State of Charge Estimation For Lithium-ion Battery Based on the Extended Kalman Filter

EECE 580B - Battery Management and Reliability
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ABSTRACT

This work aims to develop a state of charge (SOC) estimation algorithm for use in an electric vehicle (EV) battery pack. Using the average voltage readings of each cell, the pack's behavior would be modeled using a second-order RC equivalent circuit (ECM). Since all cells are of the same type and undergo charge/discharge simultaneously, this leads to a decent approximation.

The least squares approach is used to fit parameters based on experimentally obtained HPPC test data to determine the parameters of the ECM and model the SOC/OCV relationship. Using these parameters an Extended Kalman Filter (EKF) would be created using MATLAB to estimate SOC. The accuracy of the SOC estimation would be determined by comparing the SOC results from the Coulomb counting method as reference values.

Using MATLAB/Simulink's simulation tools, the battery pack would be built to model the real configuration and verify the SOC estimation under charge and discharge conditions used in the actual application. These include a constant current charge of 1C rate and a pulse discharging condition. Initial SOC = 0.9, pulse current at 10C rate, discharge for 10 seconds, then rest for 5 seconds.

1. Background Information

With the advancement of technology, batteries have come a long way. Batteries today not only come in a multitude of varieties, but each different kind of battery has so much information specific to itself. From different chemical structures/setups to various physical configurations, all these different specifications play a large role in how batteries operate, ultimately giving users many options for different applications.

With battery integration into almost every part of daily life, the level of charge of your batteries is crucial. One method to obtain the battery level is calculating the state of charge using measured information such as voltage, current draw, and open circuit voltage . SOC estimation is a challenging task due to the complex and nonlinear characteristics of batteries, which can be affected by factors such as temperature, aging, and discharge rate.

In this project, we will discuss our method for obtaining the SOC estimation for a lithium-ion battery pack using an Extended Kalman Filter. The battery pack being modeled is for use in an electric vehicle project for Binghamton Motorsports Formula Society of Automotive Engineers International (FSAE).

The battery pack has eight modules in series that consist of a 12s6p configuration. A CAD rendering of the physical pack can be seen in Figure 1.1. On the EV there is a module board that takes each cell's voltage and temperature readings. Then there is a master board that processes the data from each module board.

Figure 1.1 CAD Model of the battery pack used for the FSAE EV.

The aim of this work is to develop an algorithm for estimating the SOC of the battery pack to be implemented in the master control board's software. For this project, the pack is modeled using an average cell model for simplicity. When implementing the SOC algorithm the average of all instantaneous voltage readings will be taken and the overall pack current will be divided by 6 (due to the 6p configuration), to obtain a model for the "average cell" in the battery pack; the estimated SOC of this cell will be used as the estimate for the entire pack's state of charge [1].

The EV battery pack is built using Sony/Murata VTC6 battery cells. However, suitable test data was not available for these cells. As a result test data for a similar cell, the Panasonic 18650PF, was used. This cell was selected since it has similar properties to the VTC6 cells since they are both 18650 cells and have similar nominal capacities. For use with the VTC6 cells, laboratory test data using the cells should be obtained to fit the appropriate ECM parameters. Both the parameter fitting and EKF demonstrated in this work can be used as a framework for doing so.

2. Modeling and Parameter Identification of Lithium-Ion Batteries

2.1 Equivalent Circuit Model of the Battery

The equivalent circuit model of the battery simulates the external characteristics of the battery under actual working conditions by connecting different circuit components in series and parallel. Establishing an equivalent circuit model is a critical step for estimating the state of charge (SOC) using the Extended Kalman Filter (EKF) algorithm. An accurate battery model can significantly enhance the estimation accuracy of the algorithm.

In this project, a second-order RC circuit equivalent model is employed to simulate battery behavior. The RC pairs reflect the dynamic response of the battery. Theoretically, increasing the order of RC pairs improves the simulation accuracy of the battery's actual working state, but it also increases the model's complexity. A second-order RC circuit strikes a balance by sufficiently simulating battery behavior without making the model overly complex [2].

During the charging, discharging, and resting processes, the battery's voltage response is influenced by three factors: ohmic resistance, the double-layer effect, and the diffusion process. The double-layer effect is due to the kinetics of electrochemical reactions at the electrode-electrolyte interface, while the diffusion process is caused by the concentration gradient arising from Li^+ diffusion [3]. These two primary chemical processes govern the dynamic response of Li-ion batteries.

Figure 2.1 illustrates the second-order RC equivalent circuit model for a lithium-ion battery. In this model, R_0 represents the ohmic resistance, while the two RC pairs simulate the double-layer effect and diffusion process, respectively. V_t denotes the terminal voltage of the battery, V_1 and V_2 (the voltages across the two RC pairs) correspond to the double-layer voltage and diffusion voltage, respectively.

