOC is unknown, EKF converges close to the true SOC value.

In the next experiment, the test starts from precise initial SOC as 100%. The initial guess is taken from 0%- 100% in increments of 10% and the Custom test is performed. The RMSE for EKF is shown in Table IV. This result shows that, even if the initial guess is incorrect by 100%, the RMSE error in the estimation is 5.3430% using EKF, while CC is incapable of converging to true SOC due to its dependence on accurate initial SOC value.

As per comparison, CC performs well on short-time tests, but in the case of long-time Custom test, EKF estimates SOC more accurately and the convergence of EKF is discussed.

TABLE IV
ERROR COMPARISON FOR UNKNOWN INITIAL SOC FOR EKF

Initial SOC(%)	EKF RMSE(%)	CC RMSE(%)
90	2.4001	10.9797
80	1.4610	20.9076
70	1.6591	30.8220
60	1.8827	40.8690
50	2.1425	50.8610
40	2.7192	60.8557
30	2.7372	70.8519
20	3.0247	80.8490
10	3.9202	90.8468
0	5.3430	100.8450

The most critical factor in a hardware-based system is determining the true SOC for error calculation. But, in this paper, the ability to measure OCV continuously helped in validating CC as a measure of true SOC for short-time tests. A wholesome integration methodology of SOC estimation using PyBaMM and DFN model of LG50 cell is suggested with a detailed overview of each step in Section II. This aids in battery modelling, designing, tuning algorithms, and validating them on the primary level without any immediate investment.

V. CONCLUSION

In the proposed work SOC estimation mechanism, integrated with PyBaMM's experiment-conducting features, allows for flexible data acquisition of various battery chemistries. This work introduces a battery's digital twin using PyBaMM, which also facilitates the execution of numerous SOC estimation stages. A question regarding true SOC is addressed to compare the suggested CC and EKF algorithms' errors on UDDS and Custom test drive cycles. Although EKF is a reliable algorithm for SOC estimate in the long-time test, CC is identified to be matching the true SOC value in the short-time test. Hence, EKF is suitable for EV applications, whereas CC can be a good approximate of true SOC for validating different algorithms in short-time interval. EKF's performance is evaluated using an unknown initial SOC, and EKF converges quickly to offer SOC estimation. As a result, a comprehensive approach to SOC estimate is suggested while considering some vital design and validation information.

VI. FUTURE SCOPE

The work in the paper can be further expanded as –

- The designed and validated algorithms using PyBaMM can be further optimised and tuned to deploy on hardware in a real-time environment. Actual results in a real-time environment can be compared to simulation results obtained from PyBaMM drive cycle tests.
- The suggested methodology can be reused to analyse and perform tests on different types of battery chemistries in PyBaMM to evaluate the performance of cells.
- Simulating the model for different temperatures in PyBaMM, the temperature dependence of SOC can be observed.

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