2023 International Conference for Advancement in Technology (ICONAT)
Goa, India. Jan 24-26, 2023

State-Of-Charge Estimation using Extended Kalman Filter

Rakshita Hiremath
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
rakshitahiremath09@gmail.com

Sanjana Hulakund
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
sanjanahulakund186@gmail.com

Varshita R. Torgal
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
varshitatorgal5@gmail.com

Anupkumar Patil
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
anupkumar@kletech.ac.in

Hanumanthagouda R. Patil
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
hrpatil@kletech.ac.in

A B. Raju
Electrical and Electronics Engineering
KLE Technological University
Hubballi, India
abraju@kletech.ac.in

2023 International Conference for Advancement in Technology (ICONAT) | 978-1-6654-7517-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICONAT57137.2023.10080761

***Abstract*—In recent years, there has been a lot of effort into developing electric vehicle systems. It discusses the research design, function, and administration of batteries since a Battery Management System (BMS) is essential for guaranteeing the safe and dependable use of electrical energy stored in Li-ion batteries. In order to enhance system reliability and prolong battery life, most battery systems seek an accurate state-of-charge (SOC) estimation. This paper aims at analysing the lithium-ion battery performance for various battery currents using a model-based design methodology. The SOC of a lithium-ion battery cell is estimated using an Extended Kalman Filter (EKF) algorithm by measuring the cell voltage and cell current. This pertains to a single cell. Similarly, it is implemented for three identical lithium-ion cells. The outcome of the EKF model shows the effectiveness and ease of implementation of the proposed technique.**

***Index Terms*—State-Of-Charge(SOC), Extended Kalman Filter, Li-ion Battery, model-based design, Battery Management system(BMS), Battery current rating.**

I. Introduction

The popularity of electric vehicles is surging. A rechargeable high-voltage battery is a driving force for electric and hybrid electric vehicles. Different kinds of batteries are used to power electric vehicles depending on the characteristics of the battery. Hence there is a high demand for Lithium-ion batteries due to their higher energy density, higher cell voltage, and longer lifetime than regular batteries. But there is a risk of fire under unusual conditions (high temperature, low temperature, over-charge, over-discharge, etc). To ensure the safety of the user as well as the vehicle, it is important to operate the vehicle under safety limits. Therefore, the Battery Management System (BMS), which keeps track of the rechargeable batteries is a highly important factor in ensuring the safety of the electric vehicle [1]. For the safety, high reliability, and efficiency of the battery system, it is necessary to estimate accurate and instantaneous battery status information, such as State of Charge(SOC) and State of Health (SOH). This data should be provided to the operator through the BMS.

The Open-Circuit Voltage (OCV), Ampere-Hour Integral, EKF, and Fuzzy Neural Network are a few popular methods for estimating SOC [2]-[4]. The voltage versus SOC curve of Lithium batteries is generally flat, due to which a small change in voltage may lead to a large SOC change at the operating range. Therefore, SOC estimation should not be performed only by the open-circuit voltage method or load voltage method [5]. The direct lookup of terminal voltage in the OCV versus SOC table gives a very poor estimate of cell SOC.

The traditional Ampere-hour integration method yields current-based SOC estimation. This method produces smooth SOC change for a short period of operation when initial conditions are known [6]. Over time, uncertainty / error bounds increase (without limit) until the estimate is reset. This subject to drift in the accurate estimation of SOC is due to the current sensor's fluctuations, current-sensor bias, incorrect capacity estimate, and other losses. The optimum estimate criteria used in Kalman filtering is the minimal mean square error [7] . The estimation value of the current instant is obtained by updating the observed value of the current instant and the estimation value of the previous instant using the state space model of signal and noise. The statistical properties of both measurement noise and system noise must be known in advance for the conventional Kalman filter to give optimal estimation. However, the real system exhibits a large amount of unpredictability, making it challenging to exactly define the noise characteristics, which degrades the estimation accuracy.[8]

II. Model of the Battery

A. Battery Equivalent Circuit Model

The EKF is a model-based method, which indicates that accuracy is dependent on the battery model [9]. In this paper, we make use of a second-order RC model to make a trade-off between the model's accuracy and computation complexity.

Second-order RC model consist of capacitors, resistances, and a voltage source. Where R_0 is ohmic resistance. R_{p1},R_{p2} are polarization resistances. And C_{p1},C_{p2} are polarization capacitances.

