Estimation of remaining battery capacity for iot devices

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Abstract

In this paper, the soc estimation method of the lithium-ion battery is studied, the second order RC equivalent circuit model of the lithium-ion battery is established, and the FFRLS algorithm is used to improve the traditional recursive least squares for on-line parameter identification, a Simulink simulation model based on the second order RC equivalent circuit model is constructed by using the extended Kalman filter method (EKF) , and the soc accuracy of the method is verified. The results show that this method can accurately estimate the remaining battery capacity.

Keywords

Electrical engineering; state of charge； FFRLS; EKF.

1. Introduction

Power Battery, as the power source of Internet of things equipment, its state of charge SOC is one of the basic parameters in battery management system And the proper monitoring of equipment operation. Accurate soc estimation is of great importance to the life maintenance of lithium-ion battery and the stable operation of equipment. And the battery pack is easily affected by the application environment, aging degree, self-discharge, current rate and other factors. Battery is a complex non-linear system, when it is used in electric vehicles, it is difficult to get accurate noise statistics because of the numerous electronic equipments and the complicated noise interference, therefore, the anti-interference ability and self-adaptive ability of battery charge state estimation must be studied to improve the robustness of estimation and the validity of battery charge state estimation.

Current integration method, open-circuit voltage method, neural network method, Kalman filter method and least squares method are commonly used in soc estimation at home and abroad. The method of ampere-hour integration can estimate the residual power accurately in a short time, but because it is an open-loop prediction, the initial value of SOC can not be given, and the inaccuracy of current measurement leads to the cumulative error increasing gradually The open-circuit voltage method estimates the soc by measuring the open-circuit voltage of the battery, which requires the battery to stand still for a long time and can not be detected on-line, the method relies heavily on training data and training methods, so it has not been well used; the Kalman filter method relies on the voltage and current collected, the minimum variance estimation of SOC is obtained by recursive Algorithm, which can keep high precision and solve the problems of inaccurate initial value estimation and cumulative error.

2. Design of battery model

At present, the commonly used electric vehicle battery models mainly include: electrochemical model, neural network model, impedance model, equivalent circuit model and so on. Each model has its own advantages and disadvantages and scope of application, which should be chosen properly according to practical application. However, in the actual operation, the soc of the battery can not be estimated directly by ordinary sensors, only the external voltage, chargedischarge current, temperature and other measurable parameters can be used to estimate the soc, so it is very important to select and establish an accurate soc model.

The equivalent circuit model describes the external characteristics of a power battery by using a network of conventional resistors, capacitors, and constant voltage sources. The model uses a voltage source to represent the thermodynamic equilibrium of a power cell and a RC network to describe the dynamics of a power cell. The equivalent circuit model has good adaptability to various states of power battery, and the state equation of the model can be derived for analysis and application. The equivalent circuit model has been widely used in modeling and simulation of new energy vehicle and model-based BMS. The commonly used power battery equivalent circuit models include Rint model, PNGV equivalent circuit model and Thevenin equivalent circuit model. Based on the Thevenin model, the second-order RC model is used as the battery model, which can better simulate the non-linear characteristics of the battery.

