SOC Estimation Algorithm for Seismic Vibrator Power Battery with Considering Temperature Compensation

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Abstract. In the oil-producing areas and densely populated areas in east China, the resistance to seismic vibrator exploration is increasing due to its noise and exhaust emissions. Using electric energy to substitute oil for seismic vibrator is an effective way to solve this problem, and the power battery is one of the keys to ensure the successful implementation. Since the battery exhibits a high degree of non-linearity during discharge and the working temperature is poor, it is difficult to accurately estimate the SOC (state of charge). Therefore, an SOC estimation algorithm considering temperature compensation is proposed to improve the estimation accuracy. Firstly, the paper analyses the algorithm logic, then constructs the equivalent circuit model of the power battery, and establishes the simulation model in Matlab/Simulink. The accuracies of the ampere-hour integration method and the SOC estimation algorithm with temperature compensation are compared. Finally, the reason for the error of the algorithm is analyzed. The simulation results show that the SOC estimation algorithm for power battery considering temperature compensation is more accurate, and the error can be kept below 1.53%.

1. Introduction

With the strengthening of environmental protection awareness, the seismic vibrator faces more and more resistance in the old oilfields and urban densely populated areas in east China. Using electric energy instead of the current conventional fuel energy as the main energy supply to solve noise and exhaust emissions is an effect way to meet the future development of domestic and international exploration [1]. And power battery is one of the keys to ensure the successful implementation of this method. The rated power of the seismic vibrator is more than 230 kW. As the number of power batteries is huge, accurate estimation of SOC can ensure the service life of the battery and improve the endurance of the seismic vibrator [2-4]. However, the power battery shows nonlinearity during the use and the working environment temperature is poor. The estimation of SOC is not easy to achieve and has become a hot issue.
Souradip et al. [5] proposed a fuzzy logic-based lead-acid battery state estimation system, which uses temperature and current to calculate the coulomb efficiency, and thus makes up for the problem of the coulomb efficiency of the ampere-hour integration method. Li et al. [6] investigated the factors affecting the accuracy of battery SOC by studying the ampere-hour integration method, and found that the SOC initial value correction method has the great influence on improving the accuracy of the ampere-hour integration method. Wu et al. [7] designed the battery SOC Kalman filter algorithm and carried out a simulation analysis. The results show that the Kalman filter algorithm is beneficial to improve the accuracy of the SOC of the power battery. Through the analysis of the above SOC estimation algorithm, conventional estimation methods of SOC are as follows [8-11]: ampere-hour integration method, open-circuit voltage method, Kalman filter method, and neural network method. Table 1 shows comparison of the advantages and disadvantages of several common algorithms.

| Algorithm              | Advantage                        | Disadvantage                                |
|------------------------|----------------------------------|---------------------------------------------|
| ampere-hour integration method | Simple and reliable, Quick estimate | Required to calibrate the initial value of SOC |
| open-circuit voltage method  | It is easy to measure the open circuit voltage. | Need battery to stand for a long time, Can’t predict in real time |
| neural network method    | High precision                   | Need a lot of experimental data              |
| Kalman filter method     | Optimal estimate of minimum variance | Large amount of computation and not suitable for nonlinear models |

Comparing the advantages and disadvantages of the above methods, Kalman filtering and neural network algorithms are the current focus of improvement. Because the neural network model requires large data volume that is difficult to collect, this paper chooses Kalman filter method as the basis for improvement. Therefore, combined with the open-circuit voltage method and ampere-hour integration method with temperature compensation, an EKF (extended Kalman filter) algorithm with temperature compensation is proposed.

