

# Extended Kalman Filter based SOC estimation of Lithium-Ion Battery

*Girisha Joshi*\*

Nitte (Deemed to be University), Department of Electrical and Electronics Engineering, NMAM Institute of Technology (NMAMIT), Nitte, Karnataka, India. \*Email: girishjoshi85@nitte.edu.in

**Abstract.** Battery Management System (BMS) is an electronic unit used for safety, durability and maintaining the performance of a rechargeable battery. It has become an integral part of modern batteries. Key functions of the BMS are Battery monitoring, Battery control and communication. Battery monitoring unit monitors the cell temperature, voltage and current. Battery control takes care of cell balancing, calculation of state of charge (SOC) and state of health (SOH) and control unit communicates the gathered information. In this work the focus is on estimation of state of charge using extended Kalman filter. SOC is estimated for a given drive cycle at different temperatures and compared it with the SOC estimated using the coulomb counting method. To calculate the actual SOC, SOC-OCV relationship for the given battery is made use.

Keywords—EV, C rate, SOC, SOH, BMS, HPPC

## 1 Introduction

Energy storage systems will play a crucial role in the success of any renewable energy source power plant, transformation of internal combustion engine-based vehicles to electric vehicles. Battery storage is one of the preferred and most used types of energy storage systems. The auxiliary battery used in conventional internal combustion engines is Lead-acid battery. The energy density of this type of battery is 30-50 Wh/kg. Its life span will range from 3-5 years.

For this rating of the batteries' weight of lead acid battery unit will be several hundred kilograms. Due to the continuous efforts in minimizing battery weight/Wh and increasing the life span have evolved the Lithium-ion batteries. The energy density of lithium-ion batteries ranges from 150 Wh/Kg to 250 Wh/kg. This will result in three to five times the reduction of battery weight. Also, the life span of the batteries is 8-10 years. Due to these advantages Lithium-ion batteries are widely used in Electric vehicles and other applications. Any invention or new finding will have drawbacks along with the advantages. Lithium-ion batteries also have serious disadvantages such as overheating. This leads to thermal runaway in the battery, where temperature rises uncontrollably resulting in even explosion of the battery. This undesirable characteristic raises serious concerns towards safety of the vehicles and passengers of the electric vehicles. The reason for overheating is overcharging, faster discharge rate and physical damage to the battery. Lithium-ion battery performance depends on the temperature also. The seasonal changes in the temperature also

affect the performance of the battery. In extreme cold weather the internal resistance of the battery increases, and efficiency will decrease. Similarly in extreme high temperatures for the normal or rated discharge rate itself of battery might lead to thermal runaway, putting the life of people using the battery under risk. This high dependencies of performance of the battery over operating conditions and usage profile brings in the necessity of monitoring the battery states and parameters on a continuous basis and ensure that battery is functioning safely. Due to this requirement almost every lithium-ion battery is associated with a monitoring and control device called a battery management system (BMS). It takes care of multiple functions like monitoring, protection, energy recovery during the operation of electric vehicles, computation secondary data to determine variables like SOC, SOH and depth of discharge (DOD). SOC indicates the amount of charge still available in the battery to the present maximum charge holding capacity of the battery. The present maximum charge holding capacity of the battery depends on the health of the battery. SOH is an indicator of the health of the battery which is defined as the ratio of maximum charge that could be stored in the battery to its rated charge holding capacity. Over the period, the SOH of the battery degrades. It depends also on the charging and discharging cycles completed by the battery. Only based on SOC one cannot estimate the duration of battery that could support a given application. For a brand-new battery whose SOH is 100% will take more time to charge and discharge to a particular level of SOC, compared to battery with lesser SOH say 70%.

Depth of discharge (DOD) is directly proportional to the amount of charge drawn from the battery. It can be defined as the ratio of charge removed from the battery to maximum charging capacity of the battery. At any given point in time the sum, depth of discharge and state of charge will be 100%. Lithium-ion battery manufacturers provide maximum depth of discharge in the range of 70% to 80%. Discharging the batteries above the specified maximum discharge limit will have a significant effect on the life of the battery.

