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SOC Estimation of Lithium Iron Phosphate Battery Based on Kalman Filtering Algorithm

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In order to improve the estimation accuracy of the state of charge (SOC) of electric vehicle, a second-order RC equivalent circuit model considering the battery capacity time-variation is proposed. Combining the nonlinear characteristics of lithium iron phosphate battery and the second- order RC equivalent circuit model, the state space equation of lithium iron phosphate battery is established. Based on the limited estimation accuracy of the extended Kalman filtering algorithm for nonlinear state equations, a central difference Kalman filtering algorithm is proposed. The simulation results show that the central difference Kalman filtering algorithm is better than the extended Kalman filter algorithm in the same condition for the estimation accuracy of SOC.

1. Introduction

After entering twentieth century, the problems of energy crisis and environmental pollution are becoming more and more prominent all over the world. In this situation, new energy vehicles, especially electric vehicles, have attracted the attention of major automobile manufacturers all over the world. Battery management system (BMS), as an important part of electric vehicles, can effectively manage and control the power battery, and ensure the efficient use of batteries and driving safety (Xiong, 2014). Battery management technology is still in the development stage, and many technologies are not mature. The focus and difficulty of the research is how to improve the estimation accuracy of battery SOC (Yinjiao et al., 2014). In this paper, the lithium iron phosphate battery (Saeed et al., 2014) is selected as research object, while the two aspects of battery model and model-based SOC estimation method are deeply studied.

2. Establishment of lithium iron phosphate battery model

BMS system of electric vehicle has no high-performance processor. But in the face of complex traffic conditions, complex computing will make higher demands on processors (He et al., 2014). From the point of view of economic applicability, it makes higher requirements on the modeling of the battery.
First of all, the battery model can accurately reflect the dynamic and static characteristics of the battery, so the appropriate order is needed. Secondly, in order to adapt to the processor performance of BMS system, its order cannot be too high (Wladislaw et al., 2014). Therefore, the traditional equivalent circuit model is compared and the advantages and disadvantages of each other are considered. Combined with the basic characteristics of battery research and analysis, a nonlinear second-order RC equivalent circuit model considering the nonlinear change of capacity is proposed (Mohamed et al., 2013).
As shown in Figure 1, the SOC estimation module is added to the left of the graph. The open circuit voltage and ampere hour method are combined to estimate the nonlinear change of battery capacity. Among them, 0SOC is the initial value of SOC, and I is the load current. The calculation formula of the battery SOC is as follows (Claude et al., 2017):

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$$SOC(t) = SOC_0 - \frac{\int \eta I(t)dt}{Q_N} \tag{1}$$

In the formula, QN is the rated capacity of battery, and ηis the charge discharge efficiency. In lithium ion batteries, η≈1 is considered. I is the circuital current and it is symbolic (Charge I<0, discharge I>0).

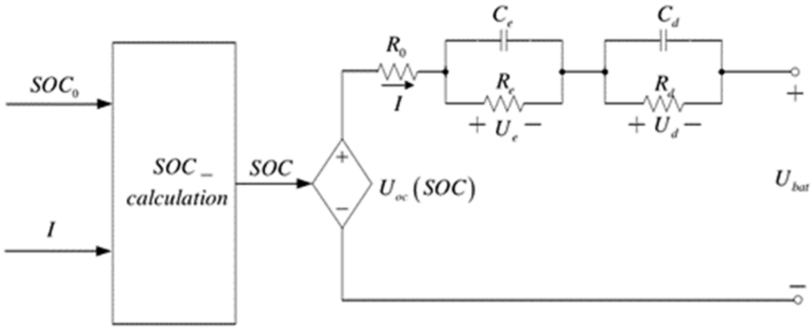

Figure 1: The second order RC circuit model that considering the capacity becomes

The right side of the graph is a common second-order RC equivalent circuit. The voltage source Uoc is the open circuit voltage of the second-order circuit, and presents a functional relationship with the SOC value estimated on the left side. R0 is the ohmic resistance of the second-order circuit. ReCe is the fast response process of voltage after the sudden change for loop current. The RdCd loop is used to describe the slow response of the voltage after the sudden change of the current, and the Ubat is the load voltage.

3. SOC estimation based on central difference Kalman filtering algorithm

Considering the complex operating conditions and nonlinear characteristics of the battery, two nonlinear Kalman filtering algorithms, EKF algorithm and CDKF algorithm, are emphatically discussed (Dong et al., 2017). Two algorithms are used to estimate the SOC of the battery, and the estimation results are analyzed and compared.

