An improved SOC estimation method based on noise-adaptive particle filter for intelligent connected vehicle battery

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Abstract: In order to effectively use the cloud data of connected vehicle to estimate the battery state of charge (SOC), an estimation method based on noise adaptive particle filter (N-APF) is proposed in this paper. Firstly, several cells are connected in series under the laboratory environment to simulate the grouping of battery packs in real vehicle. Besides, the federal test procedure (FTP) operating current for battery pack is obtained through software simulation combined with the actual vehicle parameters. Then, the Thevenin equivalent circuit model is established and the reliability of online identification of model parameters based on 10s interval data is verified. Furthermore, the effectiveness of the proposed noise adaptive particle filter method for adjusting the process noise and enhancing the stability of the SOC estimation is proved. Finally, the reliability of the improved SOC estimation method for the connected vehicle is verified based on the 10s interval cloud data, which shows the proposed noise adaptive particle filter estimation method can stabilize the SOC estimation error below 5% except for some high-current discharge phases.

Key Words: State of charge, Connected vehicle, Particle Filter, Nosie-adaptive

1. INTRODUCTION

As one of the key state parameters of electric vehicles, the accurate SOC estimation of Battery plays an important role in ensuring the normal operation of the vehicle. It will often bring about a large accumulated Ah deviation when a car runs continuously for a long time, and more advanced prediction algorithms need to be adopted to improve the SOC estimation accuracy. However, the vehicle battery management system (BMS) usually can only accomplish the algorithm with better implementation due to the cost pressure and technical difficulty. The rapid development of intelligent networked vehicles provides a solution to this contradiction, because the state of battery can be periodically evaluated and calibrated through cloud platform data.

Because of the cumulative deviation of the Ah integral method, a joint method of the Ah integral and the open circuit voltage is usually used in the actual vehicle BMS to estimate the SOC at present [1]. Other commonly used SOC estimation methods [2] are divided into:

(a) Model-based estimation methods

The Model-based methods usually use the battery model to simulate the internal dynamic characteristics of the battery during the charging and discharging, and the closed-loop SOC estimation will be accomplished combining with the observer or filter algorithm. The commonly used battery models can be summarized as: equivalent circuit model (ECM) [3], impedance model [4] and electrochemical model [5]. The ECM is widely used due to its simple structure and clear physical meaning [6]. The commonly used algorithms can be summarized as: extended Kalman filter (EKF) [7], particle filter [8], H∞ filter [9] and so on. In reference[10], the effects of different identification methods on SOC estimation based on Kalman filter are compared. In reference [11], a double-scale dual adaptive particle filter is applied to the battery parameter and SOC estimation.

(b) Data-driven-based estimation methods

Generally, the data-driven-based methods are dependent on the dataset to establish the mapping relationship between the input(current, voltage, temperature and other indicators) and the output(SOC). The commonly used methods can be summarized as: neural network [12], deep learning, support vector machine [13] and so on. However, because of the large data need of these black box models, the scope of their application is limited. In reference [14], the SVM-based SOC estimation method for 30s interval cloud data is adopted with the large amount of calculation.

In order to achieve the accuracy remote SOC estimation through the cloud data with large sampling period, a model-based noise adaptive particle filter estimation method is proposed in this paper. Firstly, several cells are connected in series under the laboratory environment to simulate the grouping of battery packs in real vehicle. Besides, the operating current under FTP driving cycle is simulated through the software AVL Cruise according to the real vehicle parameters. Then, the Thevenin model [15] is established and the recursive least square algorithm is used for parameter identification. And the SOC estimation effects of the traditional particle filter method and the noise adaptive particle filter method are compared. Finally, the reliability of the improved battery SOC estimation method for the connected vehicle is verified based on the cloud data.

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2. BATTERY EXPERIMENTAL SYSTEM

The recording period of the cloud data is 10s in this paper, so the battery characteristics is hard to be revealed directly because of the dynamic driving condition of electric vehicle. Therefore, several cells are connected in series under the laboratory environment for preliminary exploration.