To estimate SOC, it is essential to have a model of the battery [1]. One of the realistic methods of modeling is equivalent circuit models which are simple and able to represent dynamics. Once the equivalent circuit for a given battery is developed, equivalent circuit parameters need to be estimated[2]. Variables of equivalent circuit representing the battery could be categorized into two classes. Variables that widely change with charging and discharging of the battery like SOC, parallel branch voltages are called states. Other variables which do not change much or change slowly with charging and discharging fall under the category of parameters. The state of charge is an important state of the battery. SOC is expressed in percentages in the range 0% to 100%. 0% indicates the fully discharged state of the battery, whereas 100% SOC indicates the fully charged state of the battery. The capacity of the battery will be provided in the rating of the battery. There are different methods available to estimate the SOC of the battery like coulomb counting, SOC-OCV, Kalman filter, Extended Kalman filter, fuzzy logic-based methods and artificial intelligent based methods[3]. Coulomb counting is one of the simplest methods that could be used for SOC estimation in battery management systems used in electric vehicles[4]. Here it is essential that one should know the initial SOC. Current supplied to or drawn from the battery is measured using a high precision current sensor. Integration of current and

time multiple over a period account for increase or decrease in the SOC. The accuracy of estimated SOC using coulomb counting method depends on the correctness of initial SOC and precision of the current sensor.

SOC-OCV plot provides the relationship between open circuit voltage and state of charge (SOC) of the battery. Open circuit voltage of the battery is the potential difference between positive and negative electrodes of the battery when external circuit is disconnected, either for charging or discharging and battery is at equilibrium state. This method is simple and straight forward. By having the values of SOC and OCV in the look up table (LUT), one can easily identify the SOC for given value of OCV[5]. But the challenge involved in the method is identifying the present OCV of the battery. Even when the battery is operated at lower C-rates, it takes hours to reach the equilibrium state. Till it reaches the equilibrium state the electrode potential difference will keep changing. This change in voltage and time taken to reach a steady state depends on the C-rate at which the battery is operating. Also, SOC-OCV relationships are temperature dependent. For a given SOC, open circuit voltage will be higher at low temperatures compared to higher battery temperature[6]. On the other hand, SOC-OCV relationships for charging and discharging are not the same. To simplify the model average of charging and discharging relationships are considered. Any error introduced while determining the OCV will introduce error in SOC estimation[7]. Since this method of SOC estimation cannot be implemented online, as external circuitry needs to be disconnected and battery takes a long time to reach equilibrium state, one cannot use this directly for estimating SOC in applications like electric vehicles or any other application where battery power is required on continuous basis [8] .

Due to the limitations of above-mentioned coulomb counting and SOC-OCV method of SOC estimations we cannot use them in practical applications. A procedure called Kalman filtering uses measurements taken over time to estimate some unknown variables. The Kalman filtering method is promising and performs well compared to conventional methods. Kalman filter is suitable for linear systems. Since the battery is a nonlinear system an improved version of the Kalman filter called extended Kalman filter is used in SOC estimation. Extended Kalman filter requires battery model in state space form and the model should be differentiable. In our work we have made two RC equivalent circuit models. The following sections will take through the battery model and algorithm used in implementing extended Kalman filter.

## **2 State-space model of two-RC equivalent circuit**

Extended Kalman Filter (EKF) requires the system model in state space form. In our work we have considered two RC equivalent circuit model to represent the functionalities of the battery. Figure 1 shows the two RC equivalent circuit model of Lithium-Ion Battery (LIB).

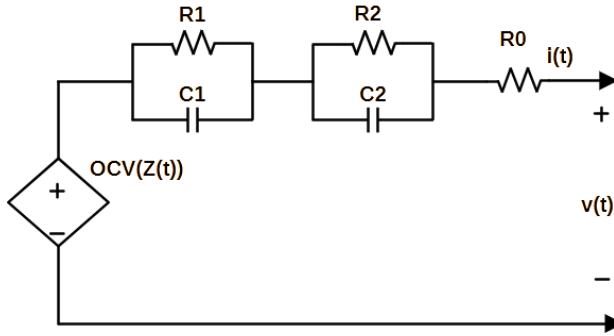


Figure 1. Two RC equivalent circuit model of LIB

In Figure 1.  $R_0$  represents internal resistance, OCV is the open circuit voltage,  $v(t)$  is the instantaneous value of terminal voltage,  $i(t)$  is the instantaneous value of current.  $R_1$ ,  $R_2$ ,  $C_1$  and  $C_2$  are the parallel branch resistances and capacitances of the model. The discrete state space model of this system representation is expressed as shown in below equations[9].

