SOC estimation of Li-ion battery using Kalman Filter

Adil Khan Mohammed:
1001667808
Department of Electrical Engineering
The *University of Texas*

Arlington, Texas, United States

adilkhan.mohammed@mavs.uta.edu

Abstract— The State of charge (SOC) is an important parameter to find the capacity of state. It is equivalent to the fuel gauge for a battery pack in a battery electric vehicle. There are different general methods to precisely estimate the battery SOC using voltage, current integration and pressure but each has its certain drawbacks. Accurate estimation of SOC is one of the major issues in a Battery Management System. To overcome these shortcomings, a Kalman filter is used which is able to adjust to the battery voltage and coulomb counting in real time. To estimate the SOC in both the batteries, an RC circuit is considered and its parameters are calculated and rewritten in state space form which in turn is converted to discrete time form to estimate SOC. This paper aims to present the method in estimating the SOC estimation of Lithium-ion battery using Kalman filter.

Keywords—State of Charge, Lithium-ion battery, Kalman filter.

I. Introduction

The State of charge displays the measure of the current state of the battery. SoC cannot be directly measured but is estimated using various methods such as reading the battery voltage to SoC discharge curve. The SoC is estimated using a voltmeter with respect to its battery parameter. The 'Culomb counting' method is another way to estimate the SoC using current. And integrating it in time. This method can lead to multiple errors over time resulting from a single calculation mistake. As such, to overcome these drawbacks as stated above, we use Kalman filtering to estimate the SoC, combined with Culomb counting, it can make an accurate estimation of the SoC. To estimate the SoC using Kalman filter, The Li-ion battery is designed and the battery model is rewritten as state space form. It is then converted into a Discrete-time form using which the SOC of the battery is estimated.

II. Description of Kalman Filter

The objective of a Kalman filter is to estimate a linear system's internal states using the information acquired from a system's input and the output measurement.

The discrete time Kalman filter is based on the linear system of the form:

$$x_{k+1} = A_k*x_k + B_k*u_k + w_k$$

$$y_{k+1} = H_k*x_k + v_k$$

where x_{k+1} is the system's state vector at a time k, u_k is the input, y_{k+1} is the output, A_k is the system matrix, B_k and C_k are the output matrix, w_k and v_k are the noise terms.

The Kalman filter is implemented in a two-step process. The predicted result is estimated depending on the order of the predictor-corrector or corrector-predictor steps. To implement the Kalman filter, the initial system state xo and an initial covariance P_0 is estimated. This results in system being linear and process noise being Gaussian. The resulting and covariance of the new estimate is given by

$$x\^{}_k = A_{k-1}*x\^{}_{k-1} + B_{k-1}*u_{k-1}$$

$$P_k = A_{k-1}*P_{k-1}*A^T_{k-1} + Q_{k-1}$$

This completes the prediction step and the nest step is corrected using next measurement at the time step. The gain term is chosen to minimize the mean squared error of the state estimate. The Kalman gain, estimate and the error covariance is given by

$$K_k = P_k\, H_k^T(H_K P_K H_K^T + R_K)^{-1}$$

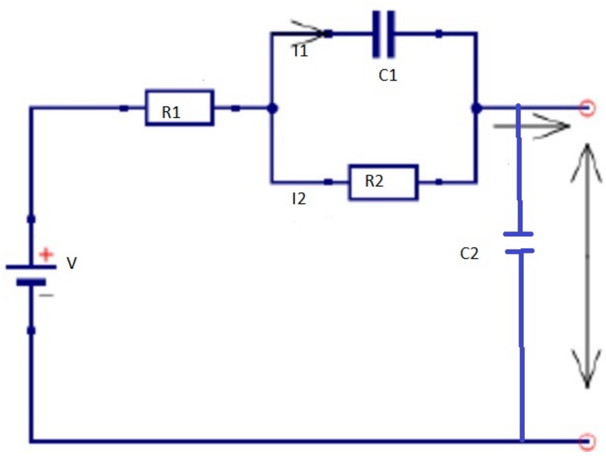
$$X_k = x\^{}_k + K_k\,(y_k - H_k x\^{}_k)$$

$$P^+_k = (I-K_kC_k)P^-_k(I-K_kC_k)^T + K_kR_KK_K$$

This completes the correction step

III. LITHIUM-ION BATTTERY

It is essential to predict the behaviour of the battery model internal states such as SOC and the internal resistance. These variables are largely depended upon external characteristics such as voltage, current and temperature. To satisfy the requirements that may occur, the Thevenin's model is used. The Thevenin's first order is



Here we have,

R1: Internal Resistance

C1: Capacitor

R2: Resistance

C2: Battery Capacitor

V: Model Voltage

V1: Voltage across capacity

The internal resistance R1 increases as the battery ages, the capacitance C1 is the contact between the electrode and the electrolyte of the battery. The transfer resistance is defined by R2. C2 is the battery storage capacitance. The test on the battery is performed at constant temperature thereby ensuring all the parameters considered are constant. V is the battery voltage of the circuit considered when 'I' is not equal to zero and a load is connected, V2 is the open circuit voltage considered when 'I' is zero.