2.1 Battery Parameter

The large-format prismatic lithium-ion battery used in real cars is selected for this experiment. The detailed parameters are shown in table 1.

Table1. Battery Parameters

Item	Specification
Cathode material	$Li(NiCoMn)O_2$
Nominal capacity	120Ah
Nominal voltage	3.66V
Operating voltage	3.0~4.25V
Operating temperature	Charge: 0~50℃ Discharge: -20~55℃
Outline dimension	173.2*51.4*127.7m

2.2 Test Equipment and Operating condition

As shown in Figure 1, seven cells are connected in series under the laboratory environment to simulate the grouping of battery packs in real vehicle. The battery test operating is controlled by the battery charge- discharge instrument with a maximum voltage 60V and a maximum current 100A. And the multi-channel collector is used to obtain the temperature and voltage information of each cell, which will be used in parameter identification and state of charge estimation.

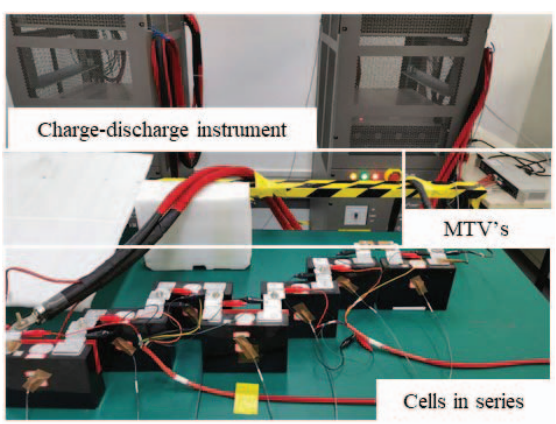

Fig 1. The experimental system for battery test

In order to better simulate the variability of discharge in real vehicle driving conditions, the operating current under FTP driving cycle (Figure 2) is simulated through the software AVL Cruise according to the real vehicle parameters. The obtained operating current curve is shown in Figure 3, which will be used in battery test. Obviously, the cells in series and the Changing charge-discharge current curve can restore the dynamic working condition of battery partly.

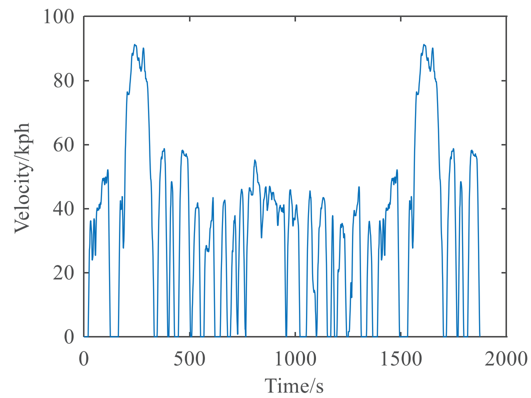

Fig 2. FTP driving cycle

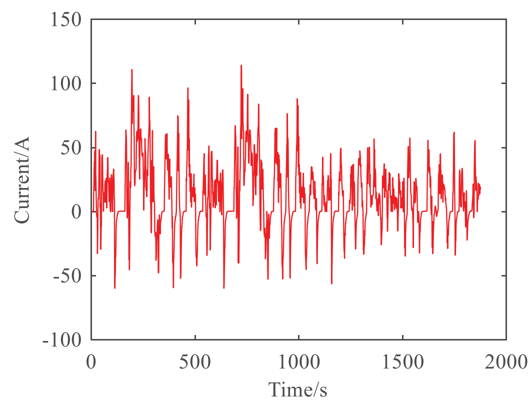

Fig 3. Current operating condition

3. SOC ESTIMATION METHOD BASED ON NOISE ADAPTIVE PARTICLE FILTER

In order to converge the Ah deviation caused by the 10s recording period under variable operating condition, the model-based noise adaptive particle filter method is proposed to enhance the stability of SOC estimation in this section. The cell with lowest voltage limits the total available capacity, which will be selected as the indicator cell for parameter identification and the SOC estimation verification.

3.1. Circuit Model and Parameter Identification

The battery model plays an important role for model-based SOC estimation method. Due to the simple structure and clear physical meaning, the Thevenin model is chosen here, which is shown in Figure 4.