$$SOC(k + 1) = SOC(k) - \frac{\eta \Delta t i(t)}{C_n} \tag{1}$$

$$V_t(k) = OCV(k) - V_1(k) - V_2(k) - i(k)R_0 \tag{2}$$

$$V_1(k + 1) = \exp\left(\frac{-\Delta t}{R_1 C_1}\right) V_1(k) + R_1 \left(1 - \exp\left(\frac{-\Delta t}{R_1 C_1}\right)\right) i(k) \tag{3}$$

$$V_2(k + 1) = \exp\left(\frac{-\Delta t}{R_2 C_2}\right) V_2(k) + R_2 \left(1 - \exp\left(\frac{-\Delta t}{R_2 C_2}\right)\right) i(k) \tag{4}$$

In the above model  $i(k)$  is the input,  $\Delta t$  is the sample time,  $V_1(k)$  and  $V_2(k)$  are the voltage across the first and second parallel branches respectively at time step  $k$ .  $\eta$  is the coulomb efficiency. OCV( $k$ ) used in equation 2 is derived from the OCV-SOC plot for the given battery. OCV is a function of SOC and temperature. Equations 3 and 4 started from expression for currents in the capacitor  $C_1$  and  $C_2$  and equations rearranged and voltage across the two capacitors  $C_1$  and  $C_2$  expressed as shown in equation 3 and 4.

$$OCV = f(SOC, Temperature) \tag{5}$$

Above equations of state and output voltage can be represented in the state space form as follows.

Where  $x_{k+1}$  is the system state at  $k+1$  time step. The state variables of the system are

$$x_{k+1} = A_k x_k + B_k u_k \tag{6}$$

$$y_k = C_k x_k + D_k u_k \tag{7}$$

SOC, parallel branch 1 voltage  $V_1$ , parallel branch 2 voltage  $V_2$ .  $u_k$  is system input  $i_k$ . System output  $y_k$  is the terminal voltage.

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & \exp^{\frac{-\Delta t}{R_2 C_2}} \end{bmatrix} \quad (8)$$

$$B = \begin{bmatrix} -\frac{\Delta t}{Q} \\ R_1(1 - \exp^{\frac{-\Delta t}{R_1 C_1}}) \\ R_2(1 - \exp^{\frac{-\Delta t}{R_2 C_2}}) \end{bmatrix} \quad (9)$$

$$C = \begin{bmatrix} \frac{\partial V_{oc}}{\partial SOC} & \frac{\partial V}{\partial V_1} & \frac{\partial V}{\partial V_2} \end{bmatrix} \quad (10)$$

$$D = -R_0 \quad (11)$$

To obtain the SOC, OCV relationship, and other equivalent circuit parameters as mentioned Figure 1, Hybrid pulse power characterization (HPPC) test is performed at different temperatures. As a first step battery under test is fully charged so that it reaches 100% SOC. After the battery is fully charged, it is kept in the open circuit mode for 3-4 hours. This relaxation time is to ensure that battery reaches its equilibrium state. Now the battery is discharged at higher C-rate ensuring discharge current is not more than maximum permissible discharge current as specified in the datasheet. This is done for very short duration say 10 seconds. A relaxation time of the order of 10 minutes is provided to ensure the battery attains the equilibrium state. At this point of time battery terminal voltage is its open circuit voltage. For different SOC levels the above procedure is repeated to obtain OCV at that SOC level. Normally SOC is decreased from 100% to 0% in step of 10% during HPPC test. Once the battery reaches 0% SOC, the above procedure is repeated by increasing the SOC in step of 10%. The above test provides the information of charging or discharging current, terminal voltage, present SOC level, amount of charge removed or added to the battery. This information is made use in determining the equivalent circuit parameters of the equivalent circuit model used in representing the battery. As shown in equation (2) battery model contains the OCV as one of the variables, only HPPC test results could be used in estimating the parameters of equivalent circuit. Regular driving cycles of electric vehicles cannot be used for the purpose of parameter estimation. From these regular driving cycles, it is not possible to obtain information of open circuit voltage. Since any regular drive cycles like LA92 will not have relaxation time as the battery is continuously discharged in a specific pattern. In our work we have taken data of HPPC test and SOC-OCV information for Turnigy Graphene 5000mAh battery is obtained from the work carried out by Fauzia Khanum, etal[10].

