Extended Kalman Filter based battery state of charge(SOC) estimation for electric vehicles

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Extended Kalman Filter Based Battery State of Charge(SOC) Estimation for Electric Vehicles

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***Abstract*- This paper proposed a battery state of charge (SOC) estimation methodology utilizing the Extended Kalman Filter. First, Extended Kalman Filter for Li-ion battery SOC was mathematically designed. Next, simulation models were developed in MATLAB/Simulink, which indicated that the battery SOC estimation with Extended Kalman filter is much more accurate than that from Coulomb Counting method. This is coincident with the mathematical analysis. At the end, a test bench with Lithium-Ion batteries was set up to experimentally verify the theoretical analysis and simulation. Experimental results showed that the average SOC estimation error using Extended Kalman Filter is <1%.**

***Index Terms*- Li-ion Battery, Kalman Filter, State of Charge(SOC), Electric Vehicles**

I. INTRODUCTION

A great factor in determining the stability of Li-ion battery packs lies within the state-of-charge (SOC) estimation. Failing to predict battery SOC will cause overcharge or over discharge during cycles, which potentially will bring irreversible permanent damage to the battery cell. The most accurate method to measure the SOC is the direct relation of OCV, however this can only be accurately measured offline when the battery has no current transfer. Presently the most commonly applied online SOC estimation is the coulomb counting (CC) method [2][6], which measures the battery current, integrates it with represent to time, and determines an estimated battery SOC. When the measured battery current has some error, the long-run integration will bring unpredictable deviation of SOC, which will lead to the overcharge or undercharge of the battery.

Compared to CC method, the Extended Kalman Filter is a better solution, which only adopts the battery terminal voltage and current. The desired SOC is related to the OCV, which is a state variable V_{cs} shown in the simplified battery model in Fig.1.

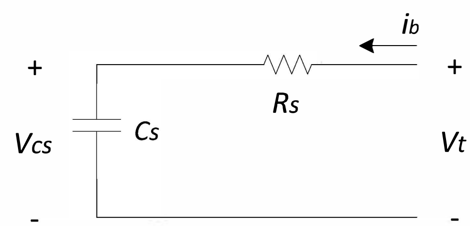

Fig.1. Battery Model

Here we assume that Vcs is the battery OCV, i_b is the battery charging current, Rs is the battery internal resistance and Vt is the terminal voltage. We also define the system state variables, outputs, and inputs in (1).

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} Vcs \\ Cs \\ Rs \end{bmatrix};$$

$$y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} Vt \\ i_b \end{bmatrix};$$

$$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} Vt \\ i_b \end{bmatrix} \tag{1}$$

Assume the state equations have some process noises w and input sensor noises v. Thus the standard state space form is represented by (2).

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases} \Rightarrow$$

$$\begin{cases} \dot{x} = \begin{bmatrix} \frac{-1}{RsCs} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Vcs \\ Cs \\ Rs \end{bmatrix} + \begin{bmatrix} \frac{1}{RsCs} & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Vt \\ i_b \end{bmatrix} + w \\ y = \begin{bmatrix} 1 & 0 & 0 \\ \frac{-1}{Rs} & 0 & 0 \end{bmatrix} \begin{bmatrix} Vcs \\ Cs \\ Rs \end{bmatrix} + \begin{bmatrix} 0 & Rs \\ \frac{1}{Rs} & 0 \end{bmatrix} \begin{bmatrix} Vt \\ i_b \end{bmatrix} + v \end{cases} \tag{2}$$

The non-linear discrete-time process with input and measurement noises can be described by Fig.2.

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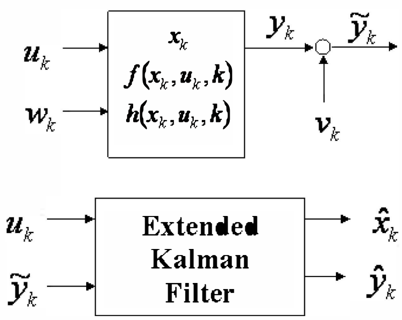


Fig.2. Non-linear Discrete-time Process

In a standard state space form[1], the process can be describe by (3)~(5).

$$x_k = f(x_{k-1}, u_k, k) + w_{k-1} \tag{3}$$

$$y_k = h(x_k, u_k, k) \tag{4}$$

$$\tilde{y}_k = y_k + v_k \tag{5}$$

Here k denotes a discrete point in time(with k-1being the immediate past time point). u_k is a vector of inputs(V_t and i_b). x_k is a vector of the actual states, which may be observable but not measured(V_{cs}, C_s and R_s). y_k is a vector of actual process outputs(V_t and i_b). $\tilde{y}_k$ is a vector of the measured process outputs. *f(.)* and *h(.)* are generic non-linear functions relating the past state, current input, and current time to the next state and current output respectively. w_k and v_k are process and output noise respectively. They are assumed to be zero mean Gaussian with covariance Q_k and R_k respectively.[2]

