Soc Estimation Of Li-Ion Battery Of Electric Vehicle Based On Ekf

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Abstract - Due to the rising concern about global warming and depletion of fossil fuels, electric vehicles powered by lithium batteries are expected to become more popular over the next decade. Effective battery management relies on precise inference of state-of-charge (SoC) parameter which alerts drivers of their vehicle's range capability. SOC is a demanding battery monitoring parameter and has a high impact on predicting the vehicle mileage, boosting battery life, and enhancing electric vehicle performance. In this work, a novel SOC prediction model based on Extended Kalman Filter (EKF) integrated with Thevenin equivalent battery circuit model is proposed. First, the LI battery is modeled in MATLAB/SIMULINK using a first - order resistor-capacitor (RC) equivalent circuit and battery parameters are calculated by conducting a pulse discharge test. As the battery's discharge characteristics are nonlinear, EKF is preferred over simple Kalman Filter. The EKF algorithm is simulated under MATLAB environment. The actual SoC of the cell is obtained from the lithium-ion cell model and the estimated SoC is obtained from output of the EKF block. When compared it was found that the estimated value following the actual value with an error of 0.01. The findings demonstrate that the algorithm has good robustness that can match the functional requirements of technological applications.

Key Words: Kalman filter; Lithium-ion battery; SOC

1. Introduction – motivation

With the ever-increasing demand for energy in green time**,** people prefer electric vehicles with features like high efficiency, energy conservation, environmental safety, etc. As an important component of electric vehicle, an electric battery has direct effect on vehicle life and mobility. State charge (SOC) is used to represent the left out power of the battery, which is one of the most important parameters to highlight the condition of the battery. An accurate and reasonable estimate of the vehicle's battery level can extend battery life, improve performance and ensure that the battery is operating within the proper working range. Therefore, the study of SOC estimation algorithms with good real time and high accuracy is very important for the promotion of electric vehicles.

An algorithm derived from the extended kalman filter technique is discussed in this paper. The main objective of the extended kalman filter algorithm is to build a model that illustrates a given condition, based on obtained data that computes parameter values with a recursive algorithm. The extended kalman filter approach has its own benefits in comparison to other approaches: if there are system errors, the self-correction might be within a definite range and a good approximation value can be obtained. The Kalman filter technique requires precise positioning to describe the model and precise measurement values.

2. Establishment of the battery model

The State Models are sets of mathematical equations that describe something physical. In this case, models or sets of equations that describe the behavior of lithium ion battery cells are designed. In order to do this, the way that a battery cell voltage responds to a change in electrical current, will be modeled by how a circuits voltage also would change to the same change in its input current.. And the model developed using these ideas is called the equivalent circuit model because this circuit behaves in same way as the battery cell .And the equivalent circuit model has some desirable characteristics. They help you understand how cells respond to different cases. And secondly, these models form the basis of algorithms for battery management systems. There are many battery models to ensure accuracy, in this article I choose Thevenin model as the lithium battery model. This model has good accuracy and can reliably replicate a lithium-ion battery's effective performance.

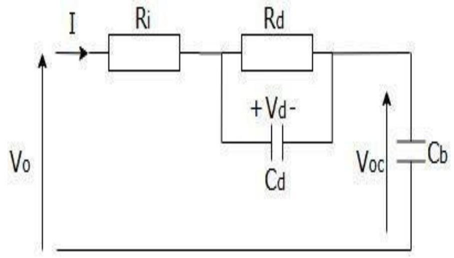

Fig. 1.THE BATTERY MODEL

In figure 1. The parameters V_{OC} , describes the open circuit voltage V_O, indicates the output voltage, *I* represents charging or discharging current, Rd, Ri, Cd , Cb are polarization resistance, internal resistance, capacitance and bulk capacitance of the battery model respectively. As per Kirchhoff's voltage and current laws, the state space equation of Thevenin circuit model can be represented as

$$Voc = \frac{1}{Cb} \dots\dots\dots\dots.1$$

$$Vd = \frac{1}{Cd} - \frac{Vd}{RdCd} \dots\dots..2$$

$$Vo = Voc + Vd + IRi \dots\dots\dots (3)$$

Open circuit voltage of a battery is a nonlinear function of state of charge. Hence this relation can be expressed as:

$$Voc = a.SOC + b \dots\dots\dots\dots (4)$$

Where the variables a and b are not constants and they vary with state of charge and temperature. Considering SoC and Vd as states, the state equation and the measurement equation can be obtained from the above battery model as shown below.

$$SOC = \frac{1}{aCb} \dots\dots\dots..(5)$$

$$Vd = \frac{1}{Cd} - \frac{Vd}{RdCd} \dots\dots..(6)$$

—

3. Parameter identification of the battery model

We have one equation that describes how state of charge changes versus time. We have another equation describing the evolution of the resistor current in a resistor-capacitor branch, and a final equation describing how to compute the cells terminal voltage. To identify model parameters of the Thevenin equivalent circuit pulse discharge tests are performed sequentially on LI battery modules at every 0.01 SOC, while maintaining temperatures within 25 ± 0.5 ° C.

