State of charge estimation for electric vehicle batteries using unscented kalman filtering

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A B S T R A C T

Due to the increasing concern over global warming and fossil fuel depletion, it is expected that electric vehicles powered by lithium batteries will become more common over the next decade. However, there are still some unresolved challenges, the most notable being state of charge estimation, which alerts drivers of their vehicle's range capability. We developed a model to simulate battery terminal voltage as a function of state of charge under dynamic loading conditions. The parameters of the model were tailored from LiFePO4 batteries cycled according to the federal driving schedule and dynamic stress testing. We used an unscented Kalman filtering-based method to self-adjust the model parameters and provide state of charge estimation. The performance of the method was demonstrated using data collected from LiFePO4 batteries cycled according to the federal driving schedule and dynamic stress testing.

1. Introduction

With increasing concerns about global warming and fossil fuel depletion, the automobile industry is facing a transition from internal combustion engines (ICEs) to electric vehicles (EVs). The major industrialized nations have outlined their plans for EV development and production. For example, the US government set a goal of having one million EVs on the road by 2015 [1], and the Chinese government plans to have five million EVs on the road by 2020 [2]. Although EVs will inevitably permeate the market, challenges still exist. One challenge is the “range anxiety” problem, which refers to the driver’s fear of running out of battery power on the road [3]. As of 2011, the driving range of an EV was only 40–100 miles, which is 3–4 times less than ICE vehicles. Adding to the problem is the current lack of battery charging infrastructure. Therefore, to prevent EVs from running out of charge on the road and leaving passengers stranded, the ability to predict their residual range is needed. The first step in residual range prediction is to know how much capacity remains in the battery, also known as its state of charge (SOC).

The most common method for SOC estimation is Coulomb counting [4,5], in which the remaining charge is calculated by integrating the current entering or leaving the battery over time. Coulomb counting is simple and easy to implement in on-board applications. However, it requires knowledge of the starting SOC. In addition, Coulomb counting is an open-loop method, and measurement noise and battery aging can cause drift. Another popular method for SOC estimation is the voltage-based method, which infers SOC by an open circuit voltage (OCV)-SOC look-up 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 errors if the model employed is not accurate. A ±0.01 V modeling error in the OCV could produce a 10% error in SOC estimation for LiFePO4 batteries. Other work has been conducted using computational intelligence algorithms, such as fuzzy-logic [7], artificial neural networks (NNs) [8–12], and support vector machines (SVMs) [13–15], which do not require detailed expert knowledge of battery systems. A typical example is the SVM-based SOC estimator for a large-scale lithium–ion polymer battery pack developed by Hansen and Wang [13]. The SVM estimator was tested with US06 dynamic operational data from the US Department of Energy’s Hybrid Electric Vehicle program, and the root-mean-square (RMS) error of the SOC estimation was within 6%. Computational intelligence methods can be accurate if the training data are sufficient to cover the loading conditions of the battery. However, collecting training data that provide good coverage of all the loading conditions can be time consuming.

Recently, effort has been focused on developing model-based filtering methods [16–24] aimed at establishing closed-loop estimation. The equivalent circuit model and electrochemical model are used to establish a battery state-space model, where the current is used as the input, the terminal voltage is the output, and the SOC is set as the hidden state. Then, a filtering method, such as the extended Kalman filter (EKF) or particle filter (PF) is utilized to estimate the hidden state. Plett [16–18] developed an EKF framework for SOC estimation of LiFePO4 batteries, which is closed-loop in nature. At each time point, the filter proposes a
voltage based on the measured accumulated current and the system model. The estimated voltage is then compared to the measured voltage. The difference between the estimated and measured voltages is then used to calculate a correction term to adjust the SOC. However, an EKF is just a first or second order approximation of a nonlinear model. Large errors can be produced if the state-space model is nonlinear.

To address these problems, we developed an unscented Kalman filter (UKF)-based SOC estimation method with a state-space model. UKF is an improved version of the Kalman filter that applies unscented transform, which is a method for calculating the statistics of a random variable propagating through a nonlinear system. In UKF, the state distribution is represented by a set of sample points called sigma points, which capture the mean and covariance of the state distribution. The posterior mean and covariance of the state distribution is represented by a set of sample points called sigma points, which capture the mean and covariance of the state distribution. The propagated sigma points. UKF has been demonstrated to be better than EKFs in terms of accuracy and robustness for nonlinear estimation, and it can be accurate to the third order for any nonlinearity [25]. We explored UKF to estimate the model parameters and SOC in real-time. The developed approach was tested using data from different batteries and different loading conditions. The paper is organized as follows: Section 2 introduces the battery model developed in this study, Section 3 illustrates the unscented Kalman filter, Section 4 provides case studies, and Section 5 presents the conclusions.

