State of Charge Estimation for Electric Vehicle Batteries under an Adaptive Filtering Framework

Wei He, Nicholas Williard, Chaochao Chen, Michael Pecht
Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD, 20742, USA
pecht@calce.umd.edu

Abstract—Electric vehicles (EVs), which are powered by lithium batteries, will penetrate the automobile market within the next few years. This is mainly due to the increasing concerns of global warming and fossil fuel depletion. However, there are still some challenges for EVs that remain to be solved. The most notable one is the state of charge (SOC) estimation and prediction for relieving EV drivers’ range anxiety. To address this problem, an equivalent circuit model is built to simulate battery behavior under dynamical loading conditions. The parameters of the model should be tuned on-line in order to handle the prediction uncertainty arising from unit to unit variations and loading condition changes. This paper proposed an Unscented Kalman filtering-based method to self-adjust the model parameters and provide the SOC estimation. The performance of the proposed method is demonstrated using data collected from LiFePO4 batteries cycled with two dynamical discharge profiles.

Keywords-State of Charge Estimation; Lithium-ion Battery; Unscented Kalman Filter; styling; Electric Vehicles

I. INTRODUCTION

With the increasing concerns on global warming and fossil fuel depletion, the automobile industry is facing a landmark transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs). The major industrialized nations have outlined their plans for the EV development and production. For example, the U.S. government set a goal to have one million EVs on the road by 2015 [1]. The Chinese government plans to have five million EVs on the road by 2020 [2].

Though EVs will inevitably permeate the market, challenges still exist. A notable one is the “range anxiety” problem, which describes the driver’s fear of running out of battery power on road [3]. The driving range of an EV is only 40-100 miles today, which is much less than ICE vehicles. What make things worse is that there are very few charging stations on road at present. To prevent EVs from being stalled on the road, predictions of its residual range is needed. The first step for residual range prediction is to know how much capacity remains in the battery or state of charge (SOC). The most common method for SOC estimation is Coulomb counting [3-5], in which the remaining charge is calculated by integrating the current entering or leaving the battery overtime. Coulomb counting is simple and easy to be implemented for on-board applications. However, it requires knowledge of the starting SOC. In addition, Coulomb counting is an open-loop method. Measurement noise and battery ageing can cause the drift in Coulomb counting. Another popular method is the voltage-based method that is to infer SOC by an open circuit voltage (OCV)-SOC lookup table [6]. However, OCV measurement requires a long period of rest before the terminal voltage converges to the actual OCV. With the use of a battery model, it is possible to infer the battery’s OCV from its terminal voltage. But this approach can generate large error if the model employed is not accurate. A ±0.01 V modeling error in the OCV could produce 10% percent error in the SOC estimation. In order to address these problems, this paper proposes a SOC estimation method using unscented Kalman filter (UKF) with a simple battery state-space model. This method does not require initial SOC information. It can self-correct the SOC estimation by adding a correcting term which is generated based on the difference between the measurement and model prediction. The proposed method is validated using two dynamical discharge profiles.

II. BATTERY MODELING

A straightforward way to model the terminal voltage $V$ of a battery is to model it by the OCV minus the voltage drop of the internal resistance $R$, as in Eq. (1):

$$V = OCV - I \times R \quad (1)$$

The schematic diagram of this model is shown in Fig.1, in which the OCV and $R$ is connected in series. OCV is the battery terminal voltage when no current is put in or draw out of the battery. OCV is a function of SOC. As SOC decrease, OCV will also decrease. The OCV-SOC relationship can be determined and stored in a loop-up table under well controlled lab experiments.

![Figure 1. A simple battery model](image)

In this research, the experiment for OCV-SOC determination contains the follow steps [7]:

- [Step 1]
- [Step 2]
- [Step 3]
- [Step 4]
- [Step 5]

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(1) Discharge the cell at 0.1 A from its fully charged state to its fully discharged state.
(2) Rest for 2 hours.
(3) Charge the cell at 0.1 A to its fully charged state.
(4) Averaging the discharge and charge voltage provides the OCV.