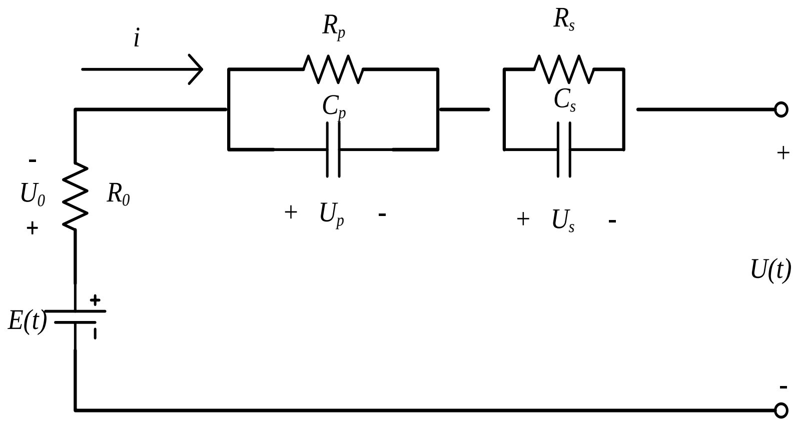

Fig. 1 Model Diagram of second order RC equivalent circuit

Figure .1 shows that the model can meet the accuracy requirements of lithium-ion battery simulation, and the complexity is appropriate, easy to programming and practical application. E_t describes the Electromotive Force, R_0 describes the ohmic internal resistance, R_p and C_p are polarization resistance and capacitance, R_s and C_s are concentration polarization resistance and concentration polarization capacitance; $U_s$and U_p are the voltage drop of RC parallel link, which are used to simulate the polarization voltage of battery; U_t is the terminal voltage of the battery.

3. Online parameter identification based on FFRLS

In order to overcome the traditional Recursive Least Squares, we can reduce the reliability of the old data by using the method of Forgetting Factor Recursive Least Squares (FFRLS) to improve the Recursive Least Squares for on-line parameter identification of battery model.

$$\boldsymbol{\theta}_{N+1} = \boldsymbol{\theta}_N + \boldsymbol{K}_{N+1}\left[z_{N+1} - \phi_{N+1}^{T}\boldsymbol{\theta}_N\right] \tag{3.1}$$

$$\boldsymbol{K}_{N+1} = \frac{\boldsymbol{P}_N \phi_{N+1}}{\rho + \phi_{N+1}^{\mathrm{T}} \boldsymbol{P}_N \phi_{N+1}} \tag{3.2}$$

$$\boldsymbol{P}_{N+1} = \frac{1}{\rho}\left[\boldsymbol{I} - \boldsymbol{K}_{N+1}\phi_{N+1}^{\mathrm{T}}\right]\boldsymbol{P}_N \tag{3.3}$$

In this equation, ρ is the gene, K_{N+1} is the gain Matrix, and P_{N+1} is the covariance matrix of the state estimate.

Laplace equation of battery model

$$E(s)-U(s)=I(s)(R+\frac{R_p}{1+R_pC_ps}+\frac{R_s}{1+R_sC_ss}) \tag{3.4}$$

Make $\tau_s = R_sC_s$， $\tau_p = R_pC_p$; The transfer function G（s） is available from (3.4)

$$\begin{aligned} G(s)&=(R_0+\frac{R_p}{1+R_pC_ps}+\frac{R_s}{1+R_sC_ss}) \\ &=\frac{R_0\tau_p\tau_s s^2+(R_0\tau_p+R_0\tau_s+R_p\tau_s+R_s\tau_p)s+R_0+R_p+R_s}{\tau_p\tau_s s^2+(\tau_p+\tau_s)s+1} \\ &=\frac{R_0s^2+\frac{1}{\tau_p\tau_s}(R_0\tau_p+R_0\tau_s+R_p\tau_s+R_s\tau_p)s+\frac{R+R_p+R_s}{\tau_p\tau_s}}{s^2+\frac{\tau_p+\tau_s}{\tau_p\tau_s}s+\frac{1}{\tau_p\tau_s}} \end{aligned} \tag{3.5}$$

The expression (3.5) is discretized by means of a bilinear transformation such that:

$$s=\frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}} \tag{3.6}$$

The discrete transfer function can be obtained:

$$G(z^{-1})=\frac{a_3+a_4z^{-1}+a_5z^{-2}}{1-a_1z^{-1}-a_2z^{-2}} \tag{3.7}$$

Where $a_1, a_2, a_3, a_4$and a_5 are constant coefficients. Write (3.7) as recurrence relation

$$\begin{aligned} y(n) &= E(n)-U(n) \\ &= a_1y(n-1)+a_2y(n-2)+a_3I(n)+a_4I(n-1)+a_5I(n-2) \end{aligned} \tag{3.8}$$

