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# An improved robust function correction-adaptive extended kalman filtering algorithm for SOC estimation of lithium-ion batteries

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***Abstract.* State of Charge (SOC) is one of the key indicators for evaluating the state of electric vehicles. In order to cope with the uncertainty of random noise in nonlinear systems, an improved robust function correction-adaptive extended Kalman filtering (RFC-AEKF) algorithm is proposed for SOC prediction. Using FFRLS method to verify the Dual Polarization model established in this paper. The robust function is an abstract method that describes system state noise and observation noise, and performs real-time correction, combined with adaptive methods to estimate SOC. The experimental results show that the proposed RFC-AEKF algorithm has the smallest mean absolute error (MAE) and root mean square error (RMSE) compared to other algorithms. Under the Beijing bus dynamic stress test (BJDST) conditions, the MAE and RMSE of the RFC-AEKF are 0.354% and 0.658%, respectively, indicating that the RFC-AEKF algorithm can improve SOC estimation accuracy and enhance robustness.**

***Keywords-Lithium-ion battery; SOC; robust function correction; adaptive extended Kalman filtering***

## I. Introduction

With the increasing use of new energy vehicles, more attention has been paid to vehicle lithium-ion batteries [1-3]. Lithium-ion batteries have advantages such as high energy density, long cycle life, and no memory effect, but they also have disadvantages related to safety and lifespan [4]. The state of charge (SOC) of the battery, indicates the remaining power of the battery [5]. It is one of the important parameters to describe the battery status [6]. Therefore, accurately estimating the SOC of batteries is of great significance for evaluating the transition state of electric vehicles.

In reference [7], using EKF to estimate the remaining battery capacity improves the accuracy of the estimation. However, the above literature cannot update the parameters of the battery model in real-time and cannot be applied to complex environments with random noise. To avoid this shortcoming, the literature [8] uses AEKF and recursive least squares (RLS) to update the model parameters in real-time [9]. The AEKF algorithm uses approximate methods to solve the nonlinear problem of battery systems and adaptive methods to reduce the impact of random noise. For typical nonlinear systems, accurately obtaining noise variance is a necessary part. A large number of experiments have shown that when the noise estimation is not accurate, the filtering accuracy will decrease, and even lead to filtering divergence [10].

Due to issues such as inaccurate noise estimation and filtering divergence, many scholars have proposed some improved methods to improve estimation accuracy. It consists of real-time estimation of noise and robust Kalman filter, respectively. The first method adds noise to the state vector and updates the noise in real-time. However, this method has some limitations due to inaccurate process noise estimation and small deviation [11]. The second method is the robust Kalman filter. For example, some scholars proposed a robust unscented Kalman filter based on H infinite norm [12]. This algorithm improves the simplified UKF in Krein space and changes the filtering gain through specific function parameters, making the filtering effect more robust.

In order to cope with the uncertainty of random noise in nonlinear systems, this paper proposes an improved estimation error processing method: robust function correction. Combining the adaptive method, an improved robust function correction-adaptive extended Kalman filtering (RFC-AEKF) algorithm is proposed for SOC prediction. The robust function is an abstract method that describes system state noise and observation noise, and performs real-time correction, combined with adaptive methods to estimate SOC. The covariance matrix Q of system state noise and the covariance matrix R are dynamically modified by the simplified robust function. Estimate and correct random noise to achieve better filtering performance. Use the FFRLS method to identify the internal parameters of the battery model using the Dual Polarization (DP) model established in this paper. Transfer the identified battery model parameters in real-time to the RFC-AEKF algorithm to obtain more accurate SOC estimates.

## II. Mathematical analysis

### *A. DP model*

In this paper, the Dual Polarization (DP) model is built as the equivalent circuit model of batteries. It can simulate concentration polarization and electrochemical polarization separately so that it can accurately simulate the dynamic characteristics of batteries. Compared to traditional equivalent circuit models, the DP model has a stronger characterization ability for batteries and can more comprehensively reflect the internal chemical changes of batteries. The Dual Polarization model is shown in Figure 1.