2. EKF Algorithm with Considering Temperature Compensation

2.1. Algorithm logic
The improved SOC estimation algorithm based on EKF is as follows:

Step 1, using the open-circuit voltage method to obtain the initial state of charge SOC₀, According to the relationship between the OCV (open circuit voltage) and the SOC value, the initial value SOC₀ is provided for the ampere-hour integration method;

Step 2, using the ampere-hour integration method to obtain a relatively accurate SOC value, and introducing a temperature compensation coefficient, reducing the convergence time of the calculation while removing the influence of temperature;
Step 3, using the EKF method, the nonlinear equation of the nonlinear battery is linearly processed by the Taylor expansion formula. The iterative convergence makes the SOC value reach the accurate.

2.2. Equivalent battery model
The battery model was studied to grasp the battery characteristics and improve the accuracy of SOC estimation. Literature [12] shows that the accuracy of the battery model and the complexity of the algorithm increase with the increase of the order of the equivalent circuit model. The second-order RC equivalent model is more accurate than the first-order RC equivalent model, and the third-order RC equivalent model is better than the second, but it’s not obvious. Considering the accuracy of the model and the complexity of the algorithm, the lithium battery model of the second-order RC equivalent circuit is determined. The equivalent model is shown in Figure 2.

\begin{align*}
\dot{U}_{oc} &= -\frac{I}{C_{oc}} \\
U_{p1} &= \frac{I}{C_{p1}} - \frac{I}{R_{p1}C_{p1}} \\
U_{p2} &= \frac{I}{C_{p2}} - \frac{U_{p2}}{R_{p2}C_{p2}} \\
U_{oc} &= IR_i + U_{p1} + U_{p2} + U_o
\end{align*}

*U_{oc}*: Open circuit voltage; *U_o*: Terminal Voltage; *U_{p1}, U_{p2}*: RC loop voltage; *R_i*: Ohmic internal resistance; *R_{p1}, R_{p2}*: Electrochemical polarization internal resistance; *C_{oc}, C_{p1}, C_{p2}*: Battery capacitor

2.3. Calculating steps
(1) Open-circuit voltage method to calculate SOC_0
The open circuit voltage of the seismic vibrator single power battery is tested as shown in Figure 3, and the OCV-SOC relationship is shown in Figure 4:
Figure 3. LP54173210-202Ah battery.

Figure 4. OCV-SOC curve.

According to the curve of Figure 4 obtained from the experiment, the fitting curve is as shown in Equation (5).

\[
U_{ocv} = 23.333x^5 - 60.804x^4 + 59.551x^3 - 27.023x^2 \\
+ 5.703x + 2.892
\]  

(5)

(2) Ampere-hour integration method calculates a relatively accurate SOC value. Traditional Ampere-hour integration method expression:

\[
SOC = SOC_0 - \frac{1}{C_N} \int_0^\lambda \eta I dt
\]  

(6)

The battery changes significantly during charging and discharging. Therefore, the charging and discharging efficiency must be considered when estimating the battery SOC. Since the working temperature of the seismic vibrator is mostly in a poor temperature area, the temperature also affects the SOC estimation, so the temperature compensation should be performed when the SOC estimation is performed. In summary, the traditional ampere-time integration method is optimized, and the improved formula is as follows (7):
Equation (7) represents the SOC relational expression at time \( k+1 \) and time \( k \).

\[
SOC_{k+1} = SOC_k - \int_k^{k+1} \eta_i \eta_t \frac{I}{C_N} dt
\]  

At present, the common method for correcting the charge and discharge efficiency of lithium batteries [13] is the Peukert equation summarized by Peukert. Where \( n \) is the constant coefficient of the Peukert equation and the general value is 1.15 to 1.42.

\[
\eta_i = \frac{Q}{Q_0} = \left( \frac{I}{I_N} \right)^n
\]  

Temperature is one of the important factors affecting lithium batteries, which directly affects the material activity and chemical reaction degree of lithium battery operation. Therefore, the lithium iron phosphate battery was used as the experimental object. Placing the power batteries in an environment of -20 °C, -10 °C, 0 °C, 10 °C, 20 °C, 25 °C, 30 °C, 40 °C, the battery is completely discharged at a standard rate of C/3, and the total discharge data of the battery at different ambient temperatures is obtained. According to the experimental test (shown in Figure 5), a graph of temperature versus discharge power is obtained, as shown in Figure 6.