### 3 Extended Kalman filter approach

The Kalman Filter is engineered to accurately estimate the state of a dynamic system within a noisy environment, characterized by its straightforward principles and user-friendly application. Kalman Filter variations, primarily the extended Kalman filter, have emerged in recent years.

(EKF) and unscented Kalman filter (UKF) are introduced for battery SOC estimation. The Unscented Kalman Filter (UKF) approximates the probability distribution using a deterministic sampling technique known as the unscented transform, whereas the Extended Kalman Filter (EKF) uses Jacobian matrices to linearize a nonlinear system [11], [12]

EKF algorithm consists of two steps, prediction and correction. The prediction phase forecasts a system's future state using its dynamic model, and the correction (or update) step adds real, noisy measurements to improve this projection. The main purpose of the prediction phase is to use the system's dynamic model and the previous state estimate to estimate the next state of the system, and the uncertainty (covariance) associated with that estimate. Prediction step has mainly functionalities such as state prediction, covariance prediction and continuity. In the absence of additional measurements, it projects the state estimate from the previous time step ( $k-1$ ) to the present time step ( $k$ ) using a (potentially nonlinear) state transition function. The uncertainty of the estimated state is represented by the a priori error covariance matrix, which is computed. This entails adding the process noise covariance, which takes into account outside disturbances or model errors, after linearizing the nonlinear system model using a Jacobian matrix. This prediction stage also has the feature of continuity. In applications like object tracking motion continuity is ensured by this phase. For instance, in object tracking, even if a sensor for instance briefly misses a detection (because of occlusion), the EKF can still provide a predicted location. By adding a fresh measurement from the system's sensors or observation devices, the correction phase—also known as the update phase corrects the expected state estimate. Correction stage has functionalities like innovation calculation, Kalman gain computation, state update and covariance update. This stage computes the residual, or difference, between the actual measurement and the estimated measurement. Kalman Gain is a weighting factor that indicates how much the forecasts should be revised based on the relative certainty of the prediction vs the new measurement, is calculated. A bigger gain from a more accurate measurement gives the measurement more sway on the final estimate. An improved, a posteriori corrected state estimate is obtained by combining the weighted innovation (residual) with the a priori anticipated state. The best predicted value for the current time step is produced as a result. It updates the error covariance matrix to reflect the reduced uncertainty after including the actual measurement, lowering the error covariance of the estimate. In essence, the EKF works in a perpetual cycle of "predict, measure, update, repeat" to continuously refine its grasp of a dynamic, nonlinear system's state [13], [14]. Figure 2. Shows the flowchart of extended Kalman filter prediction and correction process. It is important to have accurate model of the battery for the success of extended Kalman filter prediction. The work carried out in [15] has been referred for the two RC modelling of the lithium-ion battery.