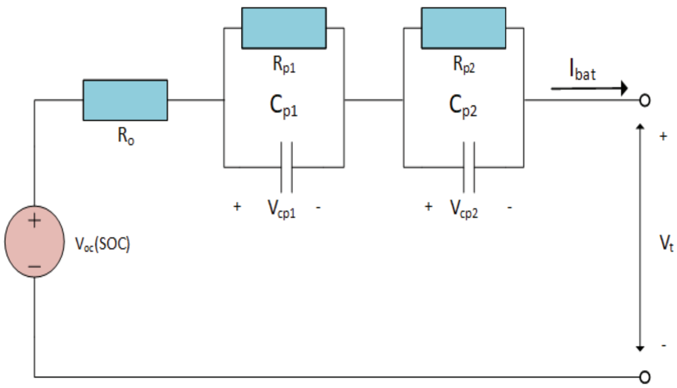

Fig. 1. Equivalent circuit model of a battery.

State space equation of second order RC model is given as,

$$\begin{cases} \bar{V_{p1}} = [-1/(R_{p1}C_{p1})]\, V_{cp1} + (1/C_{p1})\, I_{bat} \\ \bar{V_{p2}} = [-1/(R_{p2}C_{p2})]\, V_{cp2} + (1/C_{p2})\, I_{bat} \\ S\bar{O}C = (-1/Q_n)I_{bat} \\ V_t = V_{oc}(\text{SOC}) - V_{p1} - V_{p2} - R_0\, I_{bat} \end{cases} \tag{1}$$

Equation (1) in Matrix from,[10]

$$\begin{pmatrix} \bar{V_{p1}} \\ \bar{V_{p2}} \\ S\bar{O}C \end{pmatrix} = \begin{pmatrix} -1/(R_{p1}C_{p1}) & 0 & 0 \\ 0 & -1/(R_{p2}C_{p2}) & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} V_{p1} \\ V_{p2} \\ SOC \end{pmatrix} + \begin{pmatrix} 1/C_{p1} \\ C_{p2} \\ -1/Q_n \end{pmatrix} I_{bat}$$

The relationship between $(V_{oc})_i$ and SOC_i in between i.Δ_{SOC} and (i-1).Δ_{SOC} is approximated by linearization function as follows:

$$V_{oc}(\text{SOC}) = a_i.\text{SOC} + b_i \tag{2}$$

Equation(1) can be written as

$$\bar{x} = Ax + Bu + w \tag{3}$$

$$\bar{y} = Cx + Du + v \tag{4}$$

where $A = \begin{bmatrix} -1/(R_{p1}C_{p1}) & 0 & 0 \\ 0 & -1/(R_{p1}C_{p1}) & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$B = \begin{bmatrix} 1/C_{p1} \\ 1/C_{p2} \\ -1/Q_n \end{bmatrix}$ $\quad C = \begin{bmatrix} 1 & 1 & a_i \end{bmatrix}$ $\quad D = R_0$

x = $[V_{cp1} \quad V_{cp2} \quad SOC]^T$ is the state vector.

Here w, and v represents system noise and sensor noise respectively. They are assumed to be white, and independent with normal distribution. A refers to the system noise covariance matrix and C refers to the sensor noise covariance matrix, and minimum covariance is assumed. [11],[12]

B. Parameter assessment of the battery

For the purpose of developing an equivalent circuit model for a particular battery cell, battery parameters are estimated. This may be accomplished using a cell's pulse charge/discharge test. The performance of the battery at diverse SOC values is calculated using the data gathered from these tests. As a result, the cell may now be further characterized, resulting in the development of a model that can be used to simulate the battery module and optimize the battery for a variety of uses. One of the important aspects to take into account while characterizing Li-ion batteries is internal resistance. The IEC 62660-1 standard specifications are followed while conducting a test for pulse discharge to estimate internal resistance. Ten-second duration of pulses is produced at different SOCs with amplitudes of 20%, 50%, and 80%. Fig 2 describes the developed Simulink model to perform the pulse discharge test. The cell's internal parameters have been computed by performing a pulse-discharge test on it and calculated for different SOCs. [13] The calculated parameters are displayed in the Table I.