3.1 EKF algorithm

The standard Kalman filtering algorithm is suitable for linear dynamic systems, and the unbiased and optimal estimation of the state variables can be obtained. The standard Kalman filtering algorithm is suitable for linear dynamic systems, and the unbiased and optimal estimation of the state variables can be obtained (Li et al., 2017). In order to simplify the calculation process, the standard Kalman filtering algorithm with discrete form is usually adopted, and corresponding is the state space equation of linear discrete systems (Pan et al., 2017). The KF algorithm can well solve the estimation of state variables in linear dynamic systems. But for nonlinear systems, we need to extend the use of Kalman filtering by linearizing processes (Ramadan et al., 2017). Setting the state variable $x_k=[x_k^{(1)},x_k^{(2)},x_k^{(3)}]=[SOC(k), U_e(k), U_d(k)]^T$, the system input current is set to $U_k=I(k)$ (Syam and Bharath, 2017). Then the state formula (2) and the output observation formula (3) are obtained:

$$x_{k+1} = f(x_k, u_k) + w_k = \begin{bmatrix} x_k^{(1)} - \frac{\eta \Delta t}{Q} u_k \\ e^{-\frac{\Delta t}{\tau_e}} x_k^{(2)} + \left(1 - e^{-\frac{\Delta t}{\tau_e}}\right) R_e u_k \\ e^{-\frac{\Delta t}{\tau_d}} x_k^{(3)} + \left(1 - e^{-\frac{\Delta t}{\tau_d}}\right) R_d u_k \end{bmatrix} + w_k \tag{2}$$

$$y_k = h(x_k, u_k) + v_k = U_{OC}(x_k^{(1)}) - x_k^{(2)} - x_k^{(3)} - R_e u_k + V_k \tag{3}$$

The approximation of EKF to the posterior distribution of nonlinear states can only reach the first-order accuracy of Taylor series. When the system has strong nonlinearity, ignoring the higher order of second-order or more will introduce larger approximation errors in the calculation of the posterior mean and covariance, and these errors are cumulative. Finally, the accuracy of EKF filtering decreases and even diverges (Wei et al., 2017). Although EKF has been successfully applied to various fields of probabilistic reasoning in the past 20 years, it still has obvious disadvantages: (1) The complexity of Jacobian matrix derivation strengths the difficulty of many applications. (2) When the time step is not small enough and the local linear hypothesis is not established, the linearization will cause the filter instability (Mastali et al., 2013).

As mentioned earlier, EKF has two shortcomings: (1) Its linear approximation accuracy is low; (2) It need to calculate the Jacobian matrix of nonlinear function. In order to overcome the shortcomings of EKF, the central difference method is used to improve the EKF, and the differential filtering theory is proposed (Karsten et al., 2016). It uses the Sigma point transformation method to well approximate the mean and covariance, and obtains the performance similar to KF for linear systems. At the same time, it can be well applied to nonlinear systems, avoiding the linearization process required by EKF.

3.2 CDKF algorithm

The starting point of CDKF algorithm is to use Sterling interpolation formula to approximate the derivative of nonlinear equation by polynomial, so as to avoid derivative operation (Chen et al., 2016). The central difference is used to replace the first and second derivatives of the Taylor expansion around the $X = \overline{X}$ point. The CDKF algorithm can be represented as a form of symmetric sampling Sigma point. The weight corresponding to x_i, *i=0, 1, …, 2n* is shown in formula (4):

$$\begin{cases} \omega_o^{(m)} = \omega_o^{(c)} = \dfrac{h^2 - n}{h^2} \\ \omega_i^{(m)} = \omega_i^{(c)} = \dfrac{1}{2h^2}, i = 1,2...n \end{cases} \tag{4}$$

In this paper,

$$n = 3, h = \sqrt{3}, \omega_1^{(m)} = \omega_2^{(m)} = ... + \omega_{2n}^{(m)} = 0.3473, \omega_1^{(c)} = \omega_2^{(c)} = ... + \omega_{2n}^{(c)} = 0.3473$$

3.3 Matlab simulation and result analysis

Based on the previous analysis of the algorithm, it shows that the initial noise covariance Q and R of the system state vector need to be given in the initial estimation. In this model, the state variables include the polarization voltage Ue and Ud of the battery SOC and the two RC parallel networks. The initial SOC of the battery can measure the open circuit voltage, which is obtained by the relation of OCV-SOC without knowing the initial state value. When the initial error Pk is large, the Kalman gain matrix Gk is also larger. At this point, "new information" updates the system considerably, that is, it has a greater correction effect on the prediction value, making the prediction closer to the truth value (Swarup et al., 2016). After many predictions and modifications, the Kalman filtering algorithm converges to the truth value. At the beginning of the battery operation, the polarization voltage on the RC link can be considered as zero because the current has not been connected in parallel with the RC (Lin et al., 2017).