Table 1. specifications of the test cells

Type	Nominal capacity (Ah)	Nominal voltage(V)	Upper cut-off voltage(V)	Lower cut-off voltage(V)
Li FePO4	30	4	4.2	2.25

4. Ekf algorithm

Kalman Filter is a estimator of linear states. With the help of Kalman filter the error in estimating the states can be reduced greatly by the selection of appropriate error co variances. Kalman filter can only be applied to linear systems. For non-linear systems it can't be applied directly. Therefore, the Taylor series of state and measurement equations is extended to the operating point and the kalman filter algorithm is applied. It is called the EKF algorithm because it is an extended version of the column filter. Other than EKF, algorithms like Adaptive Kalman

Filter (AKF), Unscented Kalman Filter (UKF) and Particle Filter can be applied. Here in this study EKF was selected as the computations involved are less and the error in estimation is also negligible. Figure 4 gives a brief idea on the terms predicted state, optimal state estimate and measured state.

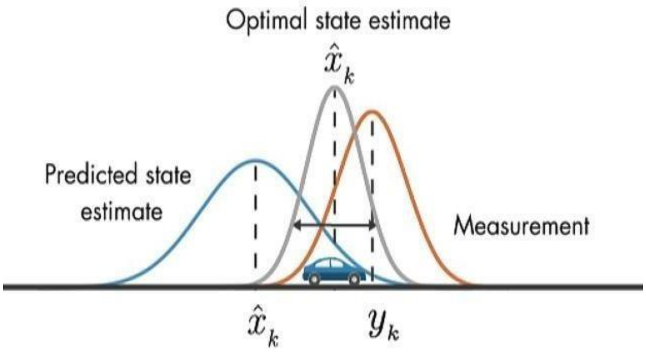

Fig .2. TERMS RELATED TO STATE ESTIMATION

The battery model can be expressed as:

$$\dot{x} = s(\dot{x}, u) + q$$

$$y = m(\dot{x}, u) + r$$

Where s(x, u) is the state equation, m(x, u) is the measurement equation, y is the output matrix, x is the state matrix, and q and r are process noise and measurement noise respectively. Then the below can be deduced as:

$$s(x,u) = \frac{1}{aCb} \ldots\ldots\ldots\ldots (A)$$

$$s(x,u) = \frac{1}{Cd} - \frac{Vd}{RdCd} \ldots\ldots\ldots (A)$$

$$m(\dot{x},u) = a.SOC + Vd + IRi + b \ldots\ldots\ldots\ldots (B)$$

The KF algorithm has two steps of computation namely prediction step and update step. In prediction step error covariance is predicted from the given values of process noise, measurement noise, and initial state. Once the predictions are made, Kalman gain is found and the states of the system and error covariance are updated which comes under update step. Figure 4 shows the flow of KF algorithm. The state space representation of any system can be written as:

$$\dot{x} = Am\dot{x} + Bm$$
$$y = Cm\dot{x} + Dm$$

Since discrete EKF is used, the battery model equations should be discretized after linearization. For linearizing the system, Taylor series expansion of the battery model equations are taken at the operating points. Let the states of the system be SoC (denoted as $x1$), Vd (denoted as $x2$) and the input be I (denoted as u). Then the equations (A) and (B) can be rewritten as:

The battery model after linearization can be written as:

$x = Ak\dot{x} + Bk$

Now the battery model which is linearized is obtained. The linearized battery model can be discretized as shown below.

Consider the above model with the matrices Ak, Bk, Ck and Dk. Then the state equation can be written as:

$$\left(Xk + 1 - \frac{Xk}{Ts}\right) = Akxk + BkUk$$
$$\dot{x}k + 1 - \dot{x}k = Ak\dot{x}kTs + BkukTs$$
$$\dot{x}k + 1 = Ak\dot{x}kTs + BkukTs + \dot{x}k$$
$$\dot{x}k + 1 = (1 + AkTs)\dot{x}k + BkukTs$$

Now the battery model which is linearized is obtained. The linearized battery model can be discretized as shown below.