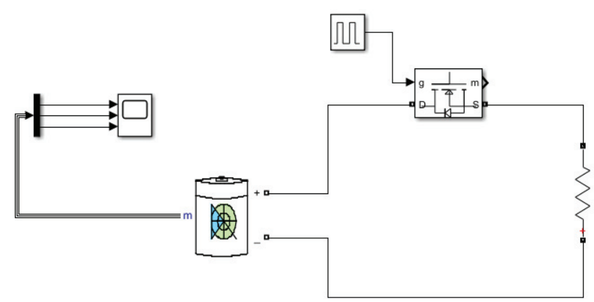

Fig. 2. Pulse discharge test Simulink model

TABLE I
ESTIMATED BATTERY PARAMETER

R0(Ω)	R1(Ω)	R2(Ω)	C1(F)	C2(F)
0.01	0.01	0.01	30000	68000

III. METHODOLOGY

The estimator in Fig. 3 can be employed to determine SOC when combined with the known model parameters, observations, and data from the battery voltage and current.

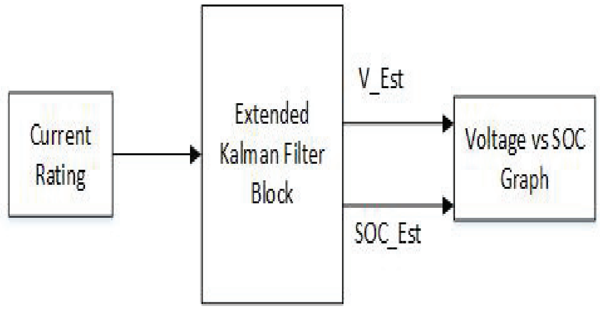

Fig. 3. EKF Block Diagram for Battery SOC Estimation

Fig. 3 depicts the overall representation of the entire model. The input refers to the cell voltage, and cell current (at room temperature). State Space representation is the central aspect of the Extended Kalman Filter model. Furthermore, the output contains the estimated battery voltage and the expected state of charge.

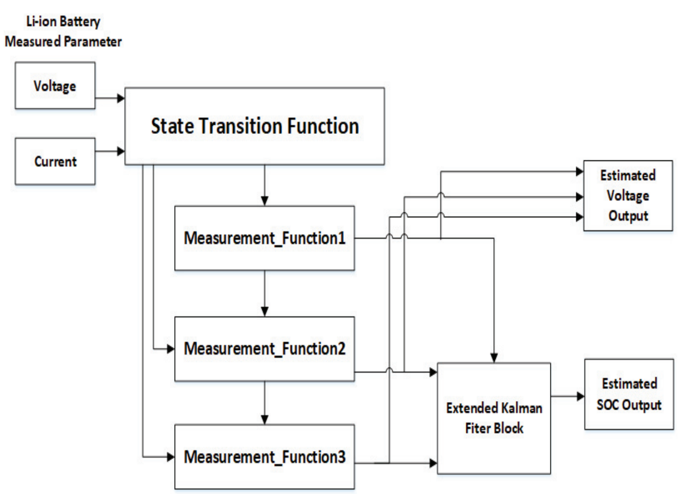

Fig. 4. Detailed representation of Extended Kalman Filter

Fig. 4 describes a detailed explanation of the Extended Kalman filter model.

Battery current measurement is necessary to determine the battery SOC based on the Coulomb counting approach. A lot of measuring noise and inaccuracy is present in current measurements, which is unfortunate. During vehicle operation, the noise and distortions from the current measurement will accumulate in the SOC calculation, which will have an impact on how the car manages its energy and batteries. Here, we introduce EKF to lessen the impact of measurement error on SOC predictions. The initial SOC's dependency can be reduced in the meantime. The Kalman filter commonly used applications are Target tracking, global positioning, navigation, and communication, a well-known method for estimating the state of a dynamic system. [14] The EKF model consists of two functions in the state space modeling of the cell.

A. State Transition Function

Through the sensors, the external parameters of the cell can be calculated. But it is impossible to forecast the cell's intrinsic properties. In order to assess the battery's state of charge, we use the EKF model to anticipate the internal drop in the cell. In the MATLAB function of state transition model, the equations described are as follows:

$$U(1) = X(1)\, exp\,(\frac{1}{R_{p1}\, C_{p1}}) + I_{batt}[1 - exp\,(\frac{R_{p1}}{C_{p1}})] \quad (5)$$

$$U(2) = X(2)\, exp\,(\frac{1}{R_{p2}\, C_{p2}}) + I_{batt}[1 - exp\,(\frac{R_{p2}}{C_{p2}})] \quad (6)$$

$$U(3) = X(3)\, - 100\,(\frac{I_{bat}}{Q_n\, 3600}) \quad (7)$$

Consequently, we may estimate the voltage losses across the cell using these equations.
Considering,