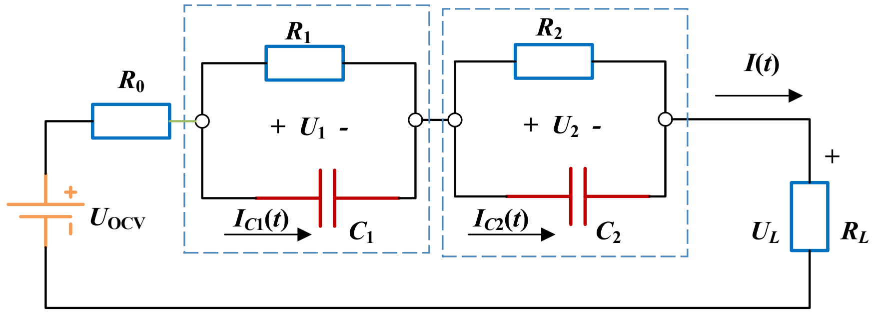



Figure 1. Dual Polarization model

$R_0$ is the internal resistance, $R_1$ is the internal resistance of polarization caused by the battery polarization effect, and $R_2$ is the internal resistance of polarization caused by the battery concentration polarization effect. $C_1$ and $C_2$ are polarized capacitors. $U_0$ is the voltage divided by $R_0$. $U_1$ and $U_2$ are voltage when resistors $R_1$ and $R_2$ are current $I$. $U_{OCV}$ is open circuit voltage. $U_L$ is output voltage. The voltage and current obtained by analyzing the equivalent circuit model are shown in equation (1).

$$\begin{cases} U_L = U_{OCV} - U_0 - U_1 - U_2 \\ I = \dfrac{U_0}{R_0} = \dfrac{U_1}{R_1} + C_1 \dfrac{dU_1}{dt} = \dfrac{U_2}{R_2} + C_2 \dfrac{dU_2}{dt} \end{cases} \tag{1}$$

*B. Parameter identification based on the FFRLS*

The forgetting factor recursive least square (FFRLS) is an improvement on RLS. It performs well in large-scale datasets and situations that require real-time computation. The forgetting factor can adjust the weights of old and new data to reduce the impact of previous data on current calculations and avoid data saturation issues. The recursive relationship of this algorithm is shown in equation (2).

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\left[ y(k) - \phi(k)\hat{\theta}(k-1) \right] \\ K(k) = P(k-1)\,\phi(k)\left[ \lambda + \phi^T(k)P(k-1)\,\phi(k) \right]^{-1} \\ P(k) = \dfrac{1}{\lambda}\left[ I - K(k)\phi^T(k) \right] P(k-1) \\ e_0(k) = y(k) - \phi(k)\hat{\theta}(k-1) \end{cases} \tag{2}$$

$\hat{\theta}(k)$ is the predicted value of the identified parameter, $\phi(k)$ is the input parameter, $y(k)$ is the output parameter, $K(k)$ is the gain, $P(k)$ is the covariance matrix, $e_0(k)$ is the system error. $\lambda$ is the forgetting factor. In this paper, $\lambda = 0.98$.

*C. SOC estimation based on the RFC-AEKF*

In order to enhance the algorithm's responsiveness to noisy environments, the robust function is abstraction and applied to the AEKF algorithm. According to the mathematical expression of the robust function, the covariance matrix $Q$ is optimized and modified in real-time. The system state noise covariance matrix $Q$ equation is shown in equation (3).

$$\hat{Q}_{k+1} = \hat{Q}_k \frac{c^2}{c^2 + r_{k+1}^2} \tag{3}$$

Wherein, $r_k = \left| (\hat{z}_k^- - z_k) / \delta_k \right|$, the value of $c$ is a number of the same order of magnitude as $r_k$. Due to objective factors such as system state noise, model error, or inaccurate state estimation, it is impossible to accurately estimate a residual of 0 between the state estimation and the actual measured values. So set a threshold $\theta$ to determine whether to correct $Q$. After multiple iterations, the $Q$ value is still not 0. After many iterations, the $Q$ value will gradually approach 0. The equations to determine whether $Q$ is corrected are shown in equation (4) and equation (5).