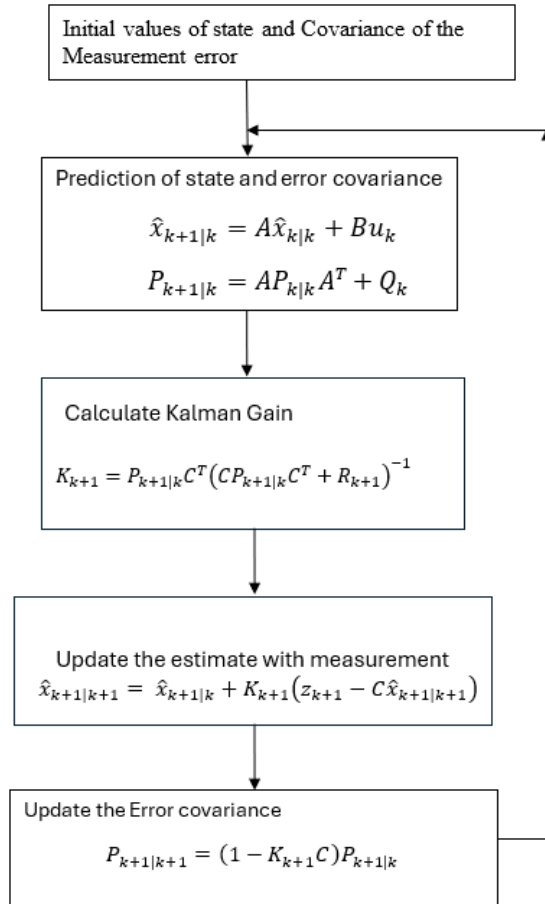


Figure 2. Flowchart of extended Kalman Filter

## 4 Results and discussion

Extended Kalman filter method of estimation is implemented in MATLAB. The information required are battery model, SOC-OCV relationship for the battery under test, Tunigy graphene and LA92 drive cycle data for different temperatures. SOC estimation is performed for different temperatures like -10 degree, 0 degree, 10 degree, 25 degree and 40 degree. SOC RMS errors and terminal voltage RMS errors are noted for different cases. Figure 3 to figure 7 shows the estimation of SOC over the drive cycle. These figures show the plot of SOC obtained from SOC-OCV, Coulomb counting and extended Kalman filter method. Figure 8 shows the SOC RMS error plots for different cases, considering SOC obtained from SOC-OCV plot as the reference. Figure 9 shows the RMS error of terminal voltage estimated using EKF compared to measured voltage data.

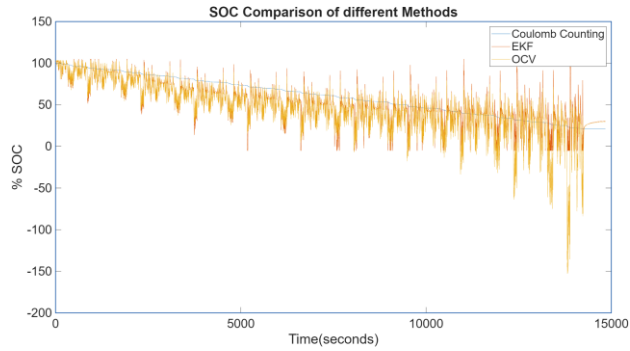


Figure 3. SOC estimation of Turnigy battery for LA 92 drive cycle at -10° Celsius using coulomb counting and Extended Kalman Filter methods

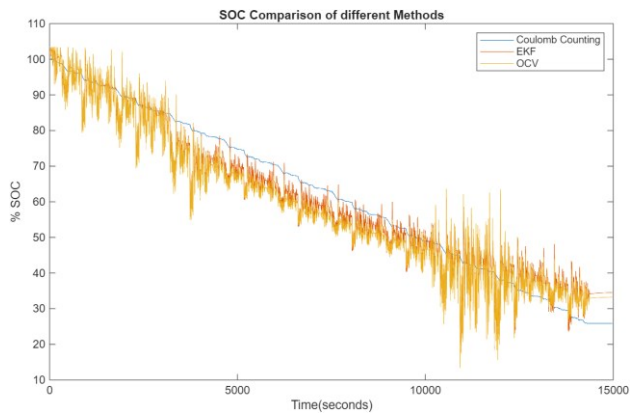


Figure 4. SOC estimation of Turnigy battery for LA 92 drive cycle at 0° Celsius using coulomb counting and Extended Kalman Filter methods

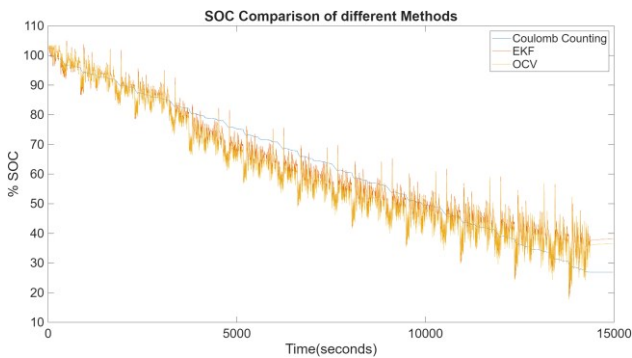


Figure 5. SOC estimation of Turnigy battery for LA 92 drive cycle at 10° Celsius using coulomb counting and Extended Kalman Filter methods

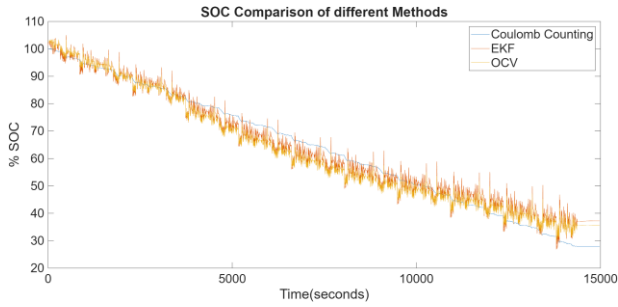


Figure 6. SOC estimation of Turnigy battery for LA 92 drive cycle at 25° Celsius using coulomb counting and Extended Kalman Filter methods