Covariance matrix $= \begin{bmatrix} 1e^{-}3 & 0 & 0 \\ 0 & 1e^{-}3 & 0 \\ 0 & 0 & 1e^{-}2 \end{bmatrix}$

and Initial Covariance matrix $= [1e^{1}]$

B. State Measurement Function

We apply the measurement function in order to measure the estimated voltage drops. Here, the values from the state vector are used. The open circuit voltage is therefore approximated. This pertains to a single cell. Similarly, three li-ion cells are employed in the battery and computed from equation (4).

Considering the initial Covariance Matrix = [2e-1]

IV. Results

A. Actual Volatge and EKF Estimated Volatge versus Time

The results of Actual Voltage and Estimated Voltage are plotted with respect to time, and the corresponding Mean Absolute Error(MAE) is determined by the following equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |(V_{actual})_i - (V_{estimated})_i|$$

Fig. 5 and 6 shows the Actual voltage (from the conventional SOC-OCV look-up table) vs. time as well as the extended Kalman filter (EKF) estimated voltage vs. time. When current is flowing through the battery is 2.8A and 5.6A the corresponding voltage mean absolute error as 2.58% and 4.54% respectively.

The observed outcomes for battery current rating (C rating) and 2C rating are illustrated in the Table II.

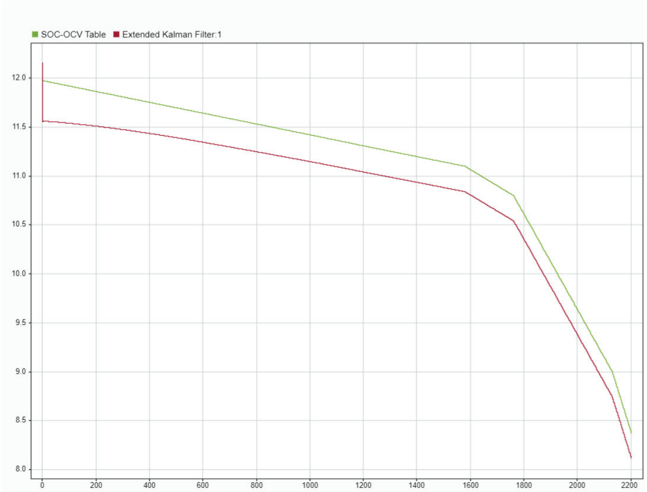

Fig. 5. Actual voltage and EKF predicted voltage versus time at a battery current of 2.8A .

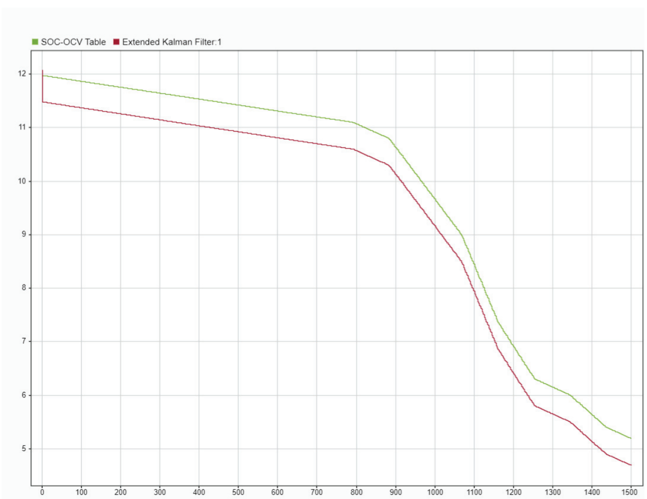

Fig. 6. Actual voltage and EKF predicted voltage versus time at a battery current of 5.6A.

TABLE II
MAE % BETWEEN ACTUAL VOLTAGE AND ESTIMATED VOLTAGE

Battery Current (A)	Mean Absolute Error (%)
2.8	2.58
5.6	4.54

B. Battery Voltage versus SOC

Depending on the degree of charge, the voltage at their terminals either drops or rises. The battery's voltage will be at its greatest point when fully charged and at its lowest point when completely discharged.

Fig.7 and 8 depicts the relationship between the battery voltage and SOC at 2.8A and 5.6A respectively.