The batteries tested have a rated capacity of 2.3 Ah. The resultant OCV-SOC is shown in Fig. 2.

The terminal voltage was measured every second. Based on the collected data, $R$ can be estimated by a least-square algorithm. Fig. 4 (a) and (b) shows the fitted result and the error respectively. The root mean square (RMS) error of the fit is 0.0212, and the mean error is 0.0180. The mean error suggests there is a bias in the model, which can also be seen from Fig. 4(b). Thus, the model can be improved by adding a constant $C$ to Eq. (1):

$$V = OCV - I \times R + C$$

The fitted result of Eq. (2) is shown in Fig. 5. The RMS error of this model is decreased to 0.0064, and the mean error is reduced to -6.6107e-016. Using Eq. (2), we can formulate a state-space model for UKF estimation. SOC and $R$ are selected as states in the state-space model, and the measurement model is the terminal voltage, which is a function of SOC and $R$.

$$
\begin{align*}
\text{SOC}(k+1) &= \text{SOC}(k) - \frac{I(k) \times \Delta T}{C_n} + \omega_1 \\
R(k+1) &= R(k) + \omega_2 \\
V(k) &= OCV[\text{SOC}(k)] - I(k) \cdot R(k) + C + \epsilon
\end{align*}
$$

Here $C_n$ is the total capacity of the battery; $\omega_1$ and $\omega_2$ are process noise, and $\epsilon$ is measurement noise.
III. UNSCENTED KALMAN FILTER

The SOC estimation is a nonlinear problem in this study. The non-linearity can be seen from the observation model, where OCV(SOC[k]) is a non-linear function as shown in Fig. 2. For non-linear state estimation problem, extended Kalman filter (EKF) is a standard approach. However, EKF uses first order terms of the Taylor series expansion of the nonlinear functions. Large error can be produced if the model is highly nonlinear. In this study, we adopted the unscented Kalman filter (UKF) which can be accurate to the 3rd order in the sense of Taylor series expansion for any nonlinearity [10]. UKF is a direct application of unscented transform (UT). In UT, a Gaussian distribution is represented by a set of carefully chosen sample points called sigma points. These sigma points can capture the mean and covariance of the Gaussian random variables (GRV) when propagated through a nonlinear function.

Assume a random variable \( x \) (dimension \( L \)) has mean \( \bar{x} \) and covariance \( P_x \). Consider propagating \( x \) through a nonlinear function \( y = g(x) \). To calculate the statistics of \( y \), we first find a matrix \( \chi \) of \( 2L+1 \) sigma vectors \( \chi_i \) with corresponding weights \( W_i \), according to the following equations [10]:

\[
\begin{align*}
\chi_0 &= \bar{x} \\
\chi_i &= \bar{x} + \sqrt{(L+\lambda)P_x}, \quad i = 1, \ldots, L \\
\chi_i &= \bar{x} - \sqrt{(L+\lambda)P_x}, \quad i = L+1, \ldots, 2L \\
W_{0}^{(m)} &= \lambda/(L+\lambda) \\
W_i^{(m)} &= W_{0}^{(m)} = 1/(2(L+\lambda)), \quad i = 1, \ldots, 2L 
\end{align*}
\]

where \( \lambda = \alpha^2 (L+\kappa) - L \) is a scaling parameter. \( \alpha \) determines the spread of the sigma points around \( \bar{x} \). \( \kappa \) is another scaling parameter which is set to \( 3-L \). \( \beta \) is used to incorporate prior knowledge of the distribution of \( x \). For Gaussian distributions, \( \beta = 2 \) is optimal [10]. \( \sqrt{(L+\lambda)P_x} \) is the \( i \)-th column of the matrix square root of \( (L+\lambda)P_x \). Then each sigma point is propagated through the nonlinear function \( y_i = g(X_i) \), \( i = 0, \ldots, 2L \). The estimated mean and covariance of \( y \) are computed by the weighted sample mean and covariance as follows:

\[
\begin{align*}
\bar{y} &= \sum_{i=0}^{2L} W_i^{(m)} y_i \\
\bar{P}_y &= \sum_{i=0}^{2L} W_i^{(m)} (y_i - \bar{y})(y_i - \bar{y})^T 
\end{align*}
\]

