New Artificial Intelligence Technology Applied in Automobile Lithium Battery Manufacturing

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Abstract. In order to improve the estimation accuracy of the state of charge (SOC) of electric vehicle power batteries, this paper is based on artificial intelligence technology for lithium-ion battery model and parameter identification algorithm, adaptive unscented Kalman filter algorithm and SOC estimation based on battery model fusion Algorithm for research. The simulation results show that the SOC error estimated by the artificial intelligence adaptive Kalman filter method is less than 2.4%, which effectively reduces the impact of unknown interference noise on the battery management system when the electric vehicle is driving. The SOC estimation accuracy is higher than that of the extended Kalman method, and has good robustness.

Keywords: Artificial intelligence technology, automobile lithium battery, battery state of charge, lithium battery manufacturing.

1. Introduction
The ampere-hour integration method estimates the remaining capacity by integrating the current. It only needs to measure the battery current. The method is simple and easy to carry. However, it needs an accurate initial value and the estimation error is affected by the current drift. The open circuit voltage method relies on the relationship between OCV and SOC to estimate SOC, which has high accuracy [1]. However, the open circuit voltage method requires long-term standing and is not suitable for online estimation. Neural network method uses fuzzy neural network to model and train the battery, and then estimate its SOC. This method requires a large amount of experimental data for training, and the estimation result is greatly affected by the data sample [2]. Fuzzy logic method uses expert experience and knowledge to create control rules to control nonlinear, time-varying, lagging, and incomplete model systems. It is suitable for highly nonlinear battery models, but this method requires high engineering experience. And a lot of experimental data is required. The paper uses an improved extended Kalman filter method (EKF) to estimate the remaining power of the lithium battery, expands through the first-order Taylor formula, converts the non-linear problem of the battery into a linearization method, and adjusts the state equation of the remaining power to an appropriate temperature make up. Current and temperature are used as input, voltage is used as output, and the predicted remaining battery capacity is estimated as state variables. The simulation results prove that the voltage, current, and temperature of the battery mainly affect the remaining charge of the battery, and the error of estimating the SOC based on EKF will be reduced and the accuracy will be improved.
2. SOC estimation method

Estimate the state of charge SOC of the battery pack to determine the driving range of the car. The remaining capacity of the battery pack is numerically defined as the ratio of the remaining capacity of the battery to the total calibrated capacity of the battery:

\[
SOC = \frac{Q_N}{C} \times 100\%
\]

\[
SOC(t) = SOC(t_0) - \int_{t_0}^{t} i dt + Q_T(i, T, t) + Q_S(i, T, t, t_0)/\xi)
\]

In the formula: \(SOC(t)\) means the battery means the value of \(SOC\) at time \(t\); \(SOC(t_0)\) means the battery means the value of \(SOC\) at time \(t_0\); \(\int_{t_0}^{t} i dt\) means the battery is discharged with a current \(i\) and \(t_0\) means the amount of charge released during \(t\); \(Q_T(i, T, t)\) means the battery is caused by temperature during discharge Capacity loss; \(Q_S(i, T, t)\) represents the capacity loss caused by self-discharge of the battery during the discharge process; \(Q_N\) represents the standard capacity of the battery; \(\xi\) represents the battery's charge-discharge rate and cycle charge-discharge life that affect the total battery capacity, and \(\xi\) is the influence coefficient.

2.1. Coulomb notation (current integration)

Current integration method is also called ampere-hour integration method, which is the most commonly used SOC estimation method. The calculation formula is:

\[
SOC = SOC(t_0) - \int_{t_0}^{t} \frac{i(t) dt}{C_N}
\]

In the formula, \(i(t)\) is the accurate measurement of the current flowing through the battery pack from \(t_0\) to \(t\), \(\int_{t_0}^{t} i(t) dt\) refers to the integral value of the current in this time period, and \(C_N\) is the rated capacity of the battery.

2.2. Zero-load voltage method

The open circuit voltage method cannot accurately measure the remaining power, and then the commonly used zero-load voltage method is proposed. First establish the battery model, and then measure the open circuit voltage [3]. Figure 1 shows the battery voltage model based on zero load.
3. Kalman filter principle