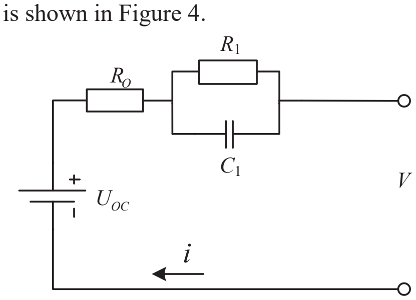

Fig 4. Thevenin model

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In figure 4, U_{oc} describes the open circuit voltage; R_0 describes the ohmic resistance; polarization resistance R_1 and polarization capacitance describe the RC circuit; I describes the input current; V describes the output terminal voltage.

The equation can be described as:

$$V = U_{oc} - IR_0 - U_1 \tag{1}$$

$$\dot{U}_1 = \frac{}{C_1} - \frac{U_1}{R_1 C_1} \tag{2}$$

The discretization equation of U_1 can be described as:

$$U_{1,k} = U_{1,k-1} e^{-\Delta t / R_1 C_1} + I_k R_1 (1 - e^{-\Delta t / R_1 C_1}) \tag{3}$$

The formula (3) describes the change of U_1 while the time change from the moment k-1 to k, where Δt is the data sampling period.

Thus, the complete output equation is:

$$\begin{cases} V_k = U_{oc}(\text{soc}) - I_k R_0(\text{soc}) - U_{1,k} \\ U_{1,k} = U_{1,k-1} e^{-\Delta t / R_1 C_1} + I_k R_1 (1 - e^{-\Delta t / R_1 C_1}) \end{cases} \tag{4}$$

In order to avoid the influence of temperature and other factors on the model parameters, the recursive least square method is used to identify the Thevenin model parameters online. Thus the model state equation need to be discretized to meet the recursive form. Firstly, the Laplace transform is performed on the original state equation to obtain the transfer function as follows:

$$G(\text{s}) = \frac{V(\text{s}) - U_{oc}(\text{s})}{I(\text{s})} = -R_0 - \frac{R_1}{1 + R_1 C_1 \text{s}} \tag{5}$$

For $\text{s} = \frac{2}{\text{T}} \frac{1 - z^{-1}}{1 + z^{-1}}$, the formula (5) can be described as:

$$G(\text{z}^{-1}) = -R_0 - \frac{R_1}{1 + R_1 C_1 \frac{2}{\text{T}} \frac{1 - z^{-1}}{1 + z^{-1}}} = \frac{c_2 + c_3 z^{-1}}{1 - c_1 z^{-1}} \tag{6}$$

For $E(\text{s}) = V(\text{s}) - U_{oc}(\text{s})$, the equation can be written as:

$$E_k = c_1 E_{k-1} + c_2 i_k + c_3 i_{k-1} \tag{7}$$

According to formula (7), seeing E_k as the output, the data matrix and parameter matrix will be described as the formula (8) and formula (9) respectively.

$$\boldsymbol{h}(\text{k}) = [E_{k-1} \;\; i_k \;\; i_{k-1}] \tag{8}$$

$$\boldsymbol{\theta} = [c_1 \; c_2 \; c_3]^{\text{T}} \tag{9}$$

Then the parameters can be identified online according to the least square algorithm.

$$\begin{cases} \boldsymbol{K}_{\text{m+1}} = \boldsymbol{P}_{\text{m}} \boldsymbol{h}^{\text{T}}(\text{m+1})[\lambda + \boldsymbol{h}(\text{m+1}) \boldsymbol{P}_{\text{m}} \boldsymbol{h}^{\text{T}}(\text{m+1})]^{-1} \\ \boldsymbol{\theta}_{\text{m+1}} = \boldsymbol{\theta}_{\text{m}} + \boldsymbol{K}_{\text{m+1}}[z(\text{m+1}) - \boldsymbol{h}(\text{m+1}) \boldsymbol{\theta}_{\text{m}}] \\ \boldsymbol{P}_{\text{m+1}} = \frac{1}{\lambda}[\boldsymbol{P}_{\text{m}} - \boldsymbol{K}_{\text{m+1}} \boldsymbol{h}(\text{m+1}) \boldsymbol{P}_{\text{m}}] \end{cases} \tag{10}$$

The open circuit voltage is provided by the hybrid pulse power characteristic (HPPC) test, the different current rate curve of which is shown in Figure 5. According to the simulated current shown in Figure 3, three cycles of FTP current test and ten minutes test without discharge are carried out while the SOC=0.9. The sampling interval is 10s and the data length is 640. The current operating curve is shown in Figure 6.