$$\text{if } \left| r_{k+1} \right| \le \theta, \hat{Q}_{k+1}^c = \hat{Q}_k^c \tag{4}$$

$$\text{else } \hat{Q}_{k+1}^c = \hat{Q}_k^c \frac{c^2}{c^2 + r_{k+1}^2} \tag{5}$$

Due to the fact that batteries are highly nonlinear systems, equivalent circuit models cannot fully simulate the characteristics of batteries. When SOC approaches 0 or 1, the internal chemistry of the battery undergoes drastic changes, resulting in significant changes in the battery model parameters. In order to suppress the reduction of SOC estimation accuracy caused by parameter errors, when the SOC is close to 0 or 1, the observation noise covariance matrix $R$ is updated in real-time. The judgment conditions and specific correction methods are shown in equation (6) to equation (8).

$$\text{if} \\ SOC \ge SOC_H, R_k = R_{k0}[1 + G_1(SOC - SOC_H)] \tag{6}$$

$$\text{if } SOC \le SOC_L, R_k = R_{k0}[1+G_2(SOC-SOC_L)] \tag{7}$$

$$\text{else } R_k = R_{k0} \tag{8}$$

Wherein, $SOC_H = 0.8$, $SOC_L = 0.2$, $G_1$ and $G_2$ are constants, $G_1 = G_2 = 10$. The SOC estimation flowchart of RFC-AEKF algorithm is shown in Figure 2.