The output of a dynamic system (battery system) will be a function of the current and past inputs of the system. This will set a “state” for the dynamic system to represent the sum of all past inputs, but this “state” may not directly measure. Therefore, the output is only a function of the current state and the current input, and has nothing to do with the past input [4]. The model equation of the random signal $s(n)$ and the Kalman standard form of the measurement model are:

$$S(n) = aS(n - 1) + w(n) \quad (4)$$

$$X(n) = cS(n) + v(n) \quad (5)$$

We use the Kalman filter to linearize the modified nonlinear system, and then form an extended Kalman filter (EKF). The battery happens to be a nonlinear system, so the input and output variables should be selected based on certain principles. The input in this paper is two variables, the input includes the battery current value $I$, the surface temperature $T$ of the battery, the output is the terminal voltage $V$ of the battery, and the predicted remaining battery power SOC is used as the state variable, as shown in Figure 2:
4. **Observation equation of power battery model based on nominal temperature**

According to the power battery model with nominal temperature:

\[
V_{bat} = U_{ac} (SOC) - I_L \cdot R_{S1} - V_{s11} - V_{s12}
\]  

(6)

\[
U_{ac} (SOC) - V_{bat} = I_L \cdot \left( R_{s1} + \frac{R_{s11}}{1 + R_{s11}C_{s11}} + \frac{R_{s12}}{1 + R_{s12}C_{s12}} \right)
\]  

(7)

\[
C = \left. \frac{\partial g(x(k), u(k))}{\partial x(k)} \right|_{x-x}
\]  

(8)

Here, \(x(k)\) represents SOC and \(u(k)\) represents current, then the expression of \(C\) is obtained:

\[
C = \left[ \frac{\partial V_{ac}}{\partial SOC} - \frac{\partial V}{\partial V_{s11}} - \frac{\partial V}{\partial V_{s12}} \right] = \left[ \frac{\partial V_{ac}}{\partial SOC} - 1 - 1 \right]
\]  

(9)

\[
D = \left. \frac{\partial g(x(k), u(k))}{\partial u(k)} \right|_{x-x} = (-R_{s1})
\]  

(10)

\[
V_{bat} = U_{ac} (SOC) - V_{s11} - V_{s12} - I_L \cdot R_{S1} + v
\]  

(11)

The current is regarded as the input of the space state equation, and the terminal voltage is the output of the measurement equation.

5. **Experimental results and analysis**

![Figure 3. The current value of the battery in operating conditions](image)

The sampling frequency of the test is 1 Hz, and the SOC of a single-cell lithium-ion battery is recorded by the host computer monitoring software with SOC estimation algorithm. The initial value
of the SOC of the multi-element composite lithium-ion battery is about 0.9, and the battery is charged and discharged at a constant current of 5C during the time t1-t8. Figure 3 shows the time-current curve in the experimental conditions. In the figure, t1 is 0-200s discharge state, t2 is 200-400s static state, t3 is 400-600s charge state, t4 is 600-800s static state, t5 is 800-1000s discharge state, t6 is 1000-1300s in the static state, t7 is the discharge state of 1300-1600s, and t8 is the static state of 1600-1800s.

Under the input of the discharge current ik, an adaptive Kalman filter method is used to estimate the terminal voltage up of the polarizing capacitor [5]. The simulation results show that when the discharge current increases, the polarization phenomenon will become more and more obvious. In an unknown noise environment, for the Thevenin model of the equivalent circuit of the lithium-ion battery given in this article, KF and adaptive Kalman filter are used to estimate the SOC value of the lithium-ion battery, and then compared with the lithium-ion battery that comes with MATLAB. Analysis and comparison of simulation results are shown in Figure 4.

![Figure 4. Comparison of estimated SOC value of lithium-ion battery with reference value](image)

From the trend of SOC estimation, the AEKF algorithm estimation result is more accurate [6]. With the advancement of the cycle of working conditions, the battery SOC is getting lower and lower, and the estimation errors of the AEKF and EKF algorithms are also increasing. When the SOC drops to the minimum value of 0.15, the relative error of the SOC estimation reaches the maximum, and the estimation error of the EKF algorithm reaches 12.8%, the large error may be related to the improper initial assignment of noise covariance. The relative error of the SOC estimation under the whole working condition is 4.94%. The AEKF algorithm has stronger adaptability and filtering effect on system noise, and is more suitable for battery SOC estimation under complex working conditions.

6. Conclusion
The experimental results show that in complex working conditions, AUKF uses adaptive adjustment of noise to obtain the statistical characteristics of the noise, and estimates the SOC of the battery in an environment with unknown noise. The average estimation error of EKF is reduced from 0.0079 to 0.0062, which solves the problem of poor estimation accuracy of EKF in working conditions with unknown noise characteristics, and is more suitable for the estimation of battery SOC under complex working conditions. In practical applications, temperature and cycle charge and discharge times have a great influence on battery SOC estimation. However, the estimation of SOC in this paper and the establishment of battery model did not take into account the influence of temperature and cycle charge and discharge times on batteries.
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