Online Estimation of Li-ion Battery SOC for Electric Vehicles Based on An Improved AEKF

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Abstract. The purpose of this paper is to discuss how to eliminate the influence of noise time - varying characteristics on the accuracy of SOC estimation. Based on the matlab/simulink platform, the Thevenin equivalent circuit model of the battery is built, and an improved Adaptive Extend Kalman Filter (AEKF) is designed, which is compared with the Extend Kalman filter algorithm (EKF). The simulation results are shown that the improved AEKF algorithm results in effective online estimation SOC and the estimation accuracy is higher than the EKF algorithm.

1 Introduction

In order to effectively alleviate the energy and environmental pressures, researchers have made electric vehicles a solution which has developed rapidly over the past decade [1, 2]. As the direct energy supply, the power battery system and its states affect a lot to the vehicle's performance. The core problem is SOC quantity, so the accurate and timely estimation of SOC has important theoretical significance and application value [3].

At present, the commonly used SOC estimation method include open circuit voltage method, ampere-hour current integration method, neural network method, kalman filter method[4,5], etc. In [6], an EKF method was proposed to estimate SOC of lead-acid battery, this method integrated the parameter identification method and EKF algorithm to update the parameters of the battery model in time, but did not consider the influence of time-varying characteristics of noise on the estimation of battery SOC.

To solve above problem, this article puts forward an improved AEKF algorithm to solve the influence of noise time - varying characteristics on the accuracy of SOC estimation. Firstly, because of the nonlinear characteristic of lithium-ion battery, Thevenin model was built. Then The AEKF algorithm is improved and the noise filter estimator suitable for lithium-ion battery is designed. Next completing SOC estimation based on improved AEKF algorithm. Finally, simulation experiment was carried out, comparative analysis was also discussed between AEKF and EKF algorithm. The result turns out that the imprived AEKF can online estimation battery SOC and the accuracy of SOC is improved.

2 Battery Modelling

The Kalman filter algorithm is an optimal estimation theory based on state space model. Accurate battery model is required, while using the Kalman filter algorithm to estimate battery SOC. The generally used battery models include Rint model, Thevenin model, PNGV model. However, the structure of Rint model is relatively rough to reveal the dynamic characteristics of the battery. The Thevenin model can well show the battery characteristic, and its structure is relatively easy to implement in engineering. Besides, the model precision also meets the requirements of this subject. So In this paper, the Thevenin equivalent circuit is chosen, as shown in the figure 1. In this circuit, the variant U_{oc} represents the open circuit voltage of the battery, U is the battery terminal voltage, I is the load current, R_0 is the internal resistance, representing the combined resistance of electrolyte and electrode material. R_1 is polarization resistor and C_1 is polarization capacitance, which indicates the diffusion phenomenon and polarization reaction of lithium-ion during charging and discharging. U_1 is the both end of the voltage of C_1 .

Fig.1. Thevenin equivalent circuit model

The dynamic equation of this circuit can be described as formula (1):

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$$\begin{cases} \dot{U}_1 = -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I \\ U = U_{oc} - U_1 - I R_0 \end{cases} \quad (1)$$

The paper sets $\tau = R_1 C_1$ is the time constant and Δt is the sampling period. The SOC expression obtained by the Anshi integral is as shown in Equation (2) :

$$SOC(t) = SOC(t-1) + \frac{\eta}{Q_n} \int_{t-1}^t i(t) dt \quad (2)$$

where, $SOC(t)$ is the SOC value at the time of t and $SOC(t-1)$ is the SOC value at the time of $t-1$. η is the coulombic efficiency of battery and its value is 1. Q_n is rated capacity of battery and its value is 36Ah. $i(t)$ is the load current.

3 SOC Online Estimation

3.1 SOC estimation based on improved AEKF

In the battery management system, sampling data will be affected by some unknown noise, often mingled with abnormal values. Using the adaptive kalman filter to deal with these interference. In order to apply AEKF algorithm, formula (1) transformed into a state space model:

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \approx A_{k-1} x_{k-1} + B_{k-1} u_{k-1} + w_{k-1} \\ y_k = h(x_k, u_k) + v_k \approx C_k x_k + D_k u_k + v_k \end{cases} \quad (3)$$

where, $x = [SOC, U_1]^T$ means that SOC and the voltage of capacitor C_1 are selected as the state variables of the system, and the charging is set as the positive current direction. $u=i$ and $y=U$ means current i is the system input and terminal voltage U is the system output, w_k and v_k respectively represents the process noise and measurement noise of the system, their mean values are q_k and r_k respectively and the covariance matrix is Q_k and R_k respectively.

By discretization, formula (1) and (2) can be transformed into the following form:

$$\begin{cases} \begin{bmatrix} SOC(k) \\ U_1(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \exp(-\Delta t / \tau) \end{bmatrix} \begin{bmatrix} SOC(k-1) \\ U_1(k-1) \end{bmatrix} + \begin{bmatrix} \eta_i \Delta t / Q_n \\ R_i (1 - \exp(-\Delta t / \tau)) \end{bmatrix} I(k-1) + \omega_k \\ U(k) = U_{oc}(SOC(k)) - U_1(k) - I(k) R_0 + v_k \end{cases} \quad (4)$$

The formula (3) and (4) are compared, and can get the following relationship :

$$A_k \triangleq \begin{bmatrix} 1 & 0 \\ 0 & \exp(-\Delta t / \tau) \end{bmatrix}, B_k \triangleq \begin{bmatrix} \eta_i \Delta t / Q_n \\ R_i [1 - \exp(-\Delta t / \tau)] \end{bmatrix} \quad (5)$$

$$C_k \triangleq \begin{bmatrix} \frac{dU_{oc}(soc)}{dsoc} & 1 \end{bmatrix}, D_k \triangleq R_0 \quad (6)$$