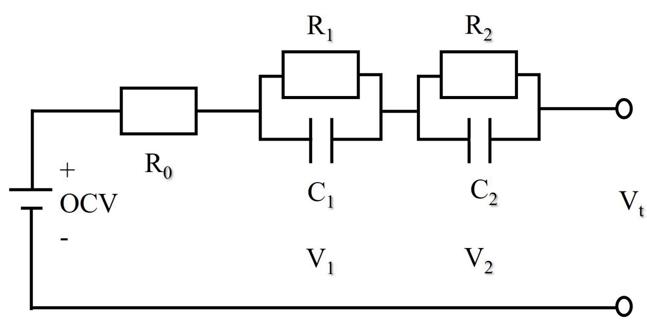


Figure 2.1 The second-order RC equivalent circuit model for a lithium-ion battery

The terminal voltage can be expressed as:

$$V_{(K)} = OCV + I_{(K)} R_0 + V_{1\,(K)} + V_{2\,(K)} \tag{1}$$

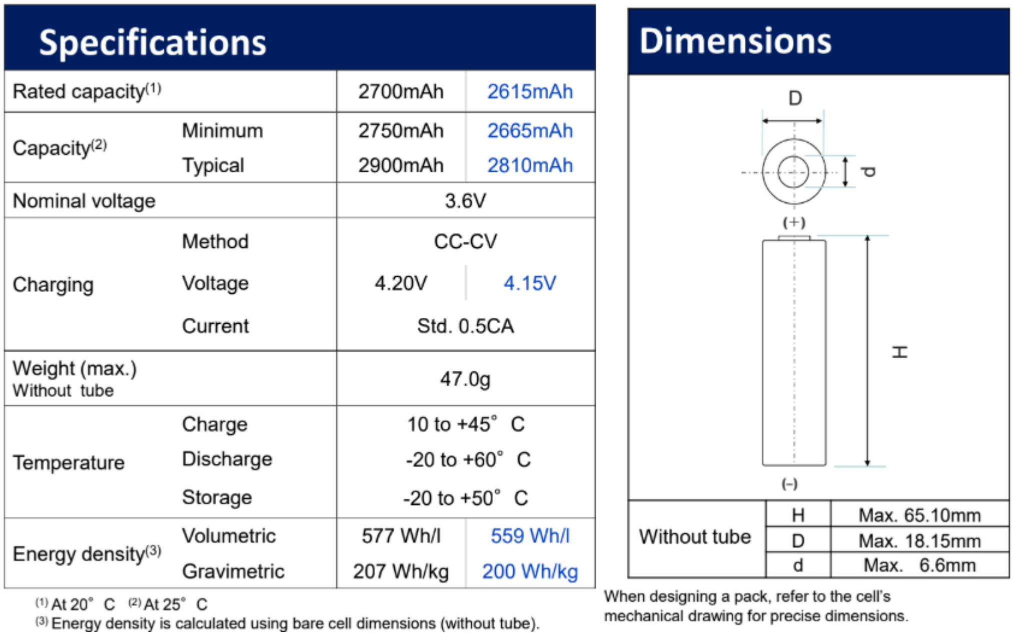
Where:

$$V_{1\,(K)} = exp\left(-\frac{\Delta t}{R_1 C_1}\right) V_{1\,(K-1)} + R_1\left(1 - exp\left(-\frac{\Delta t}{R_1 C_1}\right)\right) I_{(K-1)} \tag{2}$$

$$V_{2\,(K)} = exp\left(-\frac{\Delta t}{R_2 C_2}\right) V_{2\,(K-1)} + R_2\left(1 - exp\left(-\frac{\Delta t}{R_2 C_2}\right)\right) I_{(K-1)} \tag{3}$$

2.2 Battery Testing Data - HPPC Experiment

Due to the lack of actual battery testing data, this project uses an open-source dataset for Panasonic 18650 PF lithium-ion batteries to identify parameters for the equivalent circuit model[4]. The battery information matrix is shown in Figure 2.2.



Specifications

Rated capacity(1)		2700mAh	2615mAh
Capacity(2)	Minimum	2750mAh	2665mAh
	Typical	2900mAh	2810mAh
Nominal voltage		3.6V	
Charging	Method	CC-CV	
	Voltage	4.20V	4.15V
	Current	Std. 0.5CA	
Weight (max.) Without tube		47.0g	
Temperature	Charge	10 to +45° C	
	Discharge	-20 to +60° C	
	Storage	-20 to +50° C	
Energy density(3)	Volumetric	577 Wh/l	559 Wh/l
	Gravimetric	207 Wh/kg	200 Wh/kg

(1) At 20° C (2) At 25° C
(3) Energy density is calculated using bare cell dimensions (without tube).

Dimensions

Without tube	H	Max. 65.10mm
	D	Max. 18.15mm
	d	Max. 6.6mm

When designing a pack, refer to the cell's mechanical drawing for precise dimensions.

Figure 2.2 Specifications for NCR18650PF.

The data is obtained through the Hybrid Pulse Power Characterization (HPPC) method, which involves the following steps:

1) Fully charge the battery at a 1C rate under different temperature conditions until the SOC reaches 100%, and then rest for 2 hours.
2) Discharge the battery at a C/20 rate and stop at SOC levels of 100%, 95%, 90%, 80%, 70%, …, 30%, 25%, 20%, 15%, 10%, 5%, and 0%, resting for 2 hours after each step.
3) At each SOC point, apply pulse currents of 0.5C, 1C, 2C, 4C, and 6C to discharge the battery for 10 seconds, followed by a 20-minute rest.