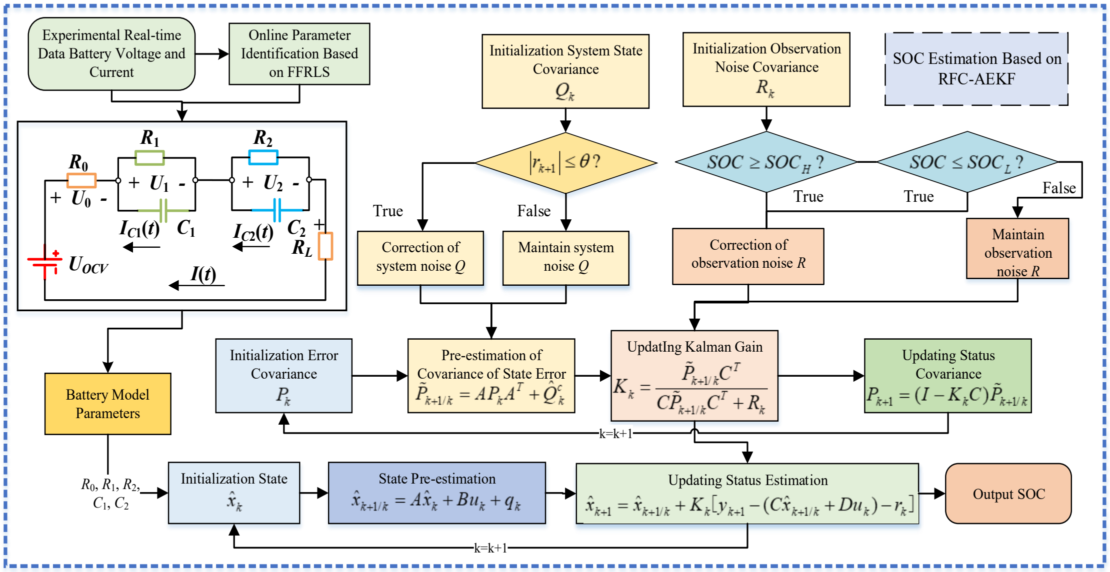


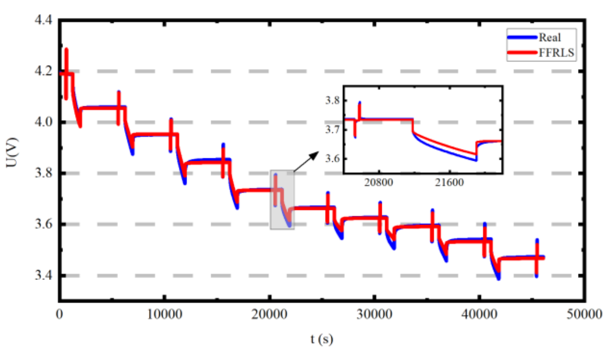

Figure 2. SOC estimation flowchart of RFC-AEKF algorithm

Firstly, the voltage and current data obtained from experimental testing are used as algorithm inputs, and the FFRLS algorithm identifies the DP model parameters online. Then, the identified model parameters are used as input again, and the SOC of the battery is estimated using the RFC-AEKF algorithm. In the RFC-AEKF algorithm, the robust function correction method is used to determine whether the system state covariance $Q$ and observation noise covariance $R$ are corrected. If it is at the set threshold, correct it; Otherwise, it remains unchanged. Then, based on the adaptive method in AEKF, $Q$ and $P$ are estimated to obtain the latest Kalman gain $K$ for system state update. Finally, output the predicted SOC value.

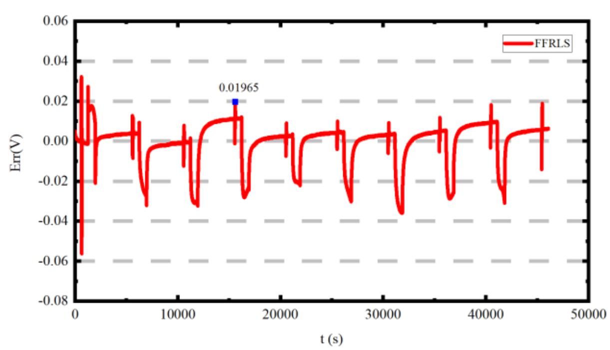
## III. Experimental verification

### A. Model validation

To verify the reliability of the established DP model, the hybrid pulse power characterization (HPPC) conditions were tested on the battery. The FFRLS algorithm was used for online parameter identification of the DP model, and the actual voltage was compared with the simulated voltage output by the FFRLS. The voltage comparison under HPPC is shown in Figure 3.




(a) Real voltage and simulation voltage



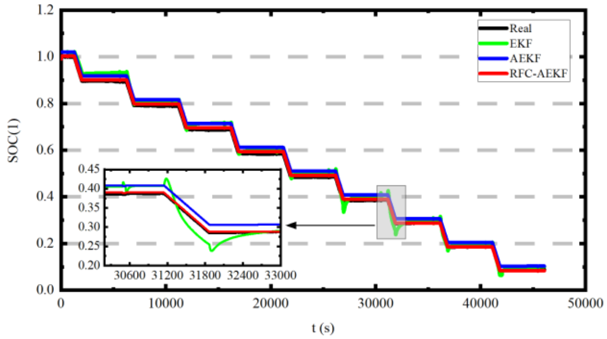

(b) Voltage simulation error

Figure 3. Voltage comparison under HPPC

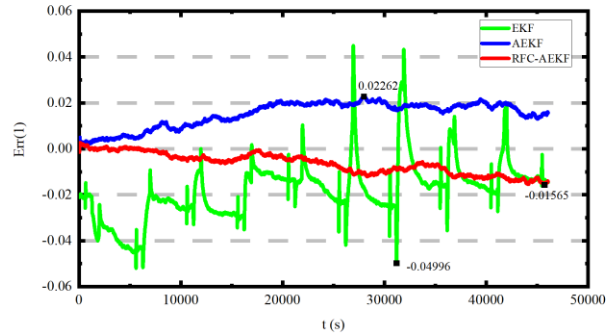
According to Figure 3, the MAE and RMSE of the FFRLS algorithm are 1.21% and 1.34%, respectively. Without regard to the error at the convergence stage of the algorithm, the maximum error is 0.01965V. The FFRLS can effectively characterize the DP model, and obtain more accurate internal parameters of the battery model.