In the formula, $I(n)$ is the current value of the battery model, $E(n)$ is the electromotive force of the battery, $U(n)$ is the open-circuit voltage value measured directly by the battery, and $y(n)$ is the output of the system. Make:

$$\boldsymbol{\theta}^T=[a_1\quad a_2\quad a_3\quad a_4\quad a_5],$$

$$\phi^{\mathrm{T}}=[y(n-1)\quad y(n-2)\quad I(n)\quad I(n-1)\quad I(n-2)]$$

By substituting ffrls formula (3.1) ~equation (3.3) , the parameter matrix can be identified on line. Make:

$$z^{-1}=\frac{1-\frac{T}{2}s}{1+\frac{T}{2}s} \tag{3.9}$$

Replace (3.9) with (3.5) to obtain:

$$G(s)=\frac{\frac{a_3-a_4+a_5}{1+a_1-a_2}s^2+\frac{4(a_3-a_5)}{(1+a_1-a_2)T}s+\frac{4(a_3+a_4+a_5)}{(1+a_1-a_2)T^2}}{s^2+\frac{4(1+a_2)}{(1+a_1-a_2)T}s+\frac{4(1-a_1-a_2)}{(1+a_1-a_2)T^2}} \tag{3.10}$$

The equivalent of formula (3.10) and formula (3.5) is:

$$\begin{aligned}&\frac{R_0s^2+\frac{1}{\tau_p\tau_s}(R_0\tau_p+R_0\tau_s+R_p\tau_s+R_s\tau_p)s+\frac{R+R_p+R_s}{\tau_p\tau_s}}{s^2+\frac{\tau_p+\tau_s}{\tau_p\tau_s}s+\frac{1}{\tau_p\tau_s}}\\&=\frac{\frac{a_3-a_4+a_5}{1+a_1-a_2}s^2+\frac{4(a_3-a_5)}{(1+a_1-a_2)T}s+\frac{4(a_3+a_4+a_5)}{(1+a_1-a_2)T^2}}{s^2+\frac{4(1+a_2)}{(1+a_1-a_2)T}s+\frac{4(1-a_1-a_2)}{(1+a_1-a_2)T^2}}\end{aligned} \tag{3.11}$$

The following equation can be derived from equation (3.11) . For ease of calculation, the variable a ~ e can be expressed as:

$$R_0=\frac{a_3-a_4+a_5}{1+a_1-a_2}=a \tag{3.12}$$

$$\tau_p\tau_s=\frac{(1+a_1-a_2)T^2}{4(1-a_1-a_2)}=b \tag{3.13}$$

$$\tau_p+\tau_s=\frac{(1+a_1)T}{1-a_1-a_2}=c \tag{3.14}$$

$$R_0+R_\mathrm{p}+R_s=\frac{a_3+a_4+a_5}{1-a_1-a_2}=d \tag{3.15}$$

$$R_0\tau_p+R_0\tau_s+R_p\tau_s+R_s\tau_p=\frac{(a_3-a_5)T}{1-a_1-a_2}=e \tag{3.16}$$

Re-order:

$$t_1=\frac{c-\sqrt{c^2-4b}}{2} \tag{3.17}$$

$$t_2=\frac{c+\sqrt{c^2-4b}}{2} \tag{3.18}$$

Simultaneous (3.12) ~ equation (3.18) yields real-time parameter values for online identification:

$$R_0 = a \tag{3.19}$$

$$R_p = \frac{e - R_0 t_1 - d t_2}{t_1 - t_2} \tag{3.20}$$

$$R_s = d - R_0 - R_p \tag{3.21}$$

$$C_s = \frac{t_2}{R_p} \tag{3.22}$$

$$C_p = \frac{t_2}{R_s} \tag{3.23}$$

So far, the above reasoning has been completed based on FFRLS Algorithm on-line identification of battery model parameters, the next section with the above reasoning to complete the simulation experiment.

4. Estimation of battery SOC based on EKF

State space equation of discrete system based on second order RC model of battery is established.