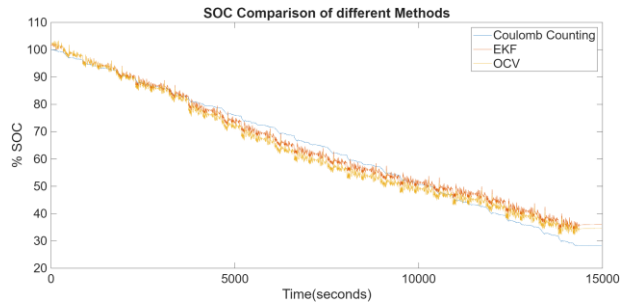


Figure 7. SOC estimation of Turnigy battery for LA 92 drive cycle at 40° Celsius using coulomb counting and Extended Kalman Filter methods

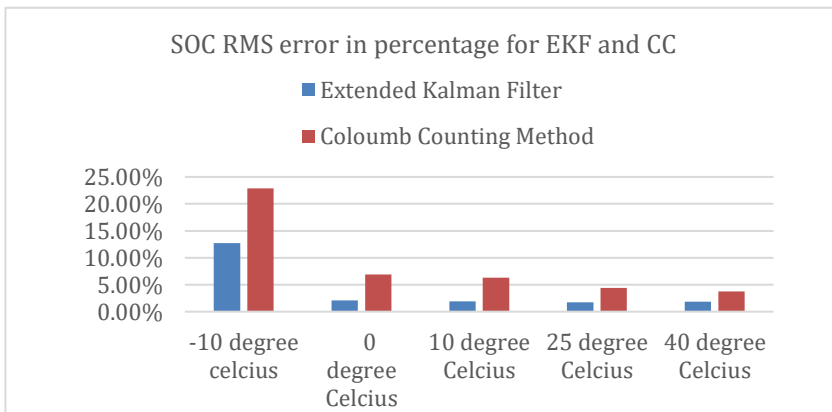


Figure 8. Bar chart of SOC RMS error in percentage for EKF and Coulomb counting methods

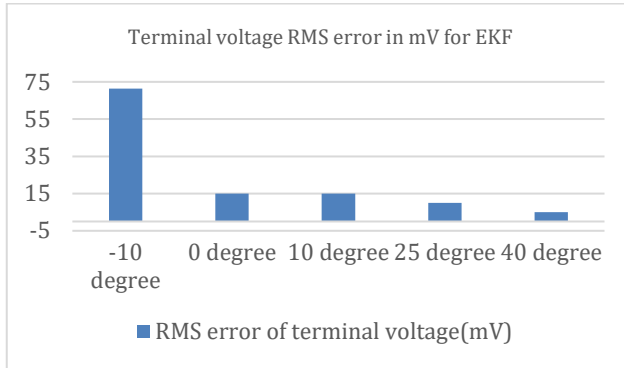


Figure 9. Bar chart of Terminal voltage RMS error in mV for EKF

Table 1: SOC and Terminal voltage RMS error for different temperatures.

Sl. No.	Temperature (degree Celsius)	SOC RMS error(EKF)	SOC RMS error(CC)	Voltage RMS error (mV)
1	-10	12.75%	22.85%	71.4
2	0	2.09%	6.92%	14.9
3	10	1.94%	6.32%	15
4	25	1.72%	4.40%	10

## 5 Conclusion

SOC estimation algorithm is developed and implemented in MATLAB. LA 92 drive cycle data is used to estimate the SOC. Drive cycle data for different temperatures were used and SOC is estimated using Coulomb counting and extended Kalman filter. It was observed from the all-test cases that EKF based SOC estimation is more accurate compared to Coulomb counting method. RMS error values of SOC are less than 2.1% for positive temperatures. Even for negative temperatures EKF performs better than Coulomb counting method.

## References

- [1] X. Lai *et al.*, “A comparative study of global optimization methods for parameter identification of different equivalent circuit models for Li-ion batteries,” *Electrochim. Acta*, vol. 295, pp. 1057–1066, Feb. 2019, doi: 10.1016/j.electacta.2018.11.134.
- [2] S. Mukhopadhyay, H. M. Usman, and H. Rehman, “Real Time Li-Ion Battery Bank Parameters Estimation via Universal Adaptive Stabilization,” *IEEE Open Journal of Control Systems*, vol. 1, pp. 268–293, 2022, doi: 10.1109/OJCSYS.2022.3206710.