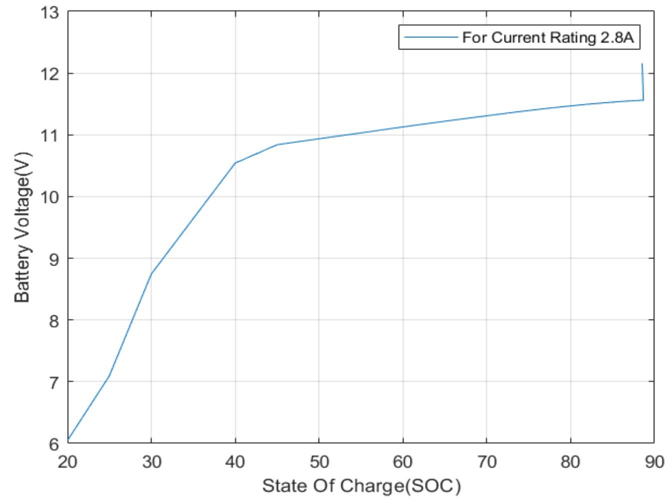

Fig. 7. Battery voltage versus EKF Estimated SOC at a battery current of 2.8A

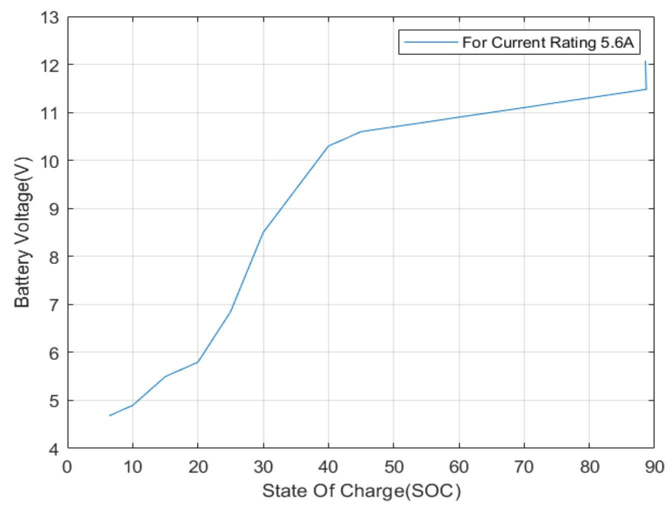

Fig. 8. Battery voltage versus EKF Estimated SOC at a battery current of 5.6A

C. Time versus EKF estimated SOC

If a battery discharges in T time for a C rating (current rating) at 20% SOC, then a 2C rating must discharge almost T/2 times.

Fig. 9 shows the relationship between Time and EKF estimated SOC. It can be observed that at 20% SOC, for a battery current (C rating) of 2.8A, the time taken to discharge is 2459 (T) sec.

Fig. 10 shows the relationship between Time and EKF estimated SOC. It can be observed that at 20% SOC, for a battery current (2C rating) of 5.6A, the time taken to discharge is 1253 (T/2) sec.

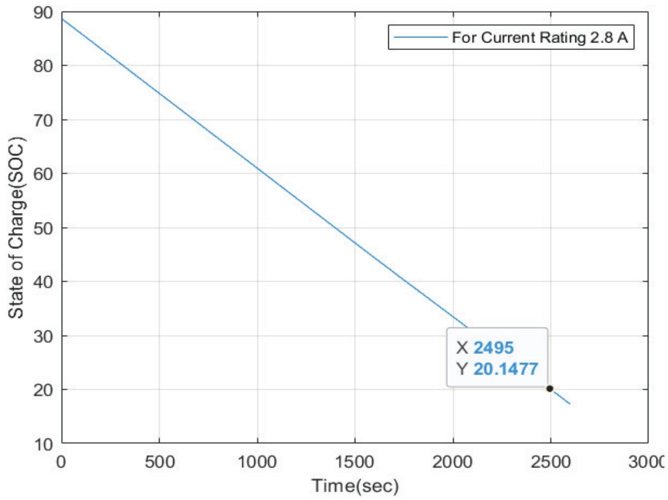

Fig. 9. Time versus EKF estimated SOC at a Battery current of 2.8A.