2. Battery modeling

To model battery system dynamics, many equivalent circuit models have been proposed to represent the electrochemical process of a battery using electric elements, such as the resistance, capacitor, and inductor. The most straightforward way to model a battery is to model its terminal voltage $V$ as the OCV minus the voltage drop of the internal resistance $R$, which is shown in Eq. (1):

$$V = \text{OCV} - I \times R$$  \hspace{1cm} (1)

where $I$ is the current.

The schematic diagram of this model is shown in Fig. 1, in which the OCV and $R$ are connected in series. OCV is the terminal voltage when no current is put in or drawn out of the battery, and it is a function of SOC. As the SOC decreases, the OCV will also decrease. The OCV–SOC relationship can be determined using controlled experiments and stored in a look-up table.

In this research, the experiment for OCV–SOC determination contains the following steps [17]:

1. Discharge the cell at 0.1 A from its fully charged state to its fully discharged state.
2. Rest for 2 h.
3. Charge the cell at 0.1 A to its fully charged state.
4. Average the discharge and charge voltages to determine the OCV.

The fitted result of Eq. (2) is shown in Fig. 5. The model parameters, as well as the RMS error and mean error, are shown in Table 2. Compared with the model in Eq. (1), the RMS error of the model in Eq. (2) is reduced by 1 order, and the mean error is reduced by at least 10 orders. Thus, the model is improved.

Eq. (2) is used to infer the OCV from the terminal voltage $V$ and then, based on the OCV–SOC curve, the SOC is estimated. Fig. 6 shows the estimation result for cell #1. The max estimation error is 28.5%, and the RMS error is 6.12%. The large error is caused by the flat OCV–SOC curve of LiFeO₄ cells. From Fig. 2, the slope of the OCV–SOC curve (i.e., $d\text{OCV}/d\text{SOC}$) between 30% and 90% SOC is approximately 0.001, which means that an error of 0.01 V in OCV causes about a 10% error in SOC estimation. Therefore, direct model-based inference requires high accuracy of modeling and measurements. In Fig. 6, modeling error is the major cause of the
estimation error, because the RMS error of the model is 0.0064, which causes approximately a 6% RMS error in SOC estimation.

To improve the estimation accuracy, we developed an unscented Kalman filter-based approach. Using Eq. (2) and the Coulomb counting principle, we can formulate a state-space model for UKF estimation. SOC and R are selected as states for the state-space model, since they cannot be directly observed from the measurement. The evolution of SOC and R follow the Coulomb counting formula and random walk, respectively. The reason for choosing R as a state is because it varies among different cells, as shown in Table 2, while C only varies slightly. In order to address unit-to-unit variations, R is updated according to specific applications. The measurement model is the terminal voltage, which is defined as a nonlinear function of SOC and R variations, because the RMS error of the model is 0.0064, which causes approximately a 6% RMS error in SOC estimation. The problem with EKF is that it only uses first-order or second-order terms of the Taylor series expansion to approximate the nonlinear functions. Large errors are produced if the model is highly nonlinear. In this study, we utilized an unscented Kalman filter (UKF), which is accurate to the third order, in the sense of a Taylor series expansion for any nonlinearity [25]. UKF is a direct application of the unscented transform (UT), which is a statistical tool. In UT, a Gaussian distribution is represented by a set of carefully chosen sample points called sigma points. These sigma points capture the mean and covariance of the Gaussian random variables (GRVs) when propagated through a nonlinear function. UKF has been applied to system estimation [28,29], anomaly detection [30,31], and prognostics [32,33].

Assume that a Gaussian random variable \( \mathbf{x} \) (dimension \( L \)) has mean \( \mathbf{x} \) and covariance \( \mathbf{P} \). Consider propagating \( \mathbf{x} \) through the nonlinear function \( \mathbf{y} = g(\mathbf{x}) \). To calculate the statistics of \( \mathbf{y} \), we first find a matrix \( \mathbf{Z} \) of \( 2L + 1 \) sigma vectors \( \mathbf{z}_i \) with corresponding weights \( W_i \), according to the following equations [25]:

\[
\begin{align*}
Z_0 &= \mathbf{x} \\
Z_i &= \mathbf{x} + \sqrt{(L + \lambda)} \mathbf{P}^{\frac{1}{2}}_x, \quad i = 1, \ldots, L \\
Z_{L+i} &= \mathbf{x} - \sqrt{(L + \lambda)} \mathbf{P}^{\frac{1}{2}}_x, \quad i = L + 1, \ldots, 2L \\
W_0^{(m)} &= \lambda/(L + \lambda) \\
W_i^{(m)} &= \lambda/(L + \lambda) + 1 - \lambda^2 + \beta \\
W_i^{(c)} &= 1/(2(L + \lambda)) \\
\end{align*}
\]

where \( \lambda = \Delta^2(L + \kappa) - L \) is a scaling parameter, \( \alpha \) determines the spread of the sigma points around \( \mathbf{x} \), \( \kappa \) is another scaling parameter.