Equation of State：

$$\begin{bmatrix} SOC_k \\ U_{p,k} \\ U_{s,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1-{T}/{R_p C_p} & 0 \\ 0 & 0 & 1-{T}/{R_s C_s} \end{bmatrix} \begin{bmatrix} SOC_{k-1} \\ U_{p,k-1} \\ U_{s,k-1} \end{bmatrix} + \begin{bmatrix} {\beta T}/{Q_N} \\ R_p(1-e^{-T/R_p C_p}) \\ R_s(1-e^{-T/R_s C_s}) \end{bmatrix} i_{k-1} + w_{k-1} \tag{4.1}$$

In the equation of state, the state variables of the equation of state are charged state SOC, electrochemical polarization voltage U_P and concentration polarization voltage U_S; T is the sampling time;β is the Correction Factor;i is the control input; w_k is the zero mean Additive white Gaussian noise.

Observation Equation:

$$U_k = f_k(SOC_k) - i_k R_{0,k} - U_{p,k} - U_{s,k} + v_k \tag{4.2}$$

In the formula,U_k is the open circuit voltage, $f_k(soc_k)$ is the cell emf, and v_k is the zero mean Additive white Gaussian noise.

The Kalman filter is a state estimation and system identification of the nonlinear model based on the standard Kalman filter algorithm for the linearization of the filter value generated by the nonlinear model. Combining with the physical model of the battery and considering the dynamic change of the battery, a SOC based on EKF is established to estimate the nonlinear state space of the battery. The following EKF equations are obtained by applying the linear kalman filter basic equations:

State estimation time update：

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{G}_{k,k-1}\hat{\boldsymbol{x}}_{k-1} + \boldsymbol{U}_{k-1} = \boldsymbol{f}_{k-1}(\hat{\boldsymbol{x}}_{k-1}, \boldsymbol{u}_{k-1}, \boldsymbol{q}_{k-1}) \tag{4.3}$$

Error covariance time update:

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{G}_{k,k-1}\boldsymbol{P}_{k-1}\boldsymbol{G}_{k,k-1}^{\mathrm{T}} + \boldsymbol{\Gamma}_{k,k-1} Q_{k-1} \boldsymbol{\Gamma}_{k,k-1}^{\mathrm{T}} \tag{4.4}$$

Emmerich kalman coefficient gain matrix:

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\mathrm{T}}(\boldsymbol{H}_k\boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{\Lambda}_k\boldsymbol{R}_k\boldsymbol{\Lambda}_k^{\mathrm{T}})^{-1} \quad (4.5)$$

Status estimation measurement update:

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}(\boldsymbol{z}_k - \hat{\boldsymbol{z}}_{k|k-1}) \quad (4.6)$$

Measurement of error covariance update:

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k|k-1} \quad (4.7)$$

5. Analysis of joint simulation Simulation conditions:

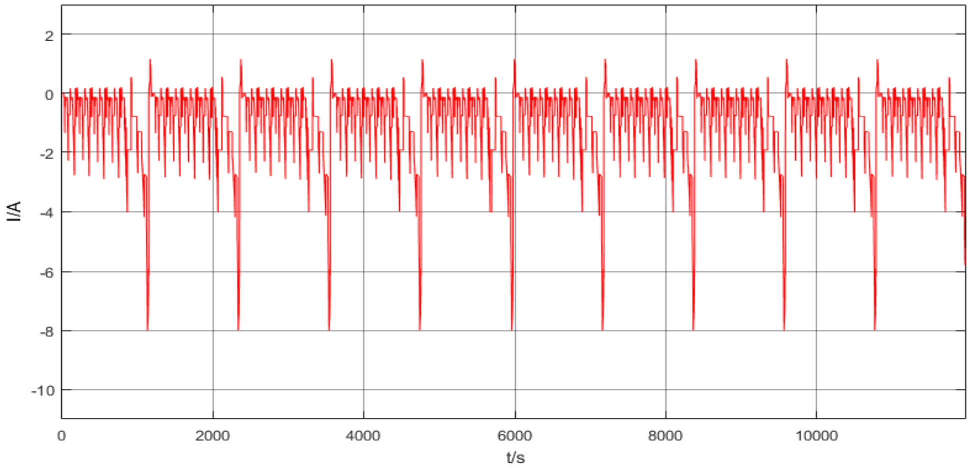

Fig. 2 Circuit Diagram

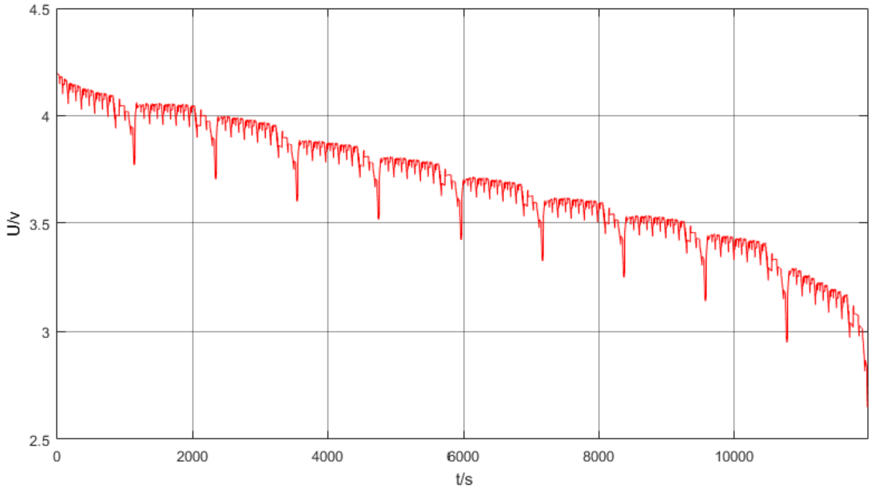

Fig. 3 Voltage Diagram

From Fig. 3, it can be seen that the traditional open-circuit voltage method is not accurate to monitor the residual power, and the whole process is a nonlinear variation with great error.

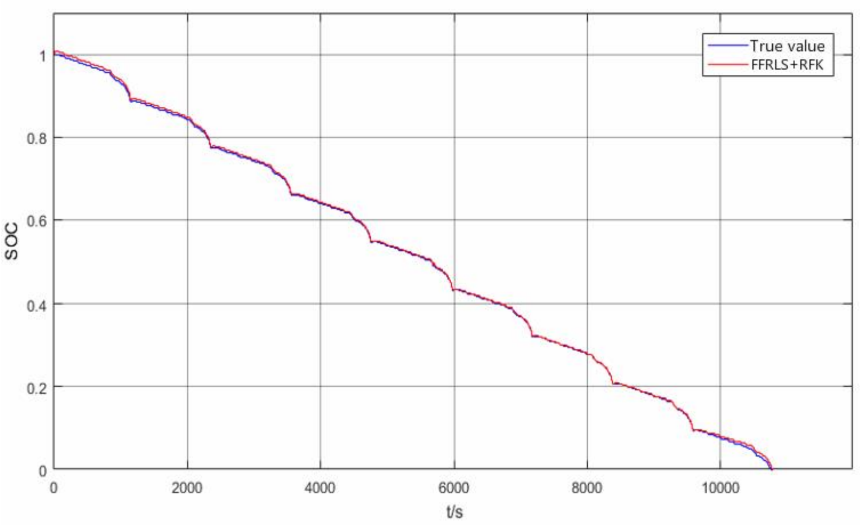

Fig. 4 SOC Estimation Diagram

As can be seen from the figure.4, the error of SOC estimation based on FFRLS + EKF is very small, which meets the expected requirements and proves its feasibility.

6. Conclusion

This paper introduces in detail the method and process of estimating the residual capacity of the battery using the extended Kalman filter. Compared with the traditional open circuit voltage method and the ampere hour integral method, the result is more accurate, and there is no cumulative error, experiments show the feasibility and accuracy of the extended Kalman filter for estimating battery life. However, the calculation process of the method proposed in this paper is rather troublesome. The next step is to simplify the algorithm under the premise of ensuring the accuracy of the estimation results.

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