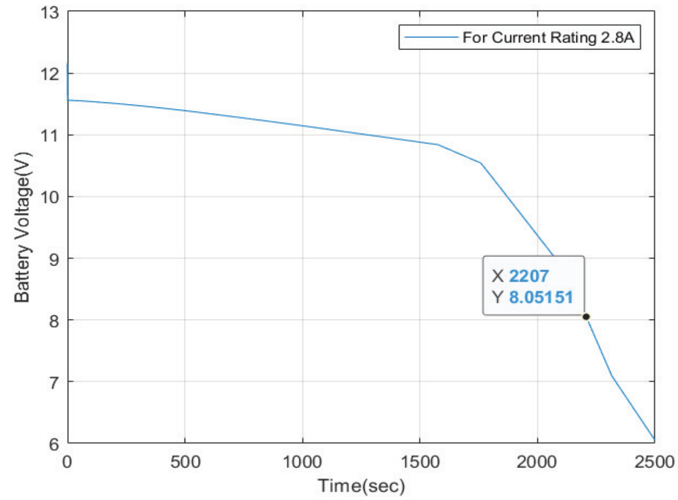

Fig. 11. Time versus EKF estimated voltage at a Battery current of 2.8A.

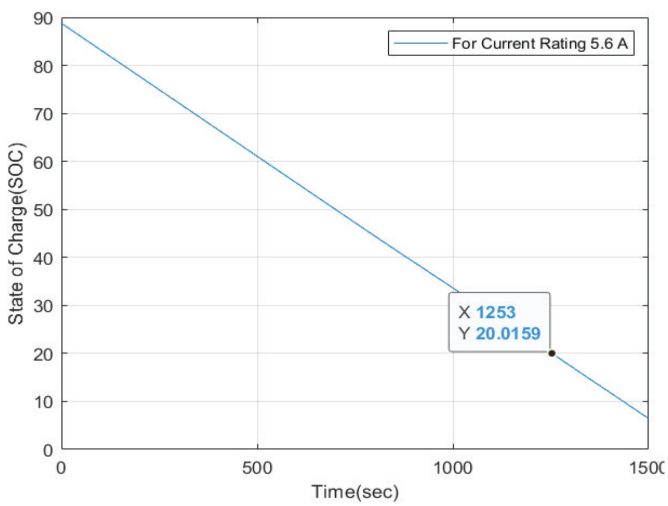

Fig. 10. Time versus EKF estimated SOC at a Battery current of 5.6A.

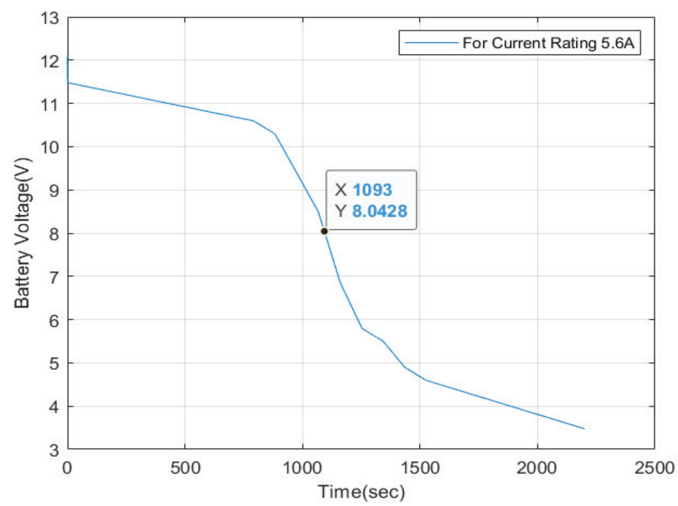

Fig. 12. Time versus EKF estimated voltage at a Battery current of 5.6A.

D. Time versus EKF estimated Voltage

If a battery discharges in T time for a C rating (current rating) at 8 V, then a 2C rating must discharge in almost T/2 times.

Fig. 11 shows the relationship between Time and Battery Voltage. It can be observed that at 8V, for a battery current rating (C rating) of 2.8A, the time taken to discharge is 2207 (T) sec.

Fig. 12 shows the relationship between Time and Battery Voltage. It can be observed that at 8V, for a battery current rating (2C rating) of 5.6A, the time taken to discharge is 1093 (T/2) sec.