The unscented Kalman Filter

SOC estimation is a nonlinear problem. The nonlinearity can be seen in the measurement model, where OCV (SOC[k]) is highly nonlinear, as shown in Fig. 2. For the nonlinear state estimation problem, the extended Kalman filter (EKF) is a standard approach.

\[
\begin{align*}
\text{SOC}(k+1) &= \text{SOC}(k) - \frac{m(k) \cdot \Delta T}{Q_{\text{max}}} + \omega_1 \\
R(k+1) &= R(k) + \omega_2 \\
V(k) &= \text{OCV}[\text{SOC}(k)] - I(k) \cdot R(k) + C + \epsilon
\end{align*}
\]
The main steps of UKF are summarized below:

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:
   \[
   \chi_{k-1}^m = \begin{bmatrix} \hat{X}_{k-1} & \hat{X}_{k-1} + \gamma \sqrt{P_{k-1}} & \hat{X}_{k-1} - \gamma \sqrt{P_{k-1}} \end{bmatrix} \]
3. State prediction:
   a. Propagate the sigma points through the state model:
   \[
   Z_{k|k-1} = H[\hat{X}_{k|k-1}] \tag{8}
   \]
   b. Calculate the propagated mean:
   \[
   \hat{X}_k = \sum_{i=0}^{2L} W_i^{(c)} \chi_{k|k-1}^m
   \]
   c. Calculate the propagated covariance:
   \[
   P_k = \sum_{i=0}^{2L} W_i^{(c)} [\chi_{k|k-1} - \hat{X}_k] [\chi_{k|k-1} - \hat{X}_k]^T \tag{10}
   \]
4. Measurement update:
   a. Propagate sigma points through the measurement function:
   \[
   y_{k|k-1} = H[\hat{X}_{k|k-1}] \tag{11}
   \]
   b. Calculate the propagated mean:
   \[
   \hat{y}_k = \sum_{i=0}^{2L} W_i^{(c)} y_{i|k-1}
   \]
   c. Calculate the estimated covariance:
   \[
   P_{y_k} = \sum_{i=0}^{2L} W_i^{(c)} [y_{i|k-1} - \hat{y}_k] [y_{i|k-1} - \hat{y}_k]^T \tag{13}
   \]

which is set to $3 - L$, and $\beta$ is used to incorporate prior knowledge of the distribution of $X$. For Gaussian distributions, $\beta = 2$ is optimal [25]. $(\sqrt{(L + \lambda)} P_i)$ is the $i$th column of the matrix square root of $(L + \lambda) P$. Then, each sigma point is propagated through the nonlinear function $y_i = g(\chi_i), i = 0, \ldots, 2L$. The estimated mean and covariance of $y$ are computed by the weighted sample mean and covariance as follows:

\[
\hat{y} = \sum_{i=0}^{2L} W_i^{(m)} y_i \tag{5}
\]
\[
P_y = \sum_{i=0}^{2L} W_i^{(c)} (y_i - \hat{y})(y_i - \hat{y})^T \tag{6}
\]

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

\[
\chi_{k-1}^m = \begin{bmatrix} \hat{X}_{k-1} & \hat{X}_{k-1} + \gamma \sqrt{P_{k-1}} & \hat{X}_{k-1} - \gamma \sqrt{P_{k-1}} \end{bmatrix} \]

Fig. 4. (a) The fitted result of the model in Eq. (1) and (b) the error of the model fit.

Table 1
Parameters and errors of the model in Eq. (1).

<table>
<thead>
<tr>
<th>Cell #1</th>
<th>Cell #2</th>
<th>Cell #3</th>
<th>Cell #4</th>
<th>Cell #5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td>0.1347</td>
<td>0.1722</td>
<td>0.1636</td>
<td>0.2006</td>
</tr>
<tr>
<td>RMS error</td>
<td>0.0212</td>
<td>0.0218</td>
<td>0.0215</td>
<td>0.0201</td>
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<tr>
<td>Mean error</td>
<td>0.0180</td>
<td>0.0176</td>
<td>0.0183</td>
<td>0.0169</td>
</tr>
</tbody>
</table>

(a) The fitted result of the model in Eq. (1) and (b) the error of the model fit.
d. Calculate the Kalman gain \( K \) and update the state estimation and covariance:

\[
\begin{align*}
K &= P_{xk} P_{yk}^{-1} \\
\hat{X}_k &= \hat{X}_k + K(y_k - \hat{y}_k) \\
P_k &= P_k - K P_{yk} K^T
\end{align*}
\]

The advantages of UKF are: (1) it is robust to noise, because it takes the measurement and process uncertainties into account and (2) it has the ability to self-correct. In other words, whenever the estimation deviates from the true value, a correction term based on the Kalman gain will be added to the estimation. The next section will present the validation results of the developed method to show its effectiveness.