Based on the equivalent circuit model, the EKF algorithm and CDKF algorithm are used to predict the battery SOC in real time. In order to verify the effect of the two algorithms in practical application, the actual working condition of the simulated battery is designed. The specific algorithm is implemented by Matlab program. The error covariance Qk of the process noise is set to 10-4, and the error covariance Rk of the measurement noise is set to 10-5. The starting point of the model SOC value is generally chosen as 100% (Liu et al., 2016).

3.4 SOC estimation of cycle charge- discharge

As shown in Figure 2, the periodic charge discharge experiment of lithium iron phosphate battery is carried out. The contrast diagram between the measured voltage and the actual measured voltage in the state equation is shown in Figure 3.

According to the relation of OCV-SOC obtained previously, the CDKF algorithm is used to obtain the optimal estimation value of SOC. At the same time, compared with the EKF algorithm, the estimation results are shown in Figure 4.

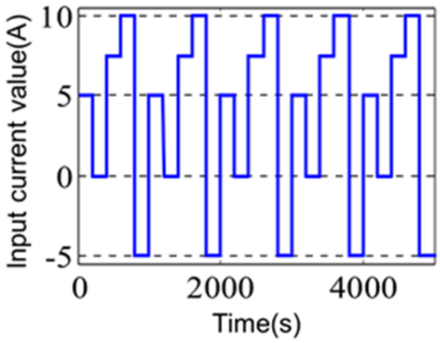

Figure 2: current curve in the case of periodic charge/discharge

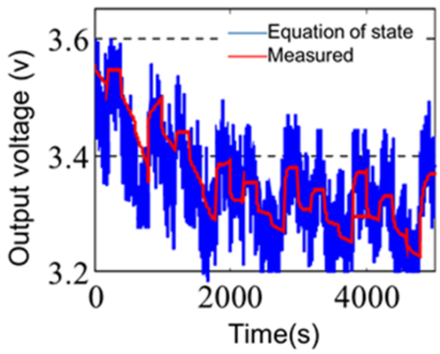

Figure 3: The output voltage comparison chart in the case of periodic charge/discharge

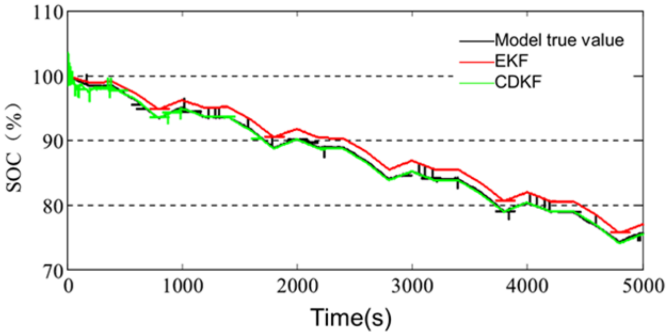

Figure 4: SOC estimation algorithm contrast curve in the case of periodic charge / discharge

The estimated reference value of SOC in Figure 4 is the true value of the model, and it has some error with the actual SOC of the battery. But this calculation formula of SO combines the open circuit voltage method with ampere hour method, while this method can avoid the initial error caused by improper selection of ampere hour accumulation. At the same time, the variation of SOC can be accurately calculated at a certain sampling time. Therefore, this value has a certain precision and can be used as the true value predicted by EKF algorithm and CDKF algorithm (Hamza et al., 2016).

From Figure 3, we can see that in the beginning of 1000s, the output voltage of the measurement equation is in error with the actual measured voltage of the battery. Moreover, when the initial error covariance 0P is small, the Kalman gain kG of EKF algorithm is smaller. Therefore, the correction range for the predicted value is not large. As shown in Figure 2, the error of EKF algorithm increases in the previous 1000s, and the CDKF algorithm has a short period of shock within 1000s, while the error decreases rapidly within about 500s. After 1000s, the Pk- tends to be stable, and the correction range for the state matrix is smaller. The reliability of the predicted value is high, so the algorithm is stationary. At the same time, the truncation error of the EKF algorithm makes the estimation error, and the maximum absolute error is about 1.8%. The CDKF algorithm converges to the true value of the model after 1000s, and the error is obviously reduced.