Consider the above model with the matrices A_k, B_k, C_k and D_k. Then the state equation can be written as:

Let the term (1 + Ak Ts) = A and BkTs = B. Then state equation can be written as

$$X_{k+1} = Ax_k + Bu_k$$

Similarly, the output equation can be written as:

$$Y_{k+1} = Cx_k + Du_k$$

Where $C = C_k$, $D = D_k$

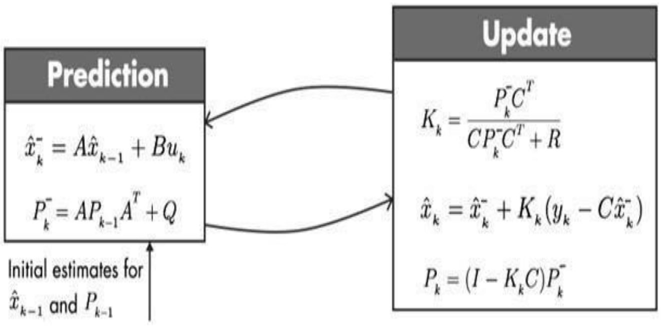

Fig.3. KALMAN FILTER ALGORITHM

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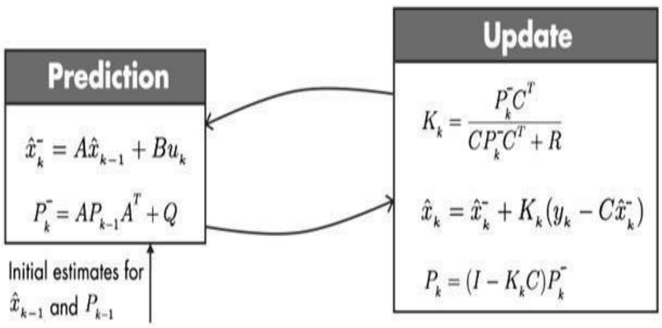


Fig.3. KALMAN FILTER ALGORITHM

5. Simulation results

The measured value 'y' is then given to Extended Kalman Filter block and the value of SoC is obtained at the output.

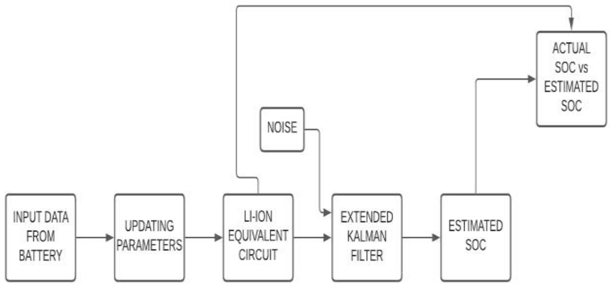


Fig.4. SCHEMATIC DIAGRAM OF PERFORMED SIMULATION

The actual SoC of the cell is obtained from the lithium-ion cell model and the estimated SoC is obtained from output of the EKF block

The values of process noise covariance (Q), measurement noise covariance (R), error covariance (P) and initial state

(x) needs to be given to the EKF block for estimation. Below are the values which were provided as initial inputs

$$Q = \begin{bmatrix} 2e-8 & 0 \\ 0 & 3e-7 \end{bmatrix}$$

Initial value:. The preliminary value of SOC is presumed to be 100% (full battery charge) whereas initial value for V_d is assumed to be 0.

$$x = (1;0)$$

Initial Covariance: Initial covariance signifies how accurate and reliable the initial assumptions are. Assume that the maximum initial approximation error is 10% for SOC and 1V for V_d.

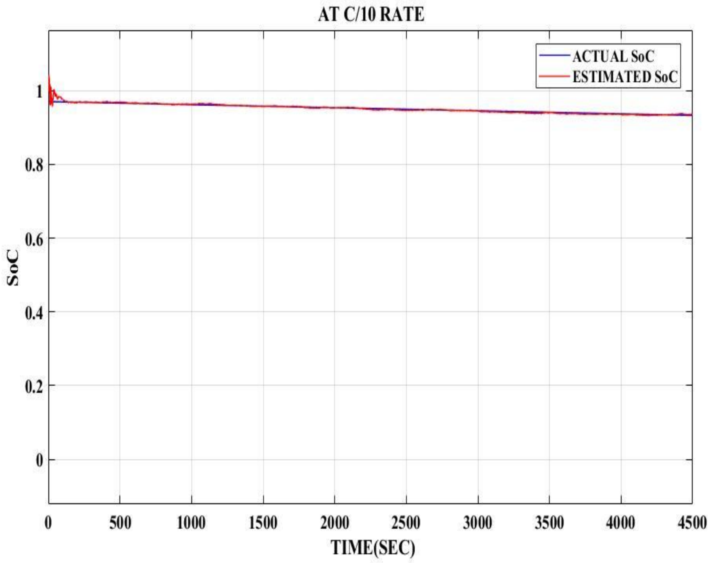
$$P = \begin{bmatrix} 0.01 & 0 \\ 0 & 1 \end{bmatrix}$$