In this project, the problem is simplified by selecting testing data at 25°C with SOC levels of 90%, 70%, 50%, 30%, and 10%, using a pulse current of 1C for parameter identification.

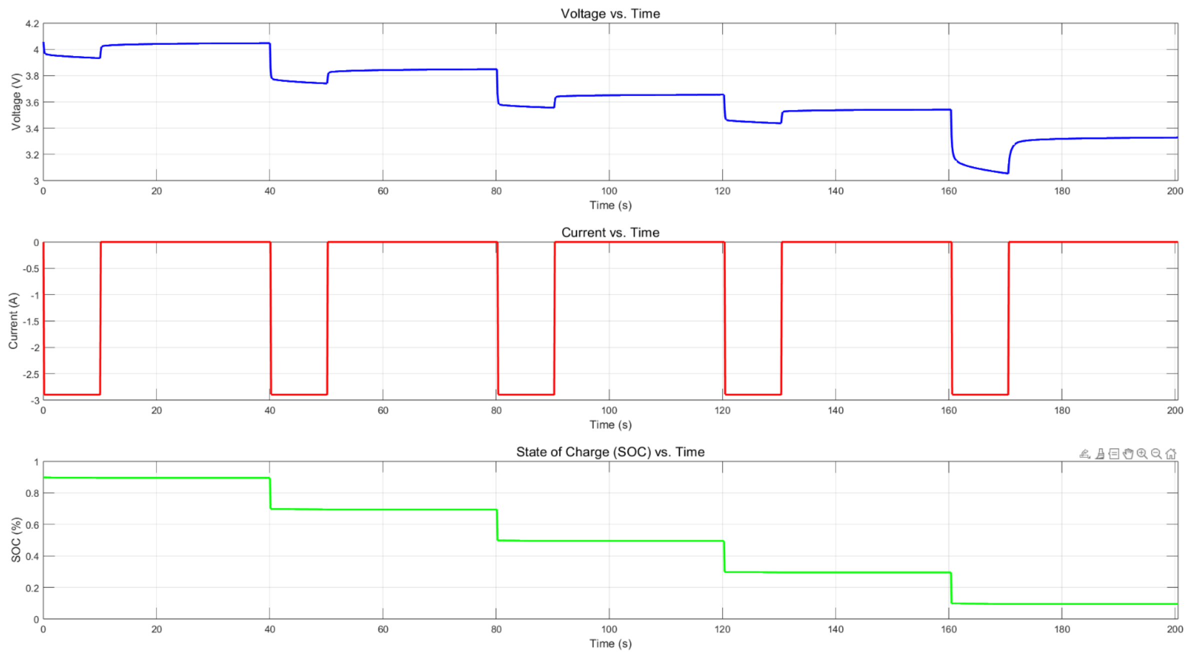


Figure 2.3 HPPC Experiment

2.3 Parameter Identification of the Equivalent Circuit Model

2.3.1 SOC-OCV Curve

The OCV is associated with SOC and temperature. This project assumes a constant temperature of 25°C, therefore, we focus on the relationship between OCV and SOC. In the HPPC experiment, the battery undergoes stepwise discharging and discharging is paused at each SOC level, allowing the battery to rest fully and reach an equilibrium state. At this point, the measured voltage is approximately equal to the OCV. These voltage values are extracted from the dataset to obtain the SOC-OCV mapping shown in Table 2.1.

Table 2.1 OCV values at different SOC levels (at 25°C)

SOC (%)	100	95	90	80	70	60	50
OCV (V)	4.17497	4.1042	4.05852	3.94657	3.86229	3.76835	3.66348
SOC (%)	40	30	25	20	15	10	5
OCV (V)	3.60236	3.55024	3.51292	3.45824	3.39068	3.34436	3.23691

The relationship between SOC and OCV is nonlinear. Therefore, the extracted data is fitted using an eighth-order polynomial in MATLAB. (In the subsequent EKF algorithm, this part is simplified to a 3rd-order polynomial fitting, as detailed in Section 3.)

The polynomial fitting equation is as follows:

$$f_{(x)} = p_1 x^8 + p_2 x^7 + p_3 x^6 + p_4 x^5 + p_5 x^6 + p_6 x^7 + p_7 x^8 + p_8 x + p_9 \qquad (4)$$

Table 2.2 Parameter Fitting Results

Parameters	p_1	p_2	p_3	p_4	p_5
Values (×e³)	-0.2811	1.1540	-1.9319	1.6994	-0.8482
Parameters	p_6	p_7	p_8	p_9	MSE
Values (×e³)	0.2460	-0.0424	0.0053	0.0031	4.2379×e⁻⁸

The fitting results are shown in Table 2.2, and SOC-OCV curve is shown in Figure 2.4.