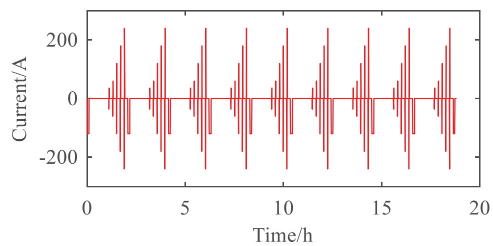

Fig 5. Current of HPPC test

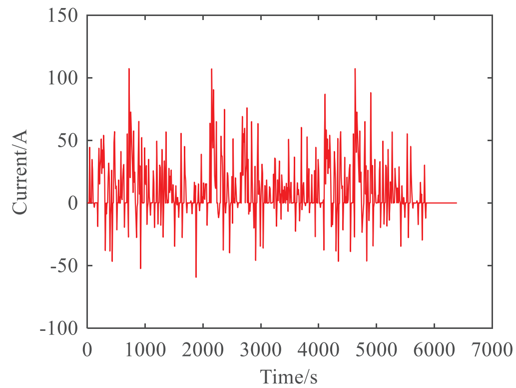

Fig 6. Current of verification test

Combing with the U_{oc}, V and I as the inputs, the online model parameter identification is realized according to the formulas (8), (9) and (10). And the model terminal voltage error is shown in Figure 7. It can be seen that the estimated error is less than 10mV.at the most moment except for a few sharp points. Therefore, the reliability of online model parameter identification with 10s interval sampling can be proved and the parameter identification method will be used in the SOC estimation based on particle filter.

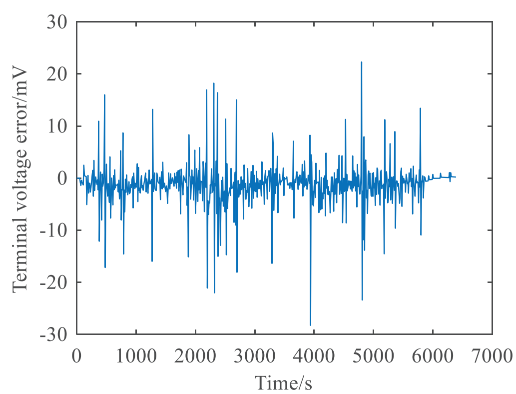

Fig 7. Terminal voltage error of ECM

3.2. Noise Adaptive Particle Filter

Particle filter is a kind of approximate Bayesian filter algorithm based on Monte Carlo simulation. The core idea is to use some random sampling points to approximate the probability density function of the system's random variables and replace the integral operation with the sample

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mean to obtain the minimum variance estimate. So it is suitable for SOC estimation to achieve the convergence of random errors.

According to the definition of SOC and the discretization result of Thevenin model, the battery state equation and measurement equation can be obtained as shown in the formula (11) and formula (12).

$$SOC_{k+1} = SOC_k - \eta \frac{I_k \Delta t}{C_N} + \omega_k \quad (11)$$

$$V_{k+1} = U_{OC}(SOC_{k+1}) - R_{0,k+1} I_{k+1} - U_{1,k+1} + v_k \quad (12)$$

Where η is the coulomb efficiency, ω_k is the process noise with the variance Q and v_k is the measurement noise with the variance P. If the data length is noted as L（$k = 1,2...L$）, the SOC will be written as X_k and the measured voltage will be written as y_{k+1}.

Therefore, the traditional particle filter algorithm [16] can be described as:

Step 1: Initialization, k=0.