## B. SOC estimation results

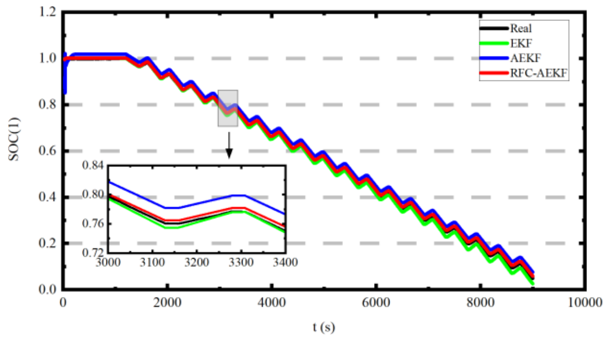
To validate the proposed RFC-AEKF algorithm, its accuracy needs to be verified under different complex working conditions, including HPPC, dynamic stress test (DST), and Beijing bus dynamic stress test (BJDST). The SOC comparison under complex conditions are shown in Figure 4.



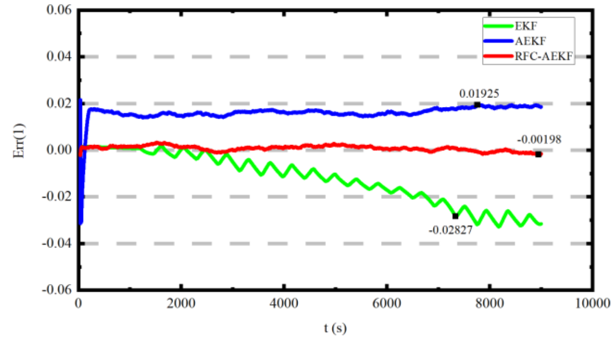

(a) SOC estimation results under HPPC



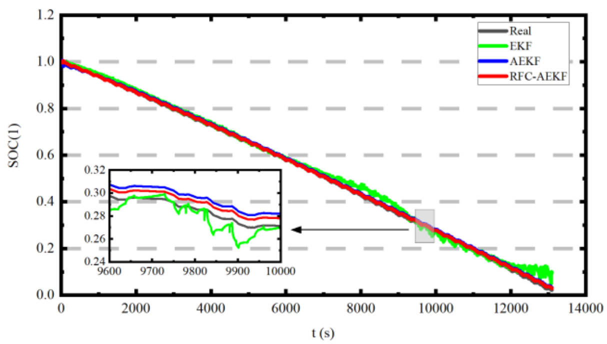

(b) error under HPPC



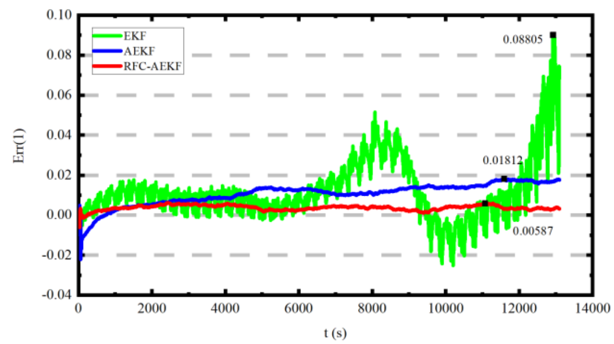

(c) SOC estimation results under DST




(d) error under DST




(e) SOC estimation results under BJDST




(f) error under BJDST

Figure 4. SOC comparison under complex working conditions

The experimental results show that the proposed RFC-AEKF algorithm has the smallest MAE and RMSE compared to EKF and AEKF under three complex working conditions. Under the BJDST conditions, the MAE and RMSE of the RFC-AEKF algorithm are 0.354% and 0.658%, respectively. The calculation time of the RFC-AEKF algorithm is 5.436 seconds, while the calculation time of the AEKF algorithm is 10.084 seconds. Table 1 shows the error analysis of SOC estimation.

Table 1. Error analysis of SOC estimation

| Metrics / Algorithm | MAE(%) | | | RMSE(%) | | |
|---|---|---|---|---|---|---|
| | HPPC | DST | BJDST | HPPC | DST | BJDST |
| EKF | 2.248 | 1.211 | 1.192 | 2.408 | 1.617 | 1.917 |
| AEKF | 1.488 | 1.142 | 1.056 | 1.564 | 1.438 | 1.196 |
| RFC-AEKF | 0.644 | 0.564 | 0.354 | 0.832 | 0.642 | 0.658 |

According to Table 1, under different complex working conditions, the various indicators of the RFC-AEKF algorithm are optimal. Under the BJDST conditions, the accuracy of SOC estimation reaches 99.65%. This indicates that robust function correction methods can reduce errors caused by uncertain noise, improve SOC prediction accuracy, and improve robustness.