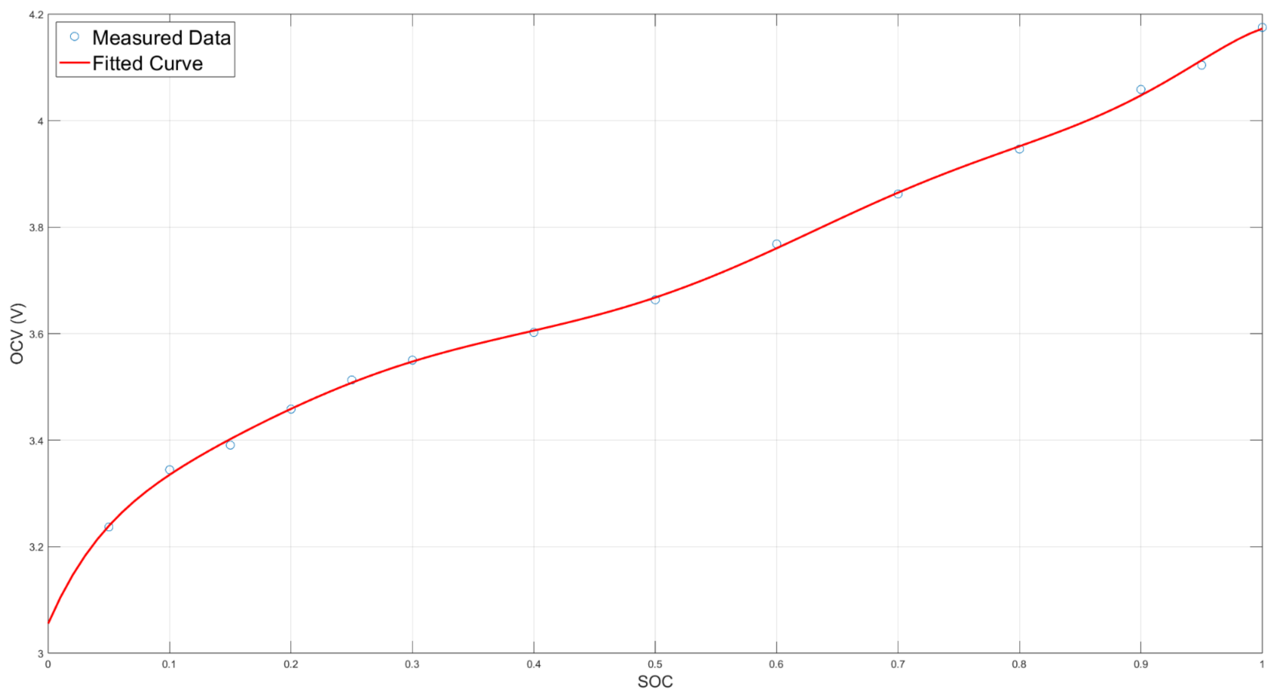


Figure 2.4 SOC-OCV curve

2.3.2 Identification of Equivalent Impedance Parameters

The accuracy of the ECM is crucial for the precision of the SOC estimation algorithm. R_0 is also associated with SOC[5, 6]. To improve the estimation accuracy, we divide the SOC range into five intervals, each covering 20% SOC: 100%-80%, 80%-60%, 60%-40%, 40%-20%, and 20%-0%. Then identify parameters for the ECM using pulse discharge data at SOC levels of 90%, 70%, 50%, 30%, and 10%, which correspond to the parameters for these five intervals.

The MATLAB-fmincon function is used to identify the model parameters R_0, R_1, C_1, R_2, and C_2 for each SOC interval. The fitting process is as follows:

1) Construct the objective function:

$$f(x) = \sum_{k=1}^{N} \left(V_{measured}(k) - V_{model}(k, x)\right)^2 \tag{5}$$

2) Minimizing the objective function(5) to identify the parameters.