Given the inputs, measured outputs and assumptions on the process and output noise, the purpose of Extended Kalman Filter is to estimate immeasurable states(V_{cs}, C_s and R_s, they are observable) and the actual process outputs. In the SOC estimation, inputs and outputs are identical (V_t and i_b). The purpose then becomes to estimate the unmeasured states V_{cs}, C_s and R_s which provide information of OCV, cell total capacitance, and internal resistance respectively. The estimated states are $\hat{x}_k$ while the estimated measured outputs are $\hat{y}_k$.[5]

Extended Kalman Filter uses a two-step predictor-corrector algorithm. The first step involves projecting both the most recent state estimate and an estimate of the error covariance (from previous time period) forward in time to compute a predicted estimate of the states at the current time. The second step involves correcting the predicted state estimate calculated in the first step by incorporating the most recent process measurement to generate an updated state estimate. [5]

Due to the non-linear nature of the process being the covariance prediction, update equations cannot use *f(.)* and *h(.)* directly. Rather they use the Jacobian of *f(.)* and *h(.)*. The Jacobians are defined by (6) and (7).

$$F_k = \frac{\partial f}{\partial x}\bigg|_{(\hat{x}_k, u_k, k)} \tag{6}$$

$$H_k = \frac{\partial h}{\partial x}\bigg|_{(\hat{x}_k, u_k, k)} \tag{7}$$

The predictor step is given as (8) and (9).

$$\hat{x}_k^- = f(\hat{x}_k, u_k, k) \tag{8}$$

$$P_k^- = F_{k-1} P_{k-1} F_{k-1}^T + Q_k \tag{9}$$

The corrector step is given as (10)~(12).

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{10}$$

$$\hat{x}_k = \hat{x}_k^- + K_k\big(\tilde{y}_k - h(\hat{x}_k^-, u_k, k)\big) \tag{11}$$

$$P_k = (I - K_k H_k) P_k^- \tag{12}$$

In (10)~(12) P_k is an estimate of the covariance of the measurement error and K_k is the Kalman gain. After both the prediction and correction steps have been performed then $\hat{x}_k$ is the current estimate of the states and $\hat{y}_k$ can be calculated directly from it. Both $\hat{x}_k$ and P_k are stored and used in the predictor step of the next time period. As the sampling time is assigned to be T_s, the Jacobians matrices for this system can be calculated by (13) and (14).

$$F = \begin{bmatrix} \frac{\partial(\dot{Vcs})}{\partial Vcs} & \frac{\partial(\dot{Vcs})}{\partial Cs} & \frac{\partial(\dot{Vcs})}{\partial Rs} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} Ts + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow$$

$$F = \begin{bmatrix} \frac{-1}{RsCs} Ts + 1 & \frac{Vcs - Vt}{RsCs^2} Ts & \frac{Vcs - Vt}{CsRs^2} Ts \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{13}$$

$$H = \begin{bmatrix} \frac{\partial(y_1)}{\partial Vcs} & \frac{\partial(y_1)}{\partial Cs} & \frac{\partial(y_1)}{\partial Rs} \\ \frac{\partial(y_2)}{\partial Vcs} & \frac{\partial(y_2)}{\partial Cs} & \frac{\partial(y_2)}{\partial Rs} \end{bmatrix} \Rightarrow$$

$$H = \begin{bmatrix} 1 & 0 & i_b \\ \frac{-1}{Rs} & 0 & \frac{Vcs - Vt}{Rs^2} \end{bmatrix} \tag{14}$$

Q_{ij} stands for the covariance of process(V_{cs}, C_s, and R_s). R_{ij} stands for the covariance of output(Vt and i_b) noise.