The relation between open circuit voltage V2 and the SOC is given as:

$V_2 = V_0 + g.SOC$

Where, V_0 is the open circuit voltage when SOC is 0% that is the battery is completely discharged

The SOC can be estimated from the open circuit voltage V2, but it can only be done when the battery is disconnected from the system. However, it is difficult to acquire information due to 'I' in the circuit and impedance 'Z' which is unknown.

This variation of the open circuit voltage can be expressed as follows:

$V2' = I/C2$

The voltage V1 across the capacitor C1 is given as

$V1 = R2*(I-C1V1')$

The battery model can be written in the State-space form as:

$x^* = Ax + Bu$

$y = Cx + Du$

Where;

$A = [0\ 0;0\ -1/R2C1]$,

$B = [-1/gC2;\ 1/C1]$,

$C = [\ g\ 1]$.

$D = R1$.

The model state vector x consists of the variable x_1 and x_2 such as

$X_1 = SOC$

$X_2 = V1$

Therfore, the system input x_* can be written as,

$[SOC^*;\ V1^*] = [I/g.C\ ;\ -V1/R2*C + I/C1]$

$Y = V = g*SOC + V_{0=} + V1 + R1*I$.

Now, these equations need to be converted to discrete time form, to achieve this we use Euler's discretization yielding.

$X_{k+1} = A_d*x_k + B_d*u_k$

$y_k = C_d*x_k + D_d*u_k$

with

$A_d = [1\ 0;0\ 1-\Lambda t/R2.C1]$, $B_d = [-\Lambda t/gC2;\ \Lambda t/C1]$

$C_d = C$ and $D_d = D$.

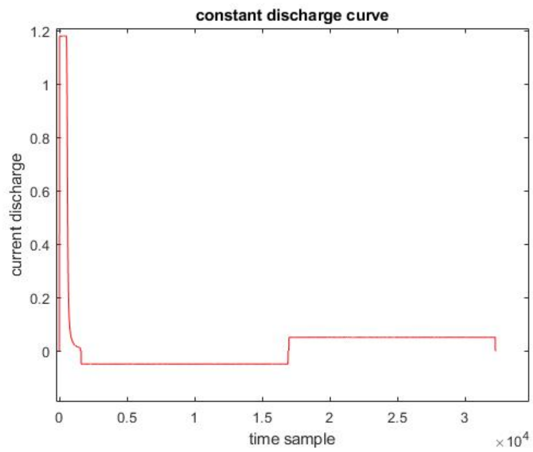
The system in the discrete form thus become,

$X_{k+1} = [SOC_{k+1};\ V_{1,k+1}] = [1\ 0;0\ 1-\Lambda t/C1R2].[SOC_k;\ V_{1,k}]$

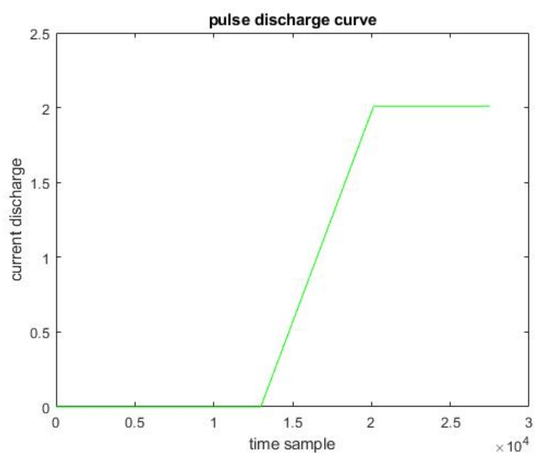
$+ [\Lambda t/C2.g\ ;\ \Lambda t/C1].I$

IV. DETERMINING THE MODEL PARAMETERS

The Parameters of the battery have been extracted based on two discharge tests, constant current discharge and pulse discharge. The data for these tests has been extracted from an A123 2330 mAh Li-ion battery measured at the University of Maryland at 25 degrees Celsius. The constant discharge curve has been obtained as follows.



Similarly, the to find the pulse discharge curve, we use the data obtained by the University of Maryland on the discharge rate on an INR 18650-20R battery. The pulse discharge curve is obtained as,



The cell resistance R1 is determined using the immediate rise as shown in the figure above. The resistance is determined as,

R1 = ΛV/I = 3.827-3.802/0.1 = 0.25 ohms. Where ΛV has been calculated according to the data referenced at the end of the paper. The diffusion resistance R2 of the cell is determined from rise of the battery voltage. Hence it is obtained as,

R2 = ΛA/I = 3.852-3.827/).1 = 0.25 ohms.

Therefore, using the data above, the time constant tau is obtained as;

tau = R2C1 = 1232-907 = 325 seconds.

Hence, the diffusion capacity is obtained as,
C1 = tau/R2 = 325/0.25 = 1300 F.