## IV. Conclusion

In order to cope with the uncertainty of random noise in nonlinear systems, this paper proposes an RFC-AEKF algorithm for SOC prediction. Dynamic correction of random noise using robust functions and combined with AEKF adaptive method. Using the FFRLS algorithm for online parameter identification of the established DP model. Transfer the identified battery model parameters in real-time to the RFC-AEKF algorithm to obtain more accurate SOC estimates. The experimental results show that under complex working conditions, the MAE and RMSE of the proposed RFC-AEKF algorithm are both smaller than EKF and AEKF. This indicates that the RFC-AEKF algorithm can reduce errors caused by uncertain noise, improve SOC prediction accuracy, and improve robustness.

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## References

[1] He, L., et al., *State of charge estimation by finite difference extended Kalman filter with HPPC parameters identification*. Science China-Technological Sciences, 2020. 63(3): p. 410-421.

[2] Jemmali, S., B. Manai, & M. Hamouda, *Pure hardware design and implementation on FPGA of an EKF based accelerated SoC estimator for a lithium-ion battery in electric vehicles*. IET Power Electronics, 2022. 15(11): p. 1004-1015.

[3] Long, T., et al., *An improved variable forgetting factor recursive least square-double extend Kalman filtering based on global mean particle swarm optimization algorithm for collaborative state of energy and state of health estimation of lithium-ion batteries*. Electrochimica Acta, 2023. 450: p. 142270.

[4] Zhang, S., & X. Zhang, *A novel non-experiment-based reconstruction method for the relationship between open-circuit-voltage and state-of-charge/state-of-energy of lithium-ion battery*. Electrochimica Acta, 2022. 403: p. 139637.

[5] Liu, B. L., et al., *An improved adaptive cubature H-infinity filter for state of charge estimation of lithium-ion battery*. Journal of Power Electronics, 2021. 21(10): p. 1520-1529.

[6] Oh, H., J. Jeon, & S. Park, *Effects of Battery Model on the Accuracy of Battery SOC Estimation Using Extended Kalman Filter under Practical Vehicle Conditions Including Parasitic Current Leakage and Diffusion Of Voltage*. International Journal of Automotive Technology, 2021. 22(5): p. 1337-1346.

[7] Liu, D. L., et al., *A novel fuzzy-extended Kalman filter-ampere-hour (F-EKF-Ah) algorithm based on improved second-order PNGV model to estimate state of charge of lithium-ion batteries*. International Journal of Circuit Theory And Applications, 2022. 50(11): p. 3811-3826.

[8] Zhu, C., et al., *An improved proportional control forgetting factor recursive least square-Monte Carlo adaptive extended Kalman filtering algorithm for high-precision state-of-charge estimation of lithium-ion batteries*. Journal of Solid State Electrochemistry, 2023. 27(9): p. 2277-2287.

[9] Wang, C., et al., *A novel back propagation neural network-dual extended Kalman filter method for state-of-charge and state-of-health co-estimation of lithium-ion batteries based on limited memory least square algorithm*. Journal of Energy Storage, 2023. 59: p. 106563.

[10] Qu, D. W., et al., *State of charge estimation for the Vanadium Redox Flow Battery based on Extended Kalman filter using modified parameter identification*. Energy Sources Part A-Recovery Utilization and Environmental Effects, 2022. 44(4): p. 9747-9763.

[11] Takyi-Aninakwa, P., et al., *A strong tracking adaptive fading-extended Kalman filter for the state of charge estimation of lithium-ion batteries*. International Journal of Energy Research, 2022. 46(12): p. 16427-16444.

[12] Liu, Y. Y., et al., *A novel adaptive H-infinity filtering method for the accurate SOC estimation of lithium-ion batteries based on optimal forgetting factor selection*. International Journal of Circuit Theory and Applications, 2022. 50(10): p. 3372-3386.