3.5 SOC estimation of battery of fast changing charge-discharge

In order to verify the accuracy of the algorithm in the case of frequent changes of the battery power, the current of the battery is shown in Figure 5. The curves of the output voltage of the battery and the output voltage of the measurement equation are obtained, as shown in Figure 6.

As shown in Figure 6, the output voltage of the measured equation has a very high fitting degree with the actual measured terminal voltage. Therefore, it shows that the truncation error of EKF algorithm has an influence on the estimation accuracy.

As shown in Figure 7, the CDKF algorithm decreases rapidly after 200s after a short period of shock, and is not affected by the frequent fluctuation of current. However, due to the accumulated truncation error, the accuracy error of EKF algorithm increases after 400s and tends to be stable.

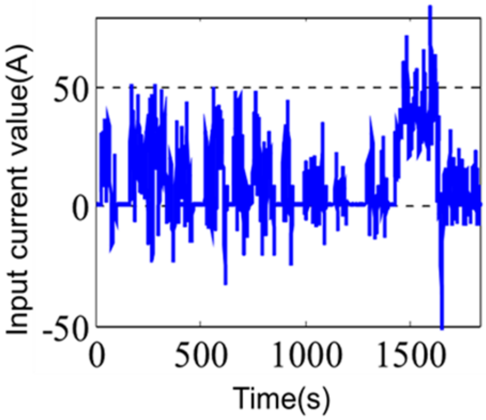

Figure 5: Input current under fast changing conditions

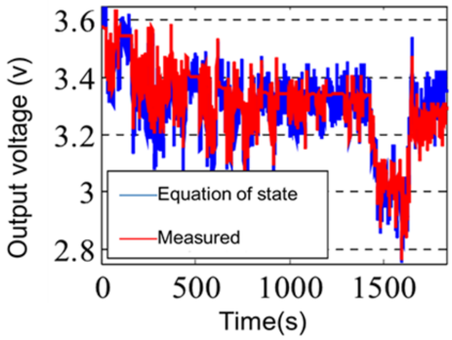

Figure 6: Output voltage under fast changing conditions

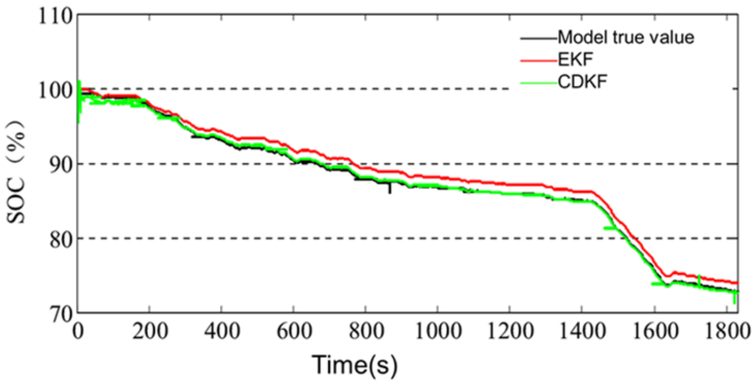

Figure 7: SOC estimation algorithm contrast curve under fast changing conditions

4. Conclusion

A lithium iron phosphate battery model is established in this paper. Two kinds of Kalman filter derivative algorithms, namely extended Kalman filter algorithm and central difference Kalman filter algorithm, are studied in this paper. The design flow of the two algorithms is introduced in detail. In this paper, the accuracy of the SOC estimation algorithm is studied by the charge-discharge current and the fast-changing current. Simulation results show that the accuracy of CDKF is significantly better than EKF algorithm. The precision errors can be analyzed from two aspects: First, the Jacobian matrix is obtained by the first-order Taylor expansion algorithm, while the truncation error is introduced due to the neglect of the higher order. Second, the error of the terminal voltage and the actual terminal voltage calculated by the measured equation leads to the fact that the EKF algorithm cannot track the true value accurately.