**Figure 5.** Temperature test experimental device.

**Figure 6.** The relationship between temperature and discharge capacity.
It can be seen from Figure 6 that between -20 °C and 20 °C, the discharge power of the battery gradually increases with increasing temperature. Above 25°C, the battery discharge power tends to be stable, and according to the test data, the temperature compensation coefficient fitting equation is obtained as shown in equation (9):

$$\eta = \frac{199.6863 + 0.1956x - 0.0036x^2}{202}$$  \hspace{2cm} (9)

(3) EKF calculates the exact SOC value

Due to the high nonlinearity of the battery, to solve the difficulty of calculating the nonlinear state variables by the Kalman filter method, the extended Kalman filter algorithm is used to linearize the state variables [14, 15]. That is, after developing the state equation by the Taylor formula, the second and above high-order terms in the equation are removed to obtain the formula (10):

$$x_k = x_{k-1} + Au_{k-1} + w_{k-1}$$
$$y_k = Cx_k + Du_k + v_k$$  \hspace{2cm} (10)

Convert (1), (2) and (3) into a space state equation:
Assuming \( x = [SOC, U_{p1}, U_{p2}] \), it can be obtained as follow:

\[
\begin{bmatrix}
    \dot{SOC} \\
    \dot{U}_{p1} \\
    \dot{U}_{p2}
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & 0 \\
    0 & 1 - \frac{T_s}{\tau_1} & 0 \\
    0 & 0 & 1 - \frac{T_s}{\tau_2}
\end{bmatrix}
\begin{bmatrix}
    SOC_{k-1} \\
    U_{p1k-1} \\
    U_{p2k-1}
\end{bmatrix}
+ \begin{bmatrix}
    \frac{\eta \eta T_s}{Q_N} \\
    \frac{T_s}{C_{p1}} \\
    \frac{T_s}{C_{p2}}
\end{bmatrix}
U
\]

From the equation (12), the SOC estimation value based on the EKF method can be obtained by the following six steps.

**Step 1, state transfer function:**

\[
\begin{bmatrix}
    SOC_k \\
    U_{p1k} \\
    U_{p2k}
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & 0 \\
    0 & 1 - \frac{T_s}{\tau_1} & 0 \\
    0 & 0 & 1 - \frac{T_s}{\tau_2}
\end{bmatrix}
\begin{bmatrix}
    SOC_{k-1} \\
    U_{p1k-1} \\
    U_{p2k-1}
\end{bmatrix}
+ \begin{bmatrix}
    \frac{\eta \eta T_s}{Q_N} \\
    \frac{T_s}{C_{p1}} \\
    \frac{T_s}{C_{p2}}
\end{bmatrix}
U
\]

Where \( \tau = RC \);

State transition matrix \( A = \begin{bmatrix}
    1 & 0 & 0 \\
    0 & 1 - \frac{T_s}{\tau_1} & 0 \\
    0 & 0 & 1 - \frac{T_s}{\tau_2}
\end{bmatrix} \);

Control input gain \( B = \begin{bmatrix}
    \frac{T_s}{C_{p1}} \\
    \frac{T_s}{C_{p2}}
\end{bmatrix} \), and \( T_s \) is sampling time;

Observing matrix \( C = \begin{bmatrix}
    \frac{\partial U(t)}{\partial SOC(t)} & -1 & -1
\end{bmatrix} \).
Step 2, Predictive estimation of mean square estimation error \( P_{k|k-1} = AP_{k-1|k-1}A^T + Q_{k-1} \); 

Assume that the initial covariance \( P_0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \);

\( Q_{k-1} \) is the system noise variance at time \( k-1 \).