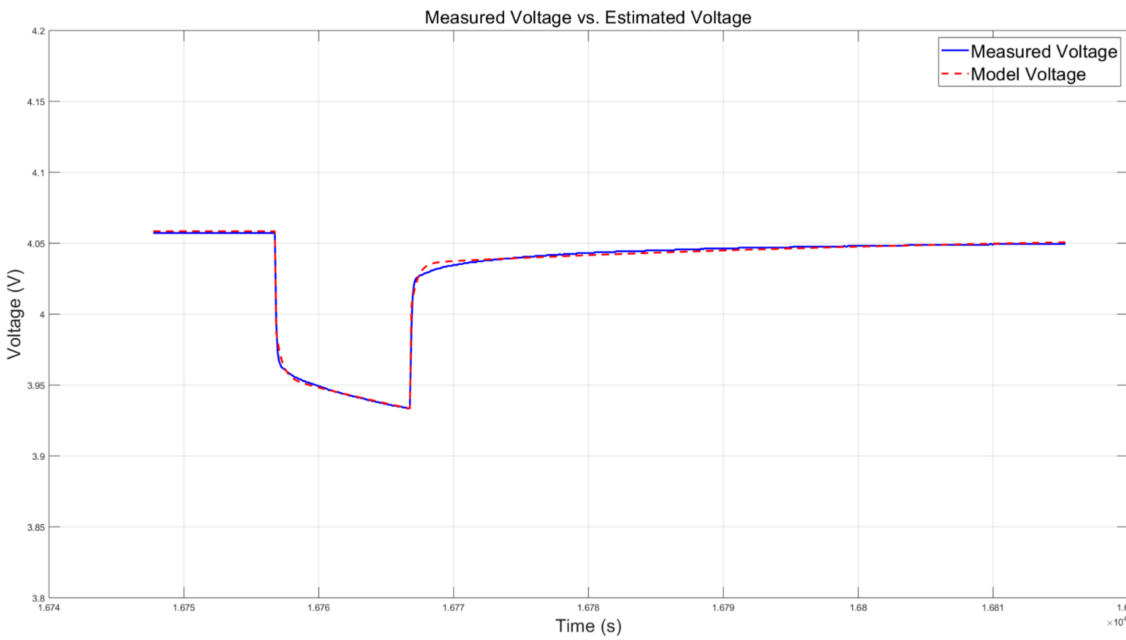


Figure 2.5 Measured voltage vs. estimated voltage at 90% SOC (25℃)

Taking SOC = 90% as an example, the fitting results are shown in Figure 2.5, The final ECM parameter matrix is shown in Table 2.3.

Table 2.3 Parameters Matrix of ECM

SOC（%）	OCV（V）	R0（Ω）	R1（Ω）	C1（F）	R2（Ω）	C2（F）
90	4.05852	0.0247	0.0107	42.1654	0.0395	1155.6742
70	3.86229	0.021	0.0122	25.2452	0.0476	996.0583
50	3.66348	0.0196	0.0114	15.313	0.0313	1500.2786
30	3.55024	0.0192	0.0133	10.2366	0.0317	1431.5031
10	3.34436	0.0353	0.0483	18.6077	0.0546	751.7144

3. Estimating State of Charge Using the Extended Kalman Filter

3.1 EKF Formulation

The Extended Kalman filter is a common method used to estimate the SOC of battery packs in EV applications. Compared to other common SOC estimation methods, namely Coulomb counting, EKF is generally considered to be more accurate since Coulomb counting is susceptible to sensor drift and noise, which is integrated over time causing errors to compound. On the other hand, EKF utilizes both current and voltage measurements, along with a system model, making it less susceptible to this noise. While electrochemical models are generally considered to be more accurate, these are too computationally complex for use within a real-time application, hence an equivalent circuit approach was taken.

The EKF was developed using the 2nd-order equivalent circuit model and model parameters derived above. Using the state vector: $x_k = [SOC_k\, V_{CT,k}\, V_{Diff,,k}]^T$ (in which SOC_k represents the battery's current state of charge and $V_{1,k}$, $V_{2,k}$ represents the voltages across each RC branch in the equivalent circuit model), a state space representation was developed. The state transition equation for SOC is shown below in equation 6 **[**1**]**, where the state transition model $V_{1,k}\, V_{2,k}$ is shown in equations 2 and 3 above.

$$SOC_{k+1} = SOC_k - \frac{\Delta t}{Q_{nom}} I_k \quad (6)$$

The matrix formulation of this model is shown below [1], where the state is given by equation 7, and the predicted output voltage is given by equation 8:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_{CT}}} & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_{Dif}}} \end{bmatrix} \quad B = \begin{bmatrix} -\frac{\Delta t}{Q_{nom}} \\ R_{CT}\left(1 - e^{-\frac{\Delta t}{\tau_{CT}}}\right) \\ R_{Dif}\left(1 - e^{-\frac{\Delta t}{\tau_{Dif}}}\right) \end{bmatrix}$$

$$x_{k+1} = Ax_k + BI_k \qquad (7)$$

$$V_{k+1} = V_{OCV}(SOC_k) - V_{CT,k} - V_{Diff,k} - R_0 I_k \quad (8)$$

For simplicity, a 3rd-order polynomial is used to fit an OCV-SOC curve, using the data provided. The fitted curve along with the data points used are shown below in Figure 3.1.