Reference

Chen X.Y., Xu Y., Li Q., Tang J., Shen C., 2016, Improving ultrasonic-based seamless navigation for indoor mobile robots utilizing EKF and LS-SVM, Measurement, 92, 243-251, DOI: 10.1016/j.measurement.2016.06.025

Claude F., Becherif M., Ramadan H.S., 2017, Experimental validation for Li-ion battery modeling using Extended Kalman Filters, International Journal of Hydrogen Energy, 42(40), 25509-25517, DOI: 10.1016/j.ijhydene.2017.01.123

Dong G., Wei J., Chen Z., Sun H., Yu X., 2017, Remaining dischargeable time prediction for lithium-ion batteries using unscented Kalman filter, 364, 316-327, DOI: 10.1016/j.jpowsour.2017.08.040

Hamza B., Alexander N., Hassen S., 2016, Quadrotor UAV state estimation based on High-Degree Cubature Kalman filter, IFAC-PapersOnLine, 49(17), 349-354, DOI: 10.1016/j.ifacol.2016.09.060

He W., Williard N., Chen C.., Pecht M., 2014, State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation, International Journal of Electrical Power & Energy Systems, 62, 783-791, DOI: 10.1016/j.ijepes.2014.04.059

Karsten P., Daniel J.A., Abbas F., Stefano L., Vaclav K., 2016, Kalman-variant estimators for state of charge in lithium-sulfur batteries, Journal of Power Sources, 343, 254-267, DOI: 10.1016/j.jpowsour.2016.12.087

Li Z., Zhang P., Wang Z., Song Q., Rong Y., 2017, State of Charge Estimation for Li-ion Battery Based on Extended Kalman Filter, Energy Procedia, 105, 3515-3520, DOI: 10.1016/j.egypro.2017.03.806

Lin C., Gong X., Xiong R., Cheng X., 2017, A novel H∞ and EKF joint estimation method for determining the center of gravity position of electric vehicles, Applied Energy, 194, 609-616, DOI: 10.1016/j.apenergy.2016.05.040

Liu L., Su Y., Zhu J., Lei Y., 2016, Data fusion based EKF-UI for real-time simultaneous identification of structural systems and unknown external inputs, Measurement, 88, 456-467, DOI: 10.1016/j.measurement.2016.02.002

Mastali M., Vazquez-Arenas J., Fraser R., Fowler M., Afshara S., 2013, Battery state of the charge estimation using Kalman filtering, Journal of Power Sources, 2013, 294-307, DOI: 10.1016/j.jpowsour.2013.03.131

Mohamed M.R., Ahmad H., Abu M.N., Razali S., Najib M.S., 2013, Electrical circuit model of a vanadium redox flow battery using extended Kalman filter, Journal of Power Sources, 239, 284-293, DOI: 10.1016/j.jpowsour.2013.03.127

Pan H., Lu Z., Lin W., Li J., Chen L., 2017, State of charge estimation of lithium-ion batteries using a grey extended Kalman filter and a novel open-circuit voltage model, Energy, 138, 764-775, DOI: 10.1016/j.energy.2017.07.099

Ramadan H.S., Becherifa M., Claude F., 2017, Extended kalman filter for accurate state of charge estimation of lithium-based batteries: a comparative analysis, International Journal of Hydrogen Energy, DOI: 10.1016/j.ijhydene.2017.07.219

Saeed S., Reza G., Bor Y.L., 2014, A novel on-board state-of-charge estimation method for aged Li-ion batteries based on model adaptive extended Kalman filter, Journal of Power Sources, 245, 337-344, DOI: 10.1016/j.jpowsour.2013.06.108

Swarup M., Arunasis C., 2016, EKF Based Parameter Identification of LTI System from Seismic Response Measurements, Procedia Engineering, 144, 360-365, DOI: 10.1016/j.proeng.2016.05.144

Syam P., Bharath B., 2017, Identification of the non-linear dynamics and state of charge estimation of a LiFePO4 battery using constrained unscented Kalman filter, IFAC-PapersOnLine, 50(1), 1571-1576, DOI: 10.1016/j.ifacol.2017.08.311

Wei J.W., Dong G.Z., Chen Z., 2017, On-board adaptive model for state of charge estimation of lithium-ion batteries based on Kalman filter with proportional integral-based error adjustment, Journal of Power Sources, 365, 308-319, DOI: 10.1016/j.jpowsour.2017.08.101

Wladislaw W., Christian F., Dirk U.S., 2014, Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles, Journal of Power Sources, 258, 321-339, DOI: 10.1016/j.jpowsour.2014.02.064

Xing Y., He W., Michael P., Kwok L.T., 2014, State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures, Applied Energy, 113, 106-115, DOI: 10.1016/j.apenergy.2013.07.008

Xiong R., Sun F., Chen Z., He H., 2014, A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion olymer battery in electric vehicles, Applied Energy, 113, 463-476, DOI: 10.1016/j.apenergy.2013.07.061