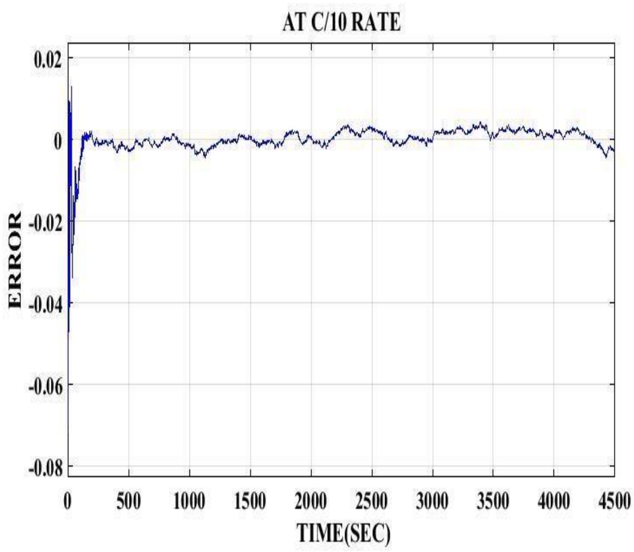
In this work , the simulink model is analysed and simulated for different C-rate conditions and the corresponding values are shown in table 5.1 and the plots of real SoC vs. estimated SoC and difference between them in terms of error are presented.

Table 5.1 Actual SoC & Estimated SoC at different C-rates

S.No	AMPLITUDE OF C-RATE	ACTUAL SoC	ESTIMATED SoC	ERROR
1.	C/10	0.9318	0.9322	-0.002784
2.	C/5	0.8937	0.8942	-0.002856
3.	C/3	0.8428	0.8432	-0.002624
4.	C/2	0.7792	0.7793	-0.002286
5.	C	0.5883	0.5888	-0.002655

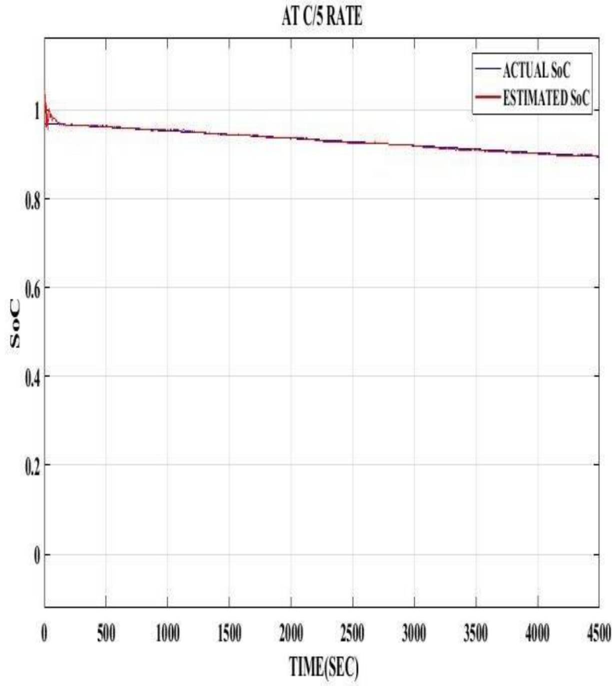
CASE (i): AT C/10 RATE (3A)