The UKF is a straightforward application of the UT for state estimation. The main steps of UKF are summarized as follows:

1. Initialize with \( \hat{X}_0 = E[X_0] \) and \( P_0 = E[(X_0 - \hat{X}_0)(X_0 - \hat{X}_0)^T] \)
2. For \( k \in \{1, \ldots, \infty \} \), calculate sigma points:
   \[
   \chi_{k+1} = [\chi_{k+1}^0, \chi_{k+1}^1 + \gamma P_{k+1}, \chi_{k+1}^1 - \gamma P_{k+1}] 
   \]
3. State prediction:
   - Propagate the sigma points through the state model:
     \( \chi_{k+1} = H[\chi_{k+1}] \)
   - Calculate the propagated mean
     \( \bar{X}_k = \sum_{i=0}^{2L} W_i^{(m)} \chi_{i,k+1} \)
   - Calculate the propagated covariance
     \( P_k = \sum_{i=0}^{2L} W_i^{(m)} (\chi_{i,k+1} - \bar{X}_k)(\chi_{i,k+1} - \bar{X}_k)^T \)
4. Measurement update:
   - Propagate sigma points through measurement function
     \( y_{k+1} = H[\chi_{k+1}] \)
   - Calculate the propagated mean
     \( \bar{y}_k = \sum_{i=0}^{2L} W_i^{(m)} y_{i,k+1} \)
   - Calculate the estimated covariance

\[
W_0^{(c)} = \frac{\lambda}{(L+\lambda)} + 1 - \alpha^2 + \beta \\
W_i^{(m)} = W_0^{(c)} = \frac{1}{2(L+\lambda)}, \quad i = 1, \ldots, 2L
\]
Calculate the Kalman gain $K$ and update the state estimation and covariance

$$K = P_{n_{y}}^{-1} P_{n_{y}}$$

$$\bar{X}_k = \bar{X}_k + K (y_k - \bar{y}_k)$$

$$P_k = P_k - K P_{n_{y}} K^T$$

IV. STATE OF CHARGE ESTIMATION RESULT

The proposed method is first tested on the data collected by the federal driving schedule as shown in Fig. 3. The true initial SOC is 80%. To simulate actual field conditions where the exact SOC at the beginning of usage is unknown, the initial SOC guess for UKF estimation is intentionally set to be 35%. The estimation result is shown in Fig. 6. Though the estimation deviates from the true value during the first 10% of the discharge cycle, it finally converges to the true SOC as more measurements became available. The RMS error of the estimation is 3.035%.

The proposed method was further tested by varying the beginning SOC of the battery and allowing the UKF to adapt to the true value. In each case, the initial SOC guesses were set to be 35%. Fig. 7 shows the result. It can be seen that the RMS errors of all case are within 3.1%. The maximum RMS error occurs when starting from 80% SOC. One possible reason for this can be the relative flat OCV slop at 80% SOC as shown in Fig. 2, which means a tiny error in the OCV can cause large error in the SOC estimation.
Validation tests were conducted on more than 100 batteries. It was found that the SOC of an EV changes due to self-discharge or varying environmental conditions, this method will be able to self-correct the SOC automatically. The RMS errors of the SOC estimation in the validation tests were smaller than 4%. In addition, the proposed method can handle unit to unit difference and loading condition variations without changing the setting of the UKF. The temperature is another influencing factor for SOC estimation. Future work will investigate the SOC estimation under simultaneous dynamical temperature and discharge conditions.

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**CONCLUSIONS**

State of charge (SOC) provides critical information for residual range prediction and for battery control unit to prevent the battery from over-charge and over-discharge. This paper proposed a SOC estimation method based on unscented Kalman filter and an empirical battery model. The proposed method does not require initial SOC information. It is able to converge to true SOC as more measurements available. This property is meaningful for real applications, like EVs. When