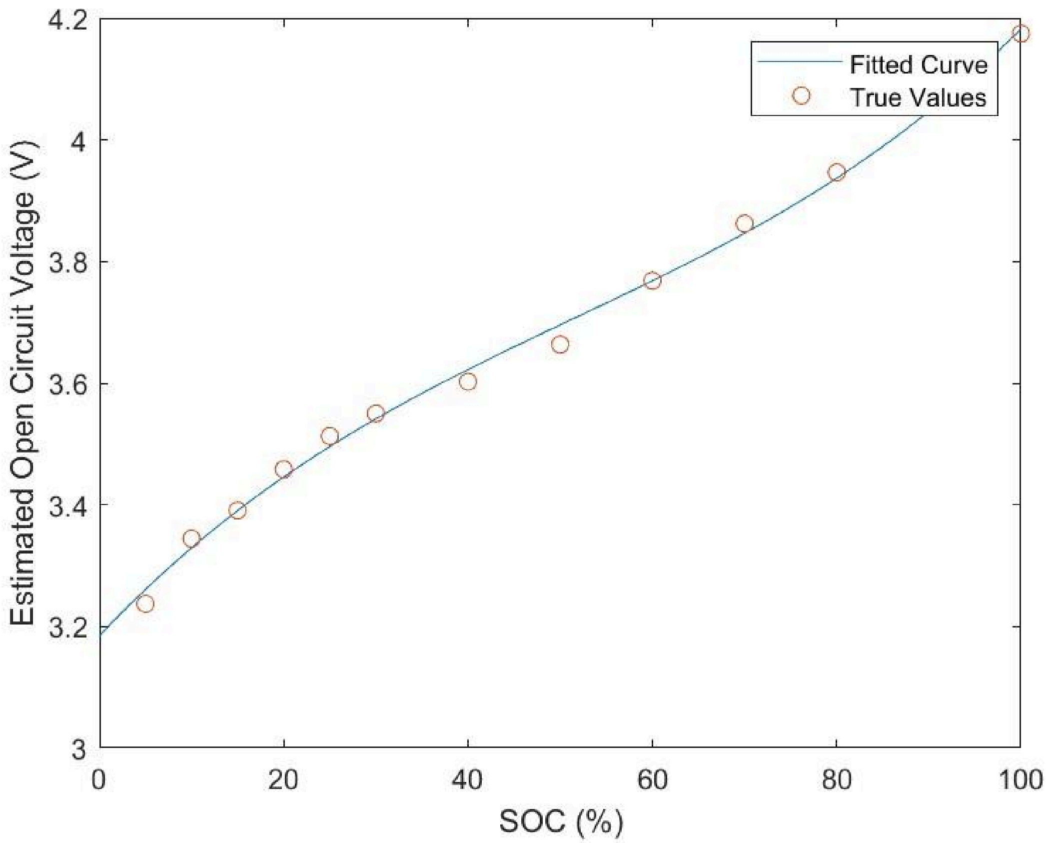


Figure 3.1 3rd Order SOC/OCV Curve Fit

To estimate the SOC given real-time voltage and current data, the general form of the EKF is used as shown below in equations 9-15. To calculate the state transition matrices A and B, linear interpolation is applied at the current SOC estimate using the ECM parameters previously estimated for each SOC level. Although this method introduces non-linearities at the transitions between SOC levels where the parameter estimates were determined, these non-linearities are disregarded for simplicity. In this case, non-linearities are only considered in the predicted voltage equation (since this uses a 3rd order relationship between the SOC and OCV). Using the EKF framework, these are linearized around the current estimate using the Jacobian matrix **C,** where $V'_{OCV}(SOC_k)$ is the derivative of the fitted SOC/OCV curve**.**

$$\textbf{1). State Transition/Prediction Step: } x_{k+1} = A \cdot x_k + B \cdot I_k \quad (9)$$

$$V_{k+1}(x_{k+1}) = V_{OCV}(SOC_{k+1}) - V_{CT,k+1} - V_{Diff,k+1} - R_0 I_{k+1} \quad (10)$$

$$\textbf{2). Prediction Error: } \Sigma_{k+1} = A \cdot \Sigma_k \cdot A^{T} + R \quad (11)$$

$$\textbf{3). Kalman Gain: } K_{k+1} = \Sigma_{k+1} C^{T} (C\, \Sigma_{k+1} C^{T} + Q)^{-1} \quad (12)$$

$$\textbf{4). Jacobian Matrix: } C = [V'_{OCV}(SOC_{k+1})) \;\; -1 \;\; -1] \quad (13)$$

$$\textbf{5). Update Step: } x = x_k + K_{k+1} (V_{meas} - V_{k+1}) \quad (14)$$

$$\textbf{6). Update Error: } \Sigma = (I - K_{k+1} C)\, \Sigma_{k+1} \quad (15)$$

In the formulation above the process noise **R**, was modeled using the standard deviations of the ECM parameters estimated in the previous section. **Q,** the measurement noise was taken to br 0.1, however, this value will need to be tuned to account for the level of noise in voltage readings in the actual system. For simplicity, the ECM parameters were assumed to be independent, leading to a diagonal covariance matrix with the squared standard deviations of each parameter placed along the diagonal ($cov(\widehat{\theta})$) . To map the parameter covariance, into the covariance of the states equation 16 was used below, where H is a Jacobian matrix defined below, containing the partial derivatives of the states with respect to each parameter (Equations 17-21).

$$cov(\widehat{x}) = H cov(\widehat{\theta}) H^{T} \quad (16)$$

$$\frac{\partial V_1}{\partial R_1} = \frac{-\Delta t}{R_1^{\,2} C_1} V_{1,k} + I_k(1 - (exp(-\frac{\Delta t}{R_1 C_1}) - \frac{\Delta t}{R_1 C_1} exp(-\frac{\Delta t}{R_1 C_1})) \quad (17)$$

$$\frac{\partial V_1}{\partial C_1} = \frac{-\Delta t}{C_1^{\,2} R_1} V_{1,k} + I_k(1 - (exp(-\frac{\Delta t}{R_1 C_1}) - \frac{\Delta t}{R_1 C_1} exp(-\frac{\Delta t}{R_1 C_1})) \quad (18)$$

$$\frac{\partial V_2}{\partial R_2} = \frac{-\Delta t}{R_2^{\,2} C_2} V_{2,k} + I_k(1 - (exp(-\frac{\Delta t}{R_2 C_2}) - \frac{\Delta t}{R_2 C_2} exp(-\frac{\Delta t}{R_2 C_2})) \quad (19)$$

$$\frac{\partial V_2}{\partial C_2} = \frac{-\Delta t}{C_2^{\,2} R_2} V_{2,k} + I_k(1 - (exp(-\frac{\Delta t}{R_2 C_2}) - \frac{\Delta t}{R_2 C_2} exp(-\frac{\Delta t}{R_2 C_2})) \quad (20)$$