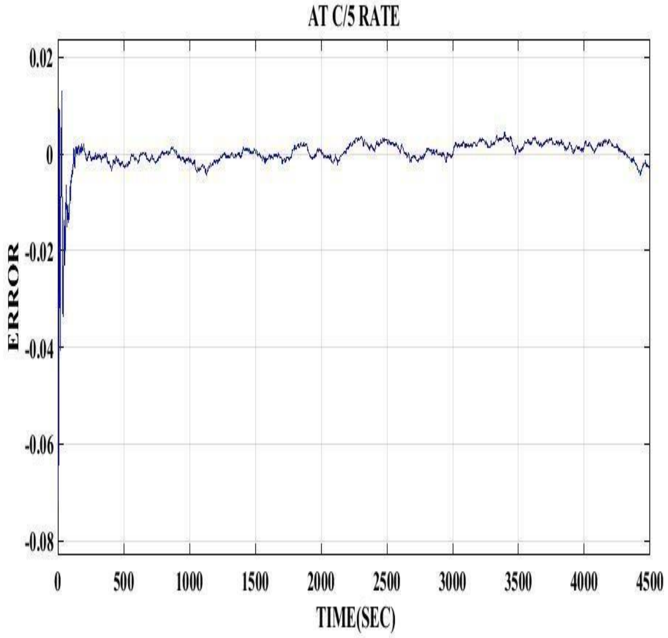


ACTUAL SoC vs. ESTIMATED SoC ERROR IN SoC ESTIMATION

CASE (ii): AT C/5 RATE (6A)

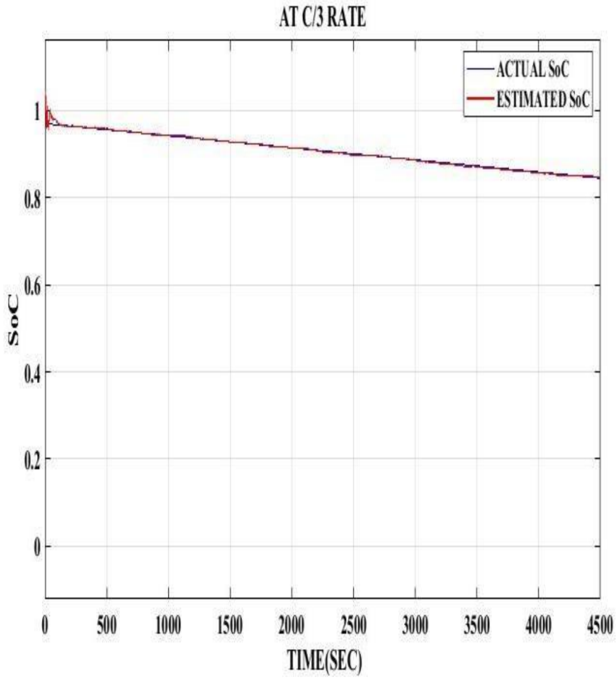


ACTUAL SoC vs. ESTIMATED SoC

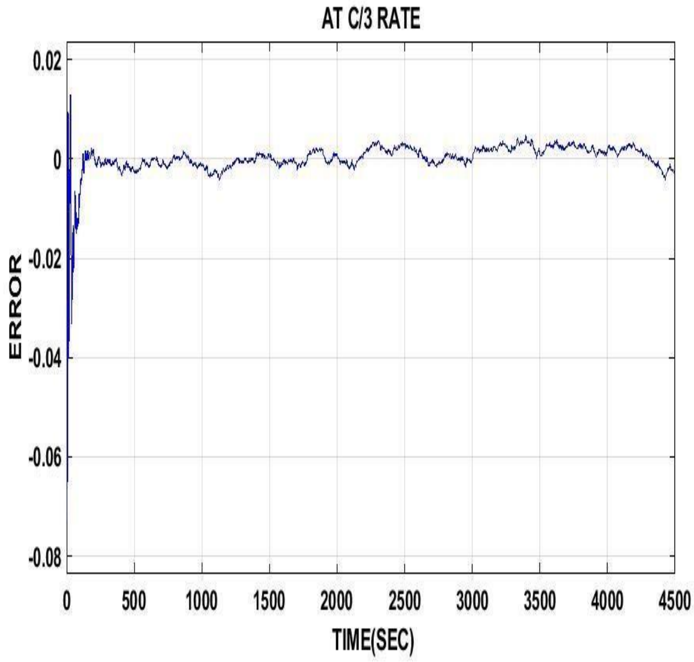


ERROR IN SoC ESTIMATION

CASE (iii): AT C/3 RATE (10A)