4. State of charge estimation case studies

The developed method was tested on data collected in the federal driving schedule, as shown in Fig. 3. The actual initial SOC was...
80%. The initial SOC guess for UKF estimation was set at 35% for two reasons: (1) to simulate the actual field conditions, where the exact SOC at the beginning of usage is unknown and (2) to test the self-correction capability of the UKF. The estimation result is shown in Fig. 7. The blue line is the actual SOC, while the red line is the UKF estimation. Although the estimation deviates from the real SOC at the beginning due to the erroneous initial guess, it converges to the real SOC as more measurements became available. After it converges, the estimation error is always smaller than 4%

In order to investigate the effect of different starting SOC conditions on the estimation accuracy, the UKF-based method was further tested by varying the beginning SOC of the battery and allowing the UKF to converge to the SOC. In each case, the initial SOC guesses were set at 35%. Fig. 8 shows the estimation results. The RMS errors of all cases were within 3.1%, and the maximum RMS error occurred when starting from 80% SOC. One reason for this is the flat OCV–SOC slope at 80% SOC, as shown in Fig. 2. Therefore, more data are required for the UKF to track back to the real SOC. As shown in Fig. 8, better accuracy was achieved when the estimation started from a low SOC region, such as 20% SOC, because it is close to the initial guess and the OCV–SOC curve at this region is steep. As a result, less data are required for the convergence.

The method was tested on data collected from a second LiFePO4 battery to see whether it can handle unit-to-unit variability. The parameter settings were the same as those used in the previous cases. As shown in Fig. 9, the maximum RMS error of the SOC estimation was less than 4%. The developed UKF method not only updates the SOC, but also updates the internal resistance. Therefore, it is able to handle the unit-to-unit variations within batteries.

A good SOC estimation should be able to function effectively under different loading profiles. To examine the applicability of the developed method to other profiles, we collected battery dis-
charge data using dynamic stress testing (DST) [34], which is a step charge/discharge profile. The current load profile and the corresponding terminal voltage response are shown in Fig. 10a and b, respectively. The parameter settings of the UKF, including the initial guess, process, and measurement noise, also remained the same. The RMS error of the SOC estimation at different starting points is shown in Fig. 11. The maximum RMS error was also less than 4%. Fig. 12 shows the SOC estimation beginning from 80%. It can be seen that the UKF-approach tracks the SOC well.

5. Conclusions

State of charge (SOC) is the actual capacity of a battery expressed as a percentage of the fully-charged capacity. SOC estimation is a major function of battery management systems (BMSs). The commonly used Coulomb counting method for SOC estimation requires knowing the exact initial SOC and suffers from the problem of drift as the error accumulates over time and the battery ages. Additionally, voltage-based estimation methods can produce large errors when applied to LiFePO4 batteries due to their flat OCV–SOC curves. To solve these problems, we developed an adaptive SOC estimation method that combines Coulomb counting and a battery voltage model using the unscented Kalman filter (UKF). The battery voltage model is readily implementable with two parameters to be determined. One parameter is the internal resistance, which is updated on-line as a hidden state to address unit-to-unit variations and loading condition changes. The other parameter is a compensatory constant term that is identified off-line. The dynamic SOC model was developed based on the Coulomb counting principle. UKF, which is close-looped in nature, was then used to infer the SOC from the current and voltage measurements. When the SOC estimation drifts, as detected by the deviation between the voltage model output and the voltage measurement, the UKF automatically generates a correction term to rectify the error. As a result, the developed method does not require prior information of the initial SOC and is robust to measurement noise. This feature is meaningful for EV applications, because when the SOC of an EV changes due to self-discharge or varying environmental conditions, this method self-corrects the SOC. The developed method was tested using data from different LiFePO4 batteries and two loading conditions, namely, the federal driving schedule and dynamic stress testing. The test results showed that the method was able to handle unit-to-unit variations and loading condition changes with an RMS error of less than 4%.

This research is significant for two reasons. First, the developed SOC estimation technique can indicate how much charge is left in the battery while taking into consideration unit-to-unit variations and loading condition changes. This is meaningful for EVs because unit-to-unit variation among the hundreds of cells in an EV battery pack is common due to uncertainties in the manufacturing, assembly, and material properties, and also because battery packs experience variant loading profiles as a result of different road conditions. Second, many battery systems for EVs are over-engineered by 25–100% to minimize the risk of premature failure caused by over-charging and over-discharging. SOC estimation provides information for the BMS to keep the battery working within a safe operating window. With an accurate SOC estimator in place, the battery pack can be used to its limit and does not need to be over-engineered, resulting in reduced cost.

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