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{\partial V_1}{\partial R_1} & \frac{\partial V_1}{\partial C_1} & 0 & 0 \\ 0 & 0 & 0 & \frac{\partial V_2}{\partial R_2} & \frac{\partial V_2}{\partial C_2} \end{bmatrix} \tag{21}$$

3.2 EKF Performance

To evaluate the effectiveness of the EKF, the filter's performance was compared to the True SOC value during charge and discharge cycles under laboratory conditions, using the same datasets used to determine the ECM parameters [4]. 3 of the following test cases were used, and the results are plotted in Figures 3.2.1 - 3.2.3 below. All tests were performed at a constant temperature of 25C. :

1. Constant Discharge at 1C, starting from 80% SOC
2. Constant Charge at 1C, starting from 10% SOC
3. Variable Discharge Rates, starting from 100% SOC

To verify filter convergence, in each of the following test cases, the initial SOC estimates were set far from the true value (0.1,0.9,0.1 respectively).

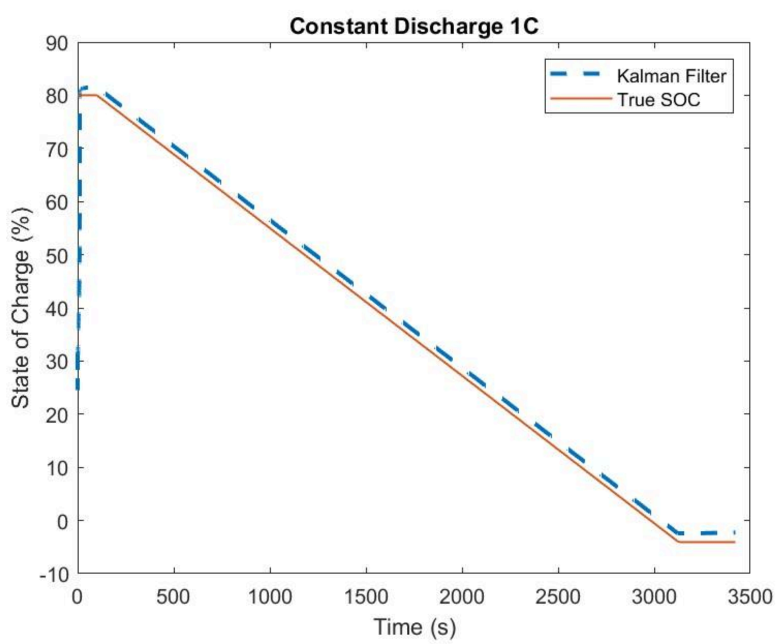


Figure 3.2.1 EKF Performance at 1C Discharge

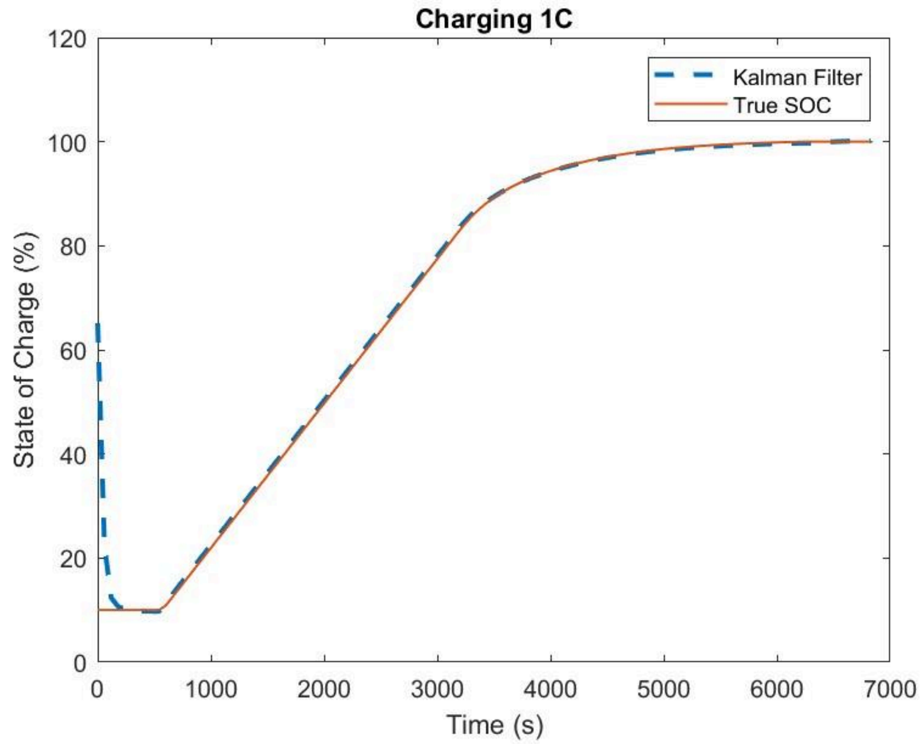


Figure 3.2.2 EKF Performance at 1C Charge

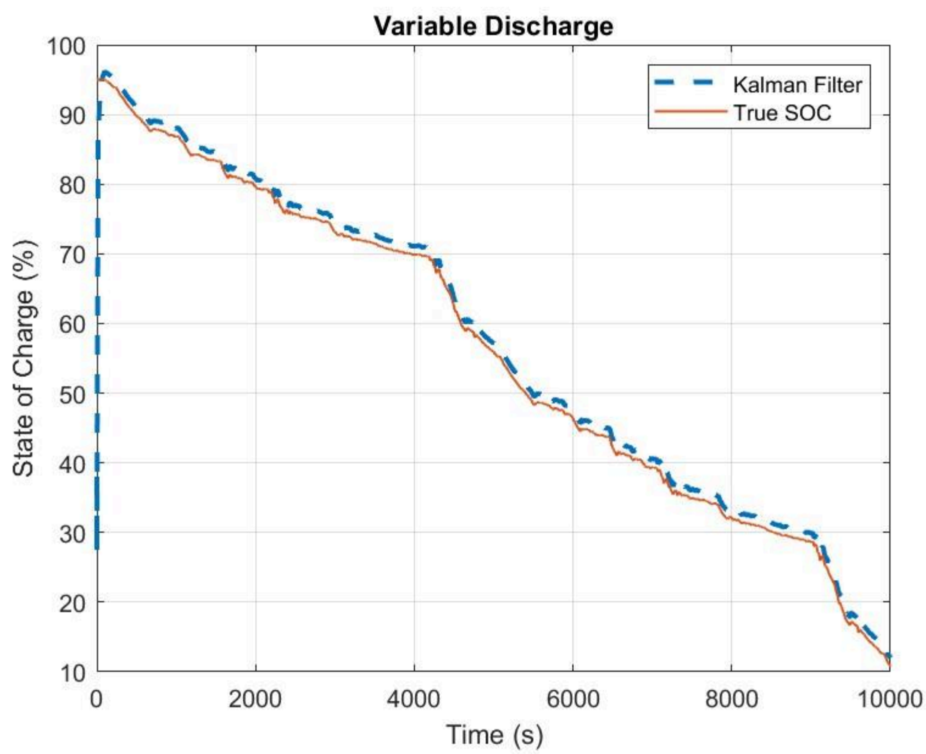


Figure 3.2.3 EKF Performance Variable Discharge

As shown in the above results, the EKF shows good performance and convergence, even when given a bad initial guess. As a result, this EKF serves as a suitable prototype for estimating the SOC of this EV battery pack. To use this filter, new parameters (and their covariance) can be fitted using the same method and the filter equations can remain the same.

4. Additional Methods & Modeling Tools

The simulations and models seen throughout this project have been completed using MATLAB. Another useful tool which could be used for further analysis is MATLAB's Simulink. Within the Simulink program, the user can choose different battery cell models from specific manufacturers, or even create their own models and implement different parameters specific to that cell. It is even possible to simulate the battery packs in a 3-D space. These battery cells