The noises are assumed to be independent from each other[6]. It is clear that

$$Q_{12} = Q_{13} = Q_{21} = Q_{23} = Q_{31} = Q_{32} = 0; \qquad (15)$$

$$Q_{11}, Q_{22}, Q_{33} = var(w(Vcs)), var(w(Cs)), var(w(Rs)) \qquad (16)$$

$$R_{12} = R_{21} = 0 \qquad (17)$$

$$R_{11}, R_{22} = var(v(Vt)), var(v(i_b)) \qquad (18)$$

Then, Q, R can be written as

$$Q = \begin{bmatrix} Q_{11} & Q_{12} & Q_{13} \\ Q_{21} & Q_{22} & Q_{23} \\ Q_{31} & Q_{32} & Q_{33} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} var(w(Vcs)) & 0 & 0 \\ 0 & var(w(Cs)) & 0 \\ 0 & 0 & var(w(Rs)) \end{bmatrix} \qquad (19)$$

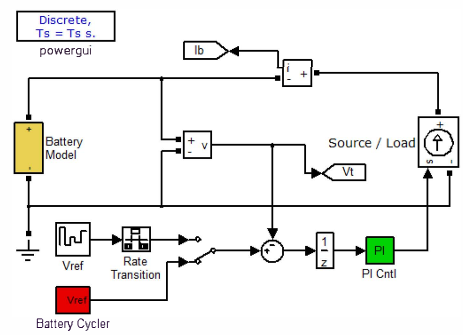
$$R = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} var(v(Vt)) & 0 \\ 0 & var(v(i_b)) \end{bmatrix} \qquad (20)$$

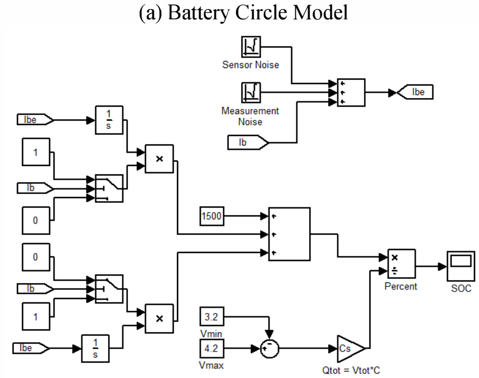
EKF is performed by (6)~(12).

II. SIMULATION VERIFICATION

Based on the analysis and mathematical description in section I, the EKF method should provide a much higher accurate SOC estimation than CC method. In order to verify the mathematical model with the iteration, simulation models for CC and EKF method were developed in MATLAB/Simulink. In the model shown in Fig.3 using CC method, the battery model simulates charge and discharge cycle repeatedly. The corresponding SOC will vary from 5% to 95%. It is worthwhile to point out that the models in simulation software are ideal without noises. Two white noise sources are added to approach the reality. Simulation result of CC is shown in Fig.4. It can be observed that as the battery gets charged and discharged periodically[2], the estimated SOC gains an increasing error from the true SOC, i.e. the estimation by CC is incapable of correcting its error[3][4]. This can be easily explained from the fact that CC method uses integration to estimate the charge and discharge capacitance with time. The measured noises will be accumulated with time in the integration process.



(a) Battery Circle Model



(b) SOC Calculation Model

Fig.3. Simulation Model for Coulomb Counting Method

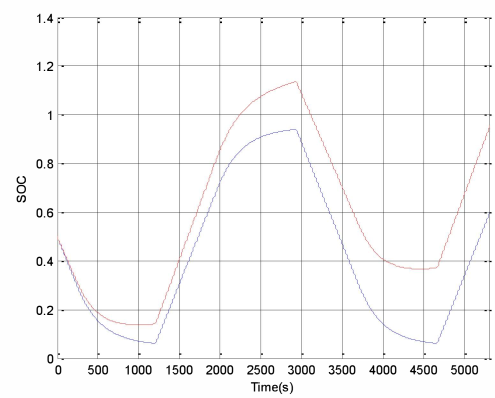
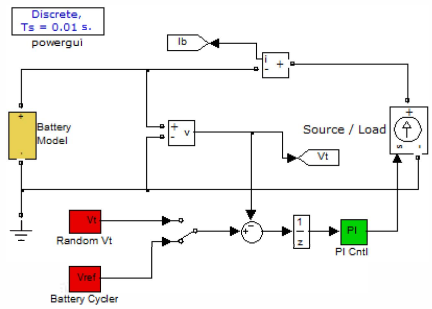
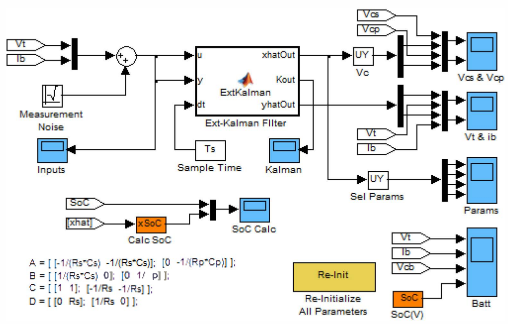


Fig.4. Coulomb Counting Simulation Results. Red→Estimated SOC, Blue→Real SOC

For EKF, the integration estimation is eliminated. EKF could perform estimation and regulate the error to minimum. Fig.5 shows the Extended Kalman Filter based MATLAB/Simulink model. The same battery charge and discharge profile as Fig.3 is adopted. Simulation results are obtained as Fig.6, which shows the EKF based SOC estimation has a much higher accuracy compared with CC. The estimated SOC curve follows the true SOC curve closely.