V. CONCLUSION

For estimating the SOC of lithium-ion batteries, equivalent circuit model-based techniques are feasible, and EKF is an effective SOC estimator. However, the lithium-ion battery system is dynamic when it is in use, making it difficult to apply offline methodologies to parameter identification. This study presents the implementation of an EKF-based SOC estimation algorithm. A nonlinear battery model is developed by designing a two-order RC circuit in series with an open circuit voltage. The proposed model uses the EKF method to determine the battery SOC. The results for three li-ion cells demonstrate how the proposed algorithm works to estimate the battery voltage and SOC.

References

[1] A. Eddahech, O. Briat and J. -M. Vinassa, "Real-time SOC and SOH estimation for EV Li-ion cell using online parameters identification," 2012 IEEE Energy Conversion Congress and Exposition (ECCE), 2012, pp. 4501-4505, doi: 10.1109/ECCE.2012.6342209.

[2] O. Caumont, P. L. Moigne, C. Rombaut, et al. "Energy gauge for leadacid batteries in electric vehicles." Energy Conversion, IEEE Transactions on 15.3 (2000): 354-360.

[3] S. Antoni, and Y. Chang. "Battery management system based on battery nonlinear dynamics modeling." Vehicular Technology, IEEE-https://www.overleaf.com/project/637dde028951ecece20e3560 Transactions on 57.3 (2008): 1425-1432.

[4] G. L. PLETT. "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification." Journal of power sources, 2004, 134(2): 262-276.

[5] M. Charkhgard, and M. Farrokhi. "State-of-charge estimation for lithium-ion batteries using neural networks and EKF." Industrial Electronics, IEEE Transactions on, 2010, 57(12): 4178-4187.

[6] Zhang, Xin Hou, Jiawei Wang, Zekun Jiang, Yueqiu. (2022). Study of SOC Estimation by the Ampere-Hour Integral Method with Capacity Correction Based on LSTM. Batteries. 8. 170. 10.3390/batteries8100170.

[7] X. Lin, "Theoretical Analysis of Battery SOC Estimation Errors Under Sensor Bias and Variance," in IEEE Transactions on Industrial Electronics, vol. 65, no. 9, pp. 7138-7148, Sept. 2018, doi: 10.1109/TIE.2018.2795521.

[8] X. Yan, Y. Yang, Q. Guo, H. Zhang and W. Qu, "Electric vehicle battery SOC estimation based on fuzzy Kalman filter," 2013 2nd International Symposium on Instrumentation and Measurement, Sensor Network and Automation (IMSNA), 2013, pp. 863-866, doi: 10.1109/IMSNA.2013.6743414.

[9] J. Feng, F. Cai, J. Yang, S. Wang and K. Huang, "An Adaptive State of Charge Estimation Method of Lithium-ion Battery Based on Residual Constraint Fading Factor Unscented Kalman Filter," in IEEE Access, vol. 10, pp. 44549-44563, 2022, doi: 10.1109/ACCESS.2022.3170093.

[10] P. Spagnol, S. Rossi and S. M. Savaresi, "Kalman Filter SoC estimation for Li-Ion batteries," 2011 IEEE International Conference on Control Applications (CCA), 2011, pp. 587-592, doi: 10.1109/CCA.2011.6044480.

[11] Y. Tian, D. Li, J. Tian and B. Xia, "A comparative study of state-of-charge estimation algorithms for lithium-ion batteries in wireless charging electric vehicles," 2016 IEEE PELS Workshop on Emerging Technologies: Wireless Power Transfer (WoW), 2016, pp. 186-190, doi: 10.1109/WoW.2016.7772089.

[12] G. Aggoun, R. Mansouri and D. O. Abdeslam, "SOC estimation based on OCV and online identification parameters of lithium ion batteries with ADALINE," 2016 8th International Conference on Modelling, Identification and Control (ICMIC), 2016, pp. 538-543, doi: 10.1109/ICMIC.2016.7804171.

[13] B. H. N, K. Desai, L. M. Biradarpatil, R. Navalur, S. S and V. M. Satawalekar, "Modeling of a power converter and investigation into EV battery optimal sizing and parameter estimation for charger stability," 2022 3rd International Conference for Emerging Technology (INCET), 2022, pp. 1-6, doi: 10.1109/INCET54531.2022.9824775.

[14] A. Lotfivand, D. Yu and B. Gomm, "State Of Charge estimation using Extended Kalman Filter in Electric Vehicles," 2022 27th International Conference on Automation and Computing (ICAC), 2022, pp. 1-5, doi: 10.1109/ICAC55051.2022.9911137.