Step 3, \( R_k \) is the observed noise variance at \( k \);

Kalman gain matrix \( K_k = P_{k|k-1}C^T(CP_{k|k-1}C^T + R_k)^{-1} \); 

Step 4, system observation vector \( y_k \); 

Optimal estimate of state variables \( x_{k|k} = x_{k|k-1} + K_k[y_k - g(x_{k|k-1}, u_k)] \); Measurement function \( g \)

\[
\begin{bmatrix}
SOC_k \\
U_{p1k} \\
U_{p2k}
\end{bmatrix} = \begin{bmatrix}
0 & -1 & -1 \\
U_{p1k} & R_k & I_k \\
U_{p2k} & \end{bmatrix} \] \(= (E - K_k C)P_{k|k-1} \)

Step 5, unit matrix is \( E \), and optimal mean square estimation error \( P_{k|k} = (E - K_k C)P_{k|k-1} \); 

Step 6, find the exact SOC value after iterative loop.

3. Simulation based on Matlab/Simulink and analysis

3.1. Establishment of simulation model

In order to verify the effectiveness of the above algorithm, according to the equivalent circuit model established in this paper and the EKF algorithm considering temperature compensation, the program model of the algorithm is established by Matlab/simulink. The simulation model, as shown in Figure 8, consists of three parts: (1) input: current, voltage, and the initial noise covariance \( Q, R \) of the system state vector; (2) the EKF algorithm considering temperature compensation; (3) Oscilloscope: SOC value and error comparison.

![Simulation model diagram](image-url)
3.2. Simulation results and analysis

![Simulation result comparison curve.](image)

Figure 9. Simulation result comparison curve.

From Figure 9, simulation results and analysis are drawn as follows:

1. Overall, the ampere-hour integration method and the temperature-compensated EKF algorithm have the same SOC estimation value as the real value trend.
2. As the discharge process deepens, the error of the SOC value measured by the ampere-hour integration method increases at the end of discharge.
3. During the whole discharge process, the error of the SOC estimated value obtained by the temperature-compensated EKF algorithm is 1.53%, and the error of the SOC estimated value obtained by the ampere-time integral method is 4.81%.

![Error curves for the two algorithms.](image)

Figure 10. Error curves for the two algorithms.

Through research and analysis, the source of error in the estimation process: (1) due to the nonlinear characteristics of the battery, the state space equation of the battery is linearized when the SOC estimation is performed, and the second-order and above derivatives are ignored in the linearization process using the Taylor formula. These processing methods also cause some errors; (2) system noise and measurement noise have some influence on the SOC estimation process, but there is no specific
quantization rule for this noise characteristic, only the estimated value is made, and the actual noise situation is more complicated, so the error will also occur. In summary, the improved Kalman filter algorithm can better estimate the SOC value of the battery, and the estimation accuracy is high, which meets the accuracy requirements, and is suitable for the estimation of the SOC of the lithium battery.

4. Conclusion
In this paper, an EKF algorithm with temperature compensation is proposed for the SOC estimation of seismic vibrator power battery. The algorithm research is carried out, which provides a reference for the SOC estimation research of large-capacity power battery with poor working environment temperature. Conclusions are as follows:

1) The method provided in this paper combines EKF, open-circuit voltage method and the ampere-hour integration method with the temperature compensation coefficient. It compensates for the shortcomings of the ampere-hour integration method that can’t provide the initial value and temperature change, and solves the limitations of the Kalman filter method in the application of the linear model, and also reduces the cumulative error, the calculation amount and convergence time.

2) By studying the equivalent battery model, the relationship between voltage, capacitance and resistance in the second-order RC equivalent circuit model is obtained.

3) The algorithm simulation model is established with Matlab/Simulink. The maximum error of SOC estimation value during discharge is 1.53%. Compared with the ampere-hour integration method, the error of the improved method is reduced by 68.19%.

Acknowledgments
This work is financially supported by the funding of China National Petroleum Corporation (Grant No. 2018B-3401 and 2018E-2106).

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