(a) Battery Circle Model



(b) SOC Calculation Model

Fig.5. Simulation Model for Extended Kalman Filter Method

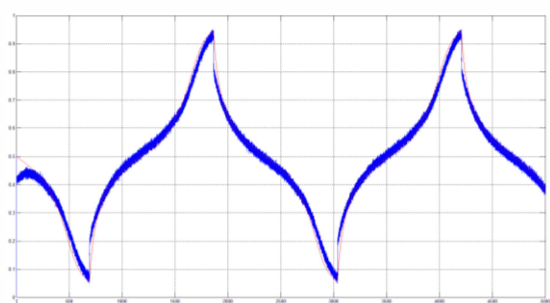


Fig.6. EKF Simulation Results; Red: Real SOC, Blue: Estimated SOC

III. Test Bench and Experimental Validation

In order to test the accuracy and feasibility of the EKF in the real application, a test bench is set up shown in Fig.7, which includes a 3-cell battery pack, a charging power supply, a current sensor to measure the battery current, and a TI DSP based control system. In order to evaluate the EKF, the battery pack is charged from 10% SOC to 90% SOC. During the charging period we extract OCV and SOC at different terminal voltage of 9.0V, 9.2V, 9.4V, 9.6V, 9.8V and 10.0V. At each point, when the estimation reaches the target voltage, the battery would be disconnected from the power supply. After 3 minutes, we read the battery OCV and compare it to the estimated value. Applying the estimated OCV values to *OCV vs. Capacity* curve provided by battery manufacturer in Fig.8, SOC can then be obtained. The EKF estimated OCV error is shown in Table I. Data in Table I is the average value collected during 10 charging cycles with 0.5C charging current.

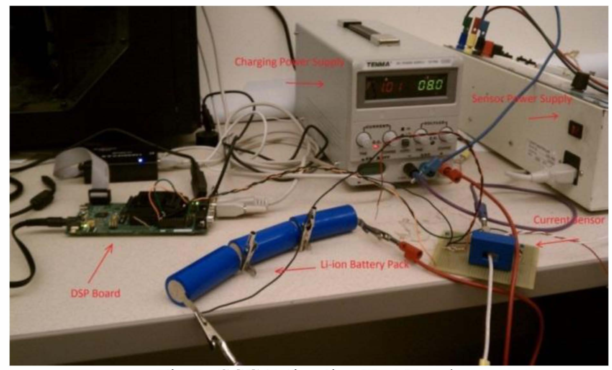


Fig.7. SOC Estimation Test Bench

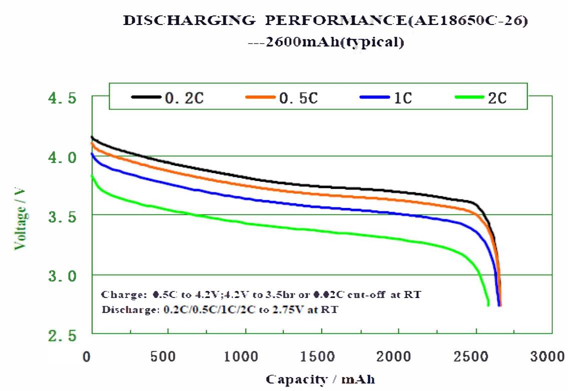


Fig.8. Cell OCV vs. Capacity Chart

Table. I EKF OCV/SOC Estimation Error

EKF Estimated OCV (V)	Corres-ponding SOC(%)	TRUE OCV (V)	Corres-ponding SOC(%)	SOC Error Percentage (%)
9.2	7.7	9.19	7.69	0.1
9.4	13.5	9.42	13.53	0.2
9.6	23.1	9.65	23.2	0.5
9.8	43.3	9.87	43.6	0.7
10	52.0	9.98	52.1	0.2

IV. CONCLUSION

The battery SOC estimation based on EKF proves to be accurate and robust. Additionally, EKF can track the battery states such as internal resistance when battery degrades. EKF method provides a number of merits compared with conventional CC method. EKF is exceptionally accurate in estimating non-linear system with multiple noise sources. It offers us the capability to monitor the SOC/SOH as well as any battery parameters as long as such parameters can be characterized in the battery model. EKF provides a series of methods for PHEV/EV battery monitoring.

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