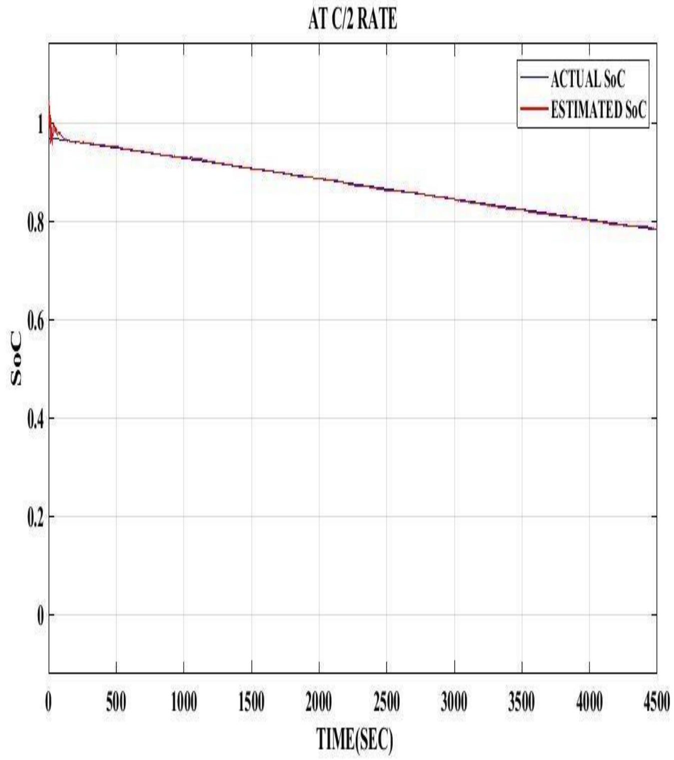


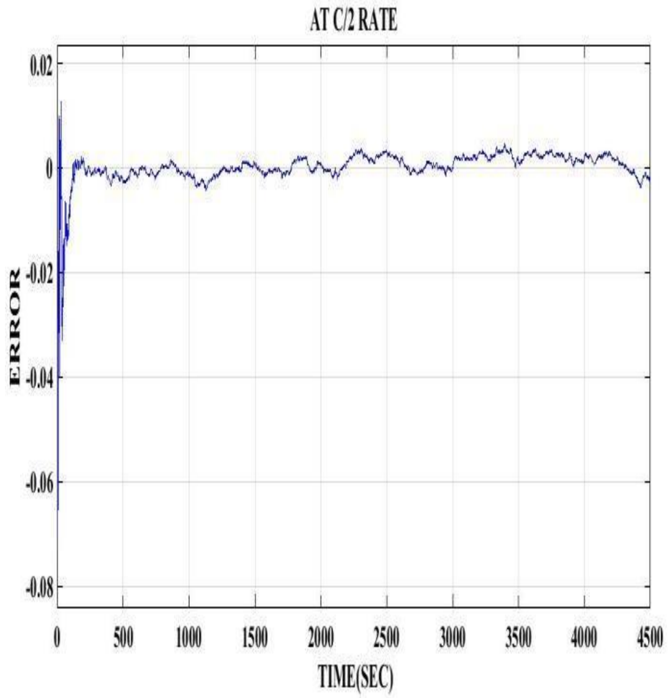
ACTUAL SoC vs. ESTIMATED SoC



ERROR IN SoC ESTIMATION

CASE (iv): AT C/2 RATE (15A)