can then be wired together in series and parallel and tested for many different things. Some test areas include but are not limited to SOC, OCV, temperature, and current to name a few. This program allows users to develop algorithms for battery control, try different design sensitivities, and observe thermal management strategies.

For this project, while the use of Simulink would have been highly useful in verifying the results as well as creating a model that can be tested, the member's knowledge of the program was not sufficient. Ideally, the pack would have been designed using the parameters of the exact battery cells being used for the EV however Simulink does have that specific cell. Another cell was tested in the program to generate some results. In Figure 4.1, a screenshot of the Simulink model that was attempted to be created is shown. In the figure there are eight packs of 12s6p which models the actual EV battery pack to be used. Ideally, from this stage the battery pack model would have followed the same test procedures and setup as described in the earlier sections to estimate the SOC.

Figure 4.1. Screenshot of Simulink model of EV battery pack.

Conclusion

The framework effectively estimates SOC using a second-order ECM and EKF, with the potential for future integration with actual Sony/Murata VTC6 cells once lab test data is obtained. A second-order ECM was obtained through a least squares minimization technique. An EKF was developed by fitting a 3rd-order polynomial for the SOC/OCV relationship and modeling the process noise by using the standard deviations of the estimated ECM parameters.

Future work will focus on fitting the ECM parameters for the VTC6 cells by obtaining HPPC test data. After this, an EKF using these parameters will be simulated in Matlab. After verifying its performance, the EKF will be implemented in embedded software and used to estimate SOC in the battery pack under test charge and discharge conditions to evaluate its effectiveness for this application.

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