The parameters of the battery are thus obtained as,

Parameters	R1	R2	C1	C2
Values	0.25Ω	0.25 Ω	1300 F	8040

V. SOC ESTIMATION

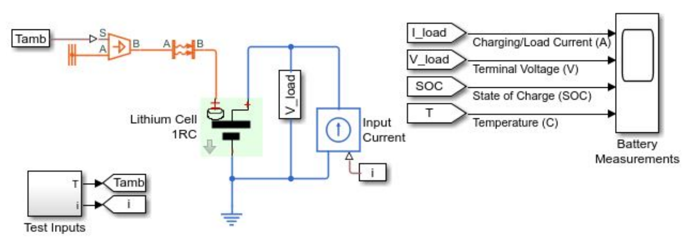
The State of Charge is the most important aspect of a Battery Management System. The SOC is mathematically defined as follows,

$SOC_{battery}$ = $SOC_{initial}$ – 1/3600*Ah int(I)dt
Where,
$SOC_{battery}$ = The State of Charge of the battery
$SOC_{initial}$ = The initial State of Charge
Ah = The battery capacity in A/H)Ampere per hour)
I = battery current

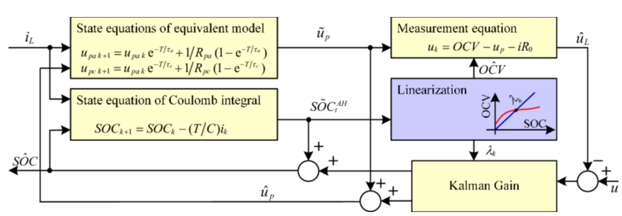
In order to estimate the SOC, the Kalman filter is used.

The Li-ion battery in the Simulink can be obtained by using the Matlab calling function, `ssc_lithium_cell_1RC.`

The Model is as follows,



The structure of the estimator based on the model is assumed as;

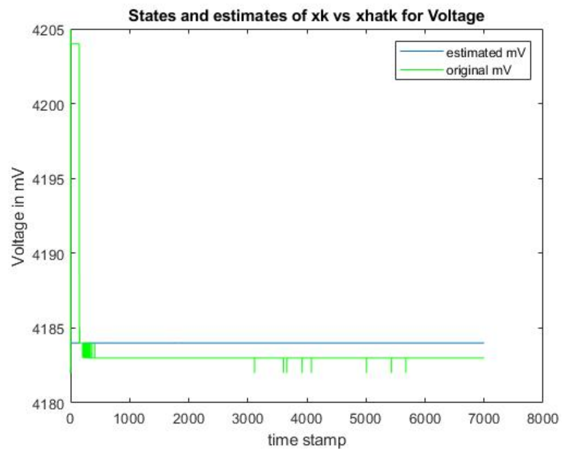


The Kalman filter is represented using the following equations:

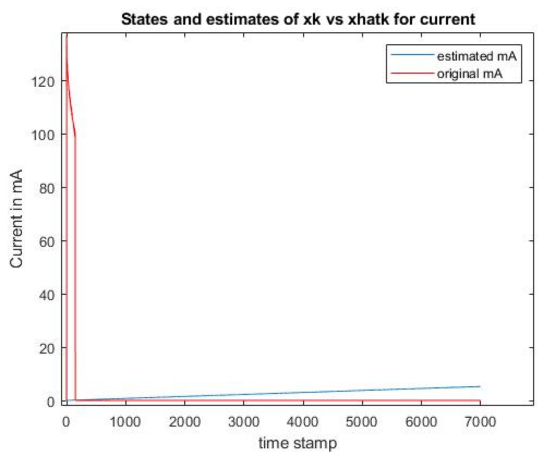
- Prediction of State space variables
  $X_k = Ax\hat{}_{k-1} + Bu_{k-1}$
- Prediction of covariance matrix
  $P_k = AP\hat{}_{k\text{-}}1.AT + Q$
- Update of Kalman gain
  $K = P_kC_k^T[C_kP_kC_k^T + R]^{-1}$
- Estimation of state variable and correction
  $X\hat{}_k = x_k + K[y_k - C_kx_k\text{-}D_ku_k]$
- Estimation of the error

VI. SIMULATION RESULTS

To validate the results, it is preferred to perform simulations in MATLAB/Simulink. We successfully predicted the curve of mV and mA plotting a low voltage OCV graph. The dataset has been acquired from the research of Fangdan Zheng on Applied Energy on Lithium-ion batteries. The plot for the States and estimates on the voltage for 7000 samples at 25 degrees are obtained as,



Similarly, the plot for states and estimates on the current for the same 7000 samples are obtained as,



Plotting estimate for from the curves, the SOC can be estimated albeit with some error.

VII. CONCLUSION

In this paper, the theory of SOC estimation was reviewed and the method of using Kalman filter to estimate the State of charge. The theory of Kalman filter was also reviewed. A first order Thevenin's model was designed to obtain the model parameters. These parameters were subsequently rewritten in state space form and then in discrete time form using Euler's discretization. The current discharge graphs were then plotted using previous data. The required resistances and capacitances are then obtained and the SOC based data is written. A Kalman estimate matlab code is written for an INR 18650-20R Li-ion battery having the characteristics capacity rating 2000 mAh and length 64.85*18.33 mm. By simulating the system using Kalman filter, we predetermine the OCV-SOC estimate for battery.

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