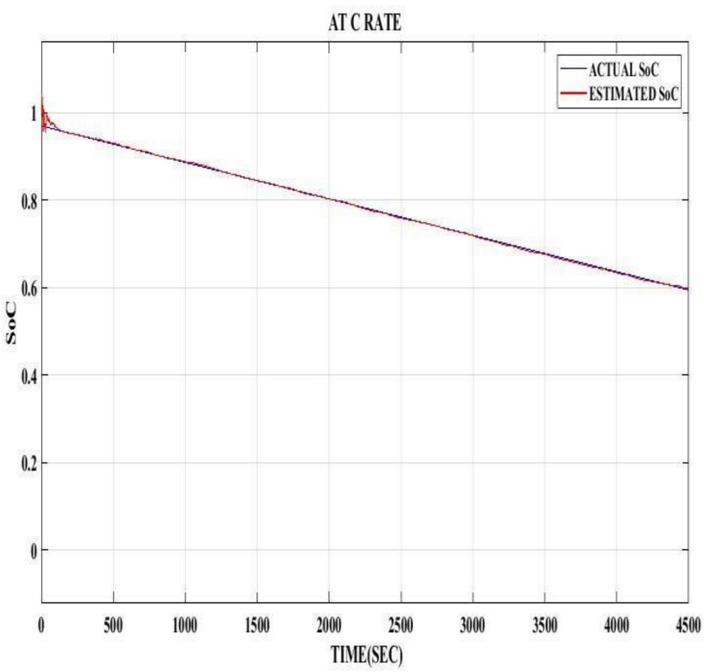


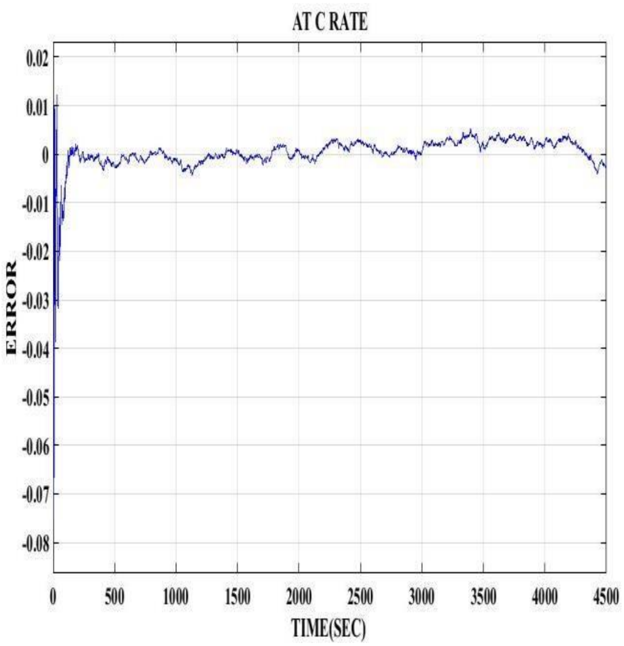


ACTUAL SoC vs. ESTIMATED SoC

ERROR IN SoC ESTIMATION

CASE (V): AT C-RATE (30A)





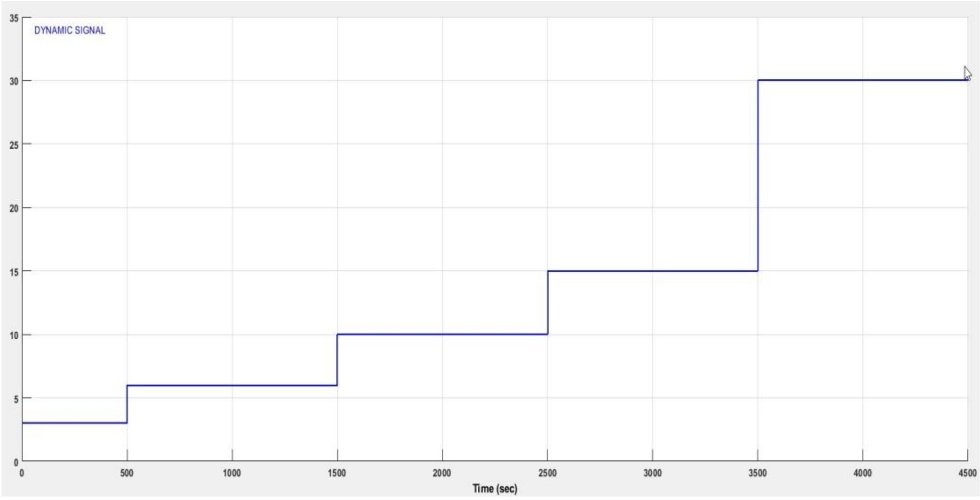
ACTUAL vs. ESTIMATED SOC

ERROR IN SoC ESTIMATION

It can be observed from graphs and table that at every C-rate, the estimated value was found to be following the actual value with an error less than 0.01. After an initial estimation error, the SOC converges quickly to the real SOC. The final estimation error is within 0.01. Thus, the Extended Kalman Filter gives an accurate estimation of SOC.

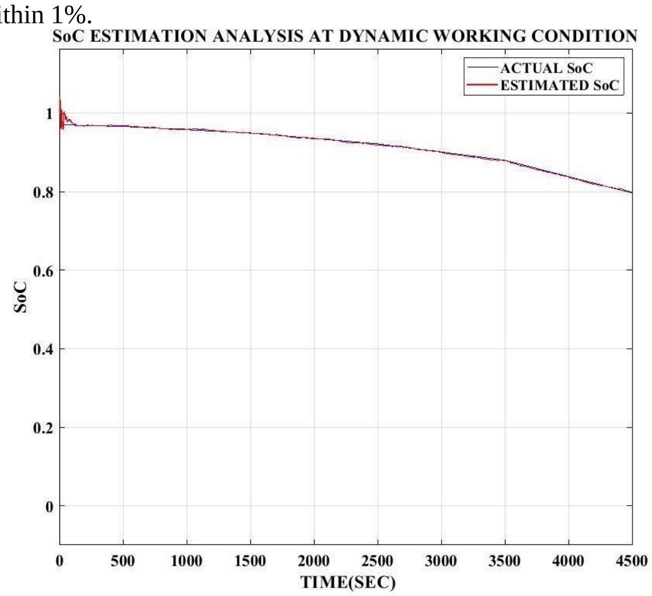
At every discharge-charge transition, the battery capacity is estimated to improve the SOC estimation. The battery system outputs indicator signals to inform what process the battery is in. Discharging process is represented by -1 in the indicator signals while charging process is represented by 1.