The traditional AEKF noise estimation filter is designed as follows:

$$\hat{q}_{k+1} = \frac{1}{k+1} G \sum_{i=0}^k (\hat{x}_{k+1} - A_k \hat{x}_k - B_k u_k) \quad (7)$$

$$\hat{Q}_{k+1} = \frac{1}{k+1} G \sum_{i=0}^k (L_{k+1} e_{k+1} e_{k+1}^T L_{k+1}^T + P_{k+1} - A_k P_{k+1/k} A_k^T) G^T \quad (8)$$

$$\hat{r}_{k+1} = \frac{1}{k+1} \sum_{i=0}^k (y_{k+1} - C_k \hat{x}_{k+1/k} - D_k u_{k+1}) \quad (9)$$

$$\hat{R}_{k+1} = \frac{1}{k+1} \sum_{i=0}^k (e_{k+1} e_{k+1}^T - C_k P_{k+1/k} C_k^T) \quad (10)$$

Where, G is unit matrix and e_{k+1} is the error of Model calculation. e_{k+1} meet the following relationship :

$$e_{k+1} = y_{k+1} - C_k \hat{x}_{k+1/k} - D_k u_{k+1} - \hat{r}_k \quad (11)$$

The formula (7)~(10) calculates the system noise mean and covariance using arithmetic mean, of which $(k+1)^{-1}$ is the weighting coefficient of each term.

Because li-ion battery is nonlinear time-varying systems, in order to better apply AEKF to battery SOC estimation, this paper uses exponential weighting method to improve it. The formula (7)~(10) Multiply by λ_i and the λ_i meet the following relationship :

$$\lambda_i = \lambda_{i-1} b, b \in (0, 1) \left(\sum_{i=0}^k \lambda_i = 1 \right) \quad (12)$$

Assume $d_k = (1-b) / (1-b^{k+1})$, then can get

$\lambda_i = d_k b^i$ ($i = 0, 1, 2, \dots$). Using the λ_{k-1} instead of $(k+1)^{-1}$ can get the improved formula 7)~(10) are as follows :

$$\hat{q}_{k+1} = (1-d_k) \hat{q}_k + d_k G (\hat{x}_{k+1} - A_k \hat{x}_k - B_k u_k) \quad (13)$$

$$\begin{aligned} \hat{Q}_{k+1} &= (1-d_k) \hat{Q}_k + d_k G \\ &\quad (L_k e_{k+1} e_{k+1}^T L_k^T + P_{k+1} - A_k P_{k+1/k} A_k^T) G^T \end{aligned} \quad (14)$$

$$\hat{r}_{k+1} = (1-d_k) \hat{r}_k + d_k (y_{k+1} - C_k \hat{x}_{k+1/k} - D_k u_{k+1}) \quad (15)$$

$$\hat{R}_{k+1} = (1-d_k) \hat{R}_k + d_k (e_{k+1} e_{k+1}^T + P_{k+1} - C_k P_{k+1/k} C_k^T) \quad (16)$$

According to the state space model of formula (4) and given the initial value of the filter. Online estimation of battery SOC can be realized according to adaptive Kalman filter iterative algorithm. The algorithm flow chart is shown in figure 2.

In the calculation of AEKF algorithm, online measurement data y_k is used to estimate the mean of noise w_k and v_k , and their variance Q_k and R_k . According to the estimated results of the mean and variance each step, the current state is revised and the state quantity and noise statistics are updated.

Fig.2. Flow chart of improved AEKF algorithm

4 Experiment & Simulation

In order to verify the effectiveness and accuracy of the improved AEKF designed in this paper, the article carries out several simulation experiments under pulsed discharge conditions. Figure 3 is pulse discharge current data. Where, the simulation period is 8000s, sampling interval is 1s, and results are figure 4 and figure 5.

According to the simulation results of figure 4 and figure 5, we can see that the improved AEKF algorithm realizes effectively the online estimation of li-ion battery SOC and the estimation convergence error less than 3%.

In order to verify the practicability and robustness of the algorithm designed in this paper, this article carries out amount of simulation analysis under UDDS conditions. At the same time, the simulation results of AEKF algorithm is compared with the EKF algorithm. Figure 6 is UDDS current curve and the simulation results are figure 7 and figure 8.

According to figure 7 and figure 8, we can see that the maximum SOC error of EKF algorithm is 6.81%, while the AEKF algorithm is 4.87%, which is

reduced by 2%, and the mean SOC error of AEKF algorithm is only 0.95%, if consider the model's error, the final precision is approximately 2.6%, which can meet the requirements of SOC accuracy of electric vehicle battery management system.

Fig.3. Pulse current curve diagram

Fig.4. SOC estimation with AEKF algorithm

Fig.5. SOC estimation error with AEKF algorithm

Fig.6. UDDS current curve diagram

Fig.7. SOC estimation with two algorithms

Fig.8. SOC estimation error with two algorithms

5 Conclusion

In this paper, an improved AEKF algorithm of online estimation for li-ion battery SOC is designed and this method can effectively reduce the influence of noise time-varying characteristics on SOC estimation accuracy. The simulation results show that the improved AEKF algorithm can realize the online estimation of li-ion battery SOC under different current conditions. The maximum estimation error is less than 5%, which satisfies the design requirement of SOC estimation accuracy of electric vehicle BMS system. In this study, although the problem of the influence of noise time-varying characteristics on SOC estimation is solved, the influence of temperature on SOC is not studied. Establishing a battery equivalent circuit model with temperature parameters, based on which the estimation of SOC will be the direction and focus of future research.

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6 References

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