- [3] J. Yun, Y. Choi, J. Lee, S. Choi, and C. Shin, “State-of-Charge Estimation Method for Lithium-Ion Batteries Using Extended Kalman Filter With Adaptive Battery Parameters,” *IEEE Access*, vol. 11, pp. 90901–90915, 2023, doi: 10.1109/ACCESS.2023.3305950.
- [4] D. Kanchan, Nihal, and A. P. Fernandes, “Estimation of SoC for Real Time EV Drive Cycle using Kalman Filter and Coulomb Counting,” in *2022 2nd International Conference on Intelligent Technologies (CONIT)*, IEEE, Jun. 2022, pp. 1–6. doi: 10.1109/CONIT55038.2022.9848066.
- [5] Z. Liu, X. Dang, and B. Jing, “A Novel Open Circuit Voltage Based State of Charge Estimation for Lithium-Ion Battery by Multi-Innovation Kalman Filter,” *IEEE Access*, vol. 7, pp. 49432–49447, 2019, doi: 10.1109/ACCESS.2019.2910882.
- [6] H. Aung and K. S. Low, “Temperature dependent state-of-charge estimation of lithium ion battery using dual spherical unscented Kalman filter,” *IET Power Electronics*, vol. 8, no. 10, pp. 2026–2033, Oct. 2015, doi: 10.1049/iet-pel.2014.0863.
- [7] I. B. Espedal, A. Jinasena, O. S. Burheim, and J. J. Lamb, “Current Trends for State-of-Charge (SoC) Estimation in Lithium-Ion Battery Electric Vehicles,” *Energies (Basel)*, vol. 14, no. 11, p. 3284, Jun. 2021, doi: 10.3390/en14113284.
- [8] B. Yang *et al.*, “Classification, summarization and perspectives on state-of-charge estimation of lithium-ion batteries used in electric vehicles: A critical comprehensive survey,” *J. Energy Storage*, vol. 39, p. 102572, Jul. 2021, doi: 10.1016/j.est.2021.102572.
- [9] Gregory Plett, *Battery Management Systems, Volume I: Battery Modeling*, .
- [10] F. Khanum, E. Louback, F. Duperly, C. Jenkins, P. J. Kollmeyer, and A. Emadi, “A Kalman Filter Based Battery State of Charge Estimation MATLAB Function,” in *2021 IEEE Transportation Electrification Conference & Expo (ITEC)*, IEEE, Jun. 2021, pp. 484–489. doi: 10.1109/ITEC51675.2021.9490163.
- [11] T. Xiao, X. Shi, B. Zhou, and X. Wang, “Comparative Study of EKF and UKF for SOC Estimation of Lithium-ion Batteries,” *2019 IEEE PES Innovative Smart Grid Technologies Asia, ISGT 2019*, pp. 1570–1575, May 2019, doi: 10.1109/ISGT-ASIA.2019.8880915.
- [12] N. Shi, Z. Chen, M. Niu, Z. He, Y. Wang, and J. Cui, “State-of-charge estimation for the lithium-ion battery based on adaptive extended Kalman filter using improved parameter identification,” *J. Energy Storage*, vol. 45, p. 103518, Jan. 2022, doi: 10.1016/J.EST.2021.103518.

- [13] X. Li, D. Dong, Z. Hu, and X. Fan, “A study of adaptive extended Kalman filter with different sliding window lengths for lithium-ion battery state-of-charge estimation,” *J. Energy Storage*, vol. 118, p. 116276, May 2025, doi: 10.1016/J.EST.2025.116276.
- [14] J. Zhang and J. Lee, “A review on prognostics and health monitoring of Li-ion battery,” *J. Power Sources*, vol. 196, no. 15, pp. 6007–6014, Aug. 2011, doi: 10.1016/J.JPOWSOUR.2011.03.101.
- [15] G. Joshi, L. Narayana Valluru, and A. Prakash Khade, “Two RC model and parameter estimation of lithium-ion battery,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 37, no. 2, p. 730, Feb. 2025, doi: 10.11591/ijeecs.v37.i2.pp730-739.