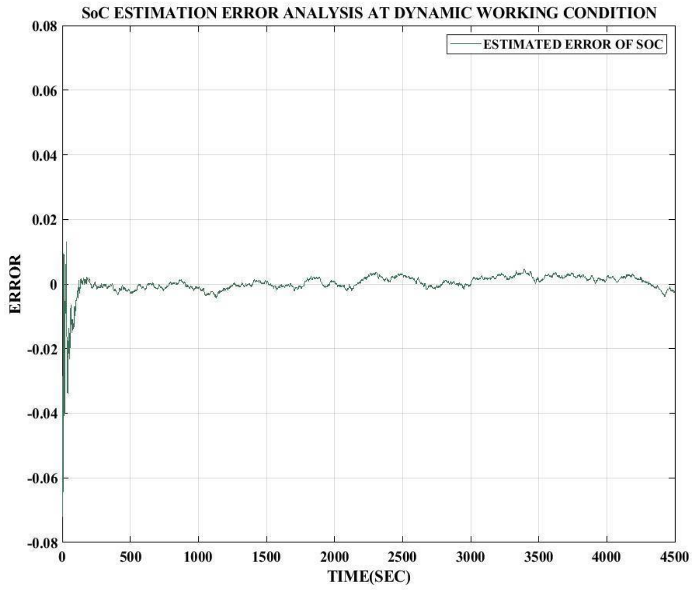
In order to verify the SOC estimation algorithm based on EKF, the experiments of simulating the dynamic condition under complex conditions are carried in this paper. The test steps of the dynamic condition are as follows. First, charge the battery fully. Then, run 500s with 3A discharge, 1000s with 6A discharge, 1000 s with 10A discharge, 1000 s with 15A discharge, 1000 s with 30 A discharge, and so on. Figure 5.5 shows the dynamic input cycle.



Dynamic working condition

The results of the experiment are shown in Figs.5.6 and 5.7. It can be seen from Fig.5.7 that at the initial stage of SOC estimation, the SOC estimation error is very large because the initial value of SOC estimation is derived from the SOC-OCV relationship of the battery. However, the estimated value of SOC quickly converges to the true value according to the Kalman filter estimation algorithm, and the estimation accuracy is improved. The final estimation error is stable within 1%.





6. Conclusion

The simulation results show that when the initial error of SOC is large, this algorithm can converge fast and have good robustness. The SOC estimation error is less than 1% in the dynamic condition, which can meet the requirements of engineering practice.

References

1. Piyush Maheshwari,"Smart Mirror: A Reflective Interface to Maximize Productivity" International Journal of Computer Applications (0975 –8887) Volume 166 – No.9, ay 2017.
2. Salu George Thandekkattu "Smart Mirror-Network Architecture Based on Iot And Cloud Computing Technology.
3. https://www.marketwatch.com/press-release/smart-m irror-market-size-key-players-analysis-sales-revenue-eme rging-technologies-industry-growth-future-trends-competi tive-landscape-and-forecast-2023-2019-03-29
4. Divyashree K J, Dr. P.A. Vijaya, Nitin Awasthi,"Design And Implementation Of Smart Mirror As A Personal Assistant Using Raspberry Pi"
5. https://ece-eee.final-year-projects.in/a/2926-smartm irror-a-glance-into-the-future.html
6. Probing The Impact Of Different Sowing Depths On Germination And Growth Performance Of Maize, J.V Sai Prathap Reddy , International Journal Of Advance Research In Science And Engineering http://www.ijarse.com IJARSE, Volume No. 09, Issue No. 10, October 2020 ISSN-2319-8354(E).
7. Lakshami N M, Chandana M S, Ishwarya P, "IoT based smart mirror using RaspberryPi".