For i=1:N, select the initial particle X_0^i（$i = 1,2,\cdots$ ）from the prior distribution p(X_0) according to the initial covariance P0.

Step 2: For k=1:L

(a) Prediction

Generate N particles X_{k+1}^i at moment k+1 according to formula (11), $X_{k+1}^i = f(X_k^i, I_k) + \omega_k$.

(b) Weights calculation and normalization

Calculate the weight of each particle according to the formula (13) and the measured voltage value y_{k+1}.

$$q_i = p(y_{k+1} \mid X_{k+1}^i) = \frac{1}{\sqrt{2\pi R}} \exp\left\{ \frac{(y_{k+1} - g(X_{k+1}^i, I_k))^2}{-2R} \right\} \quad (13)$$

Normalization:

$$\bar{q}_i = q_i / \sum_{i=1}^{N} q_i \quad (14)$$

(c) Output

$$\hat{X}_{k+1} = \sum_{i=1}^{N} \bar{q}_i X_{k+1}^i \quad (15)$$

(d) Particle resampling

Resample particles X_{k+1}^i based on weights $\bar{q}_i$, update for the moment k+1.

In the traditional particle filter algorithm, the noise variance Q is usually a fixed value by experience. However, there are many factors that affect the variance of process noise. If the value is too large, it can easily cause the divergence of particles. And if the value is too small, it is hard to converge the Ah cumulative deviation reliably. Therefore, a noise adaptive particle filter method is proposed in the paper to adaptively adjust the process noise variance Q.

Following the steps above, the noise adaptive particle filter (N-APF) can be described as:

(e) Noise adjustment adaptively

Calculate the average voltage deviation of the N particles according to the normalized results of the weights.

$$\text{e\_error}_{k+1} = \sum_{i=1}^{N} (y_{k+1} - g(X_{k+1}^i, I_k)) \bar{q}_i \quad (16)$$

As the Figure 8 shown, the open circuit voltage curve can be obtained by Polynomial fitting. And we can get the function δ(soc)=$d$soc/$d$ocv whose curve is shown in Figure 9.

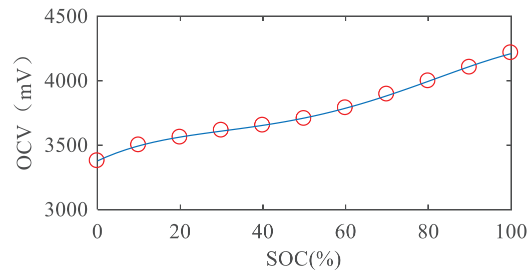

Fig 8. Curve of open circuit voltage

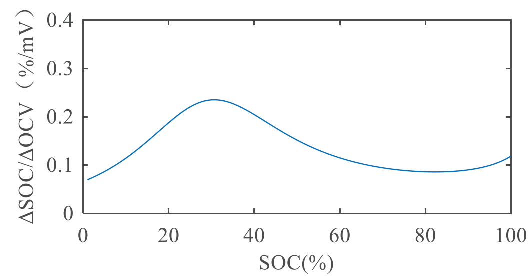

Fig 9. Curve of function δ(soc)

Thus, the process noise variance Q can be adjusted by the formula (16) and formula (17).

$$\text{sqrt}(Q_{k+1}) = \delta(\hat{X}_{k+1}) \cdot \text{e\_error}_{k+1} \quad (17)$$

At the same time, the initial noise variance is usually not too small for ensuring effective convergence. Therefore, the N-APF method is mainly used to reduce the value of Q at the moment k+1 and there is the limit $Q_k < Q_0 (k = 1,2,\cdots$ in order to avoid accidental terminal voltage deviation leading the excessive state noise.

3.3. Experimental Verification

According to the operating current shown in Figure 6, the effect of noise adaptive particle filter for estimating SOC has been preliminarily verified. The algorithm parameters are set as: number of particles N=500, initial covariance P0=0.01, measured noise variance R=0.0004, the process noise variance $Q_0 = \sigma^2 = 0.0001$. The results comparison of the traditional particle filter and the noise adaptive particle filter for SOC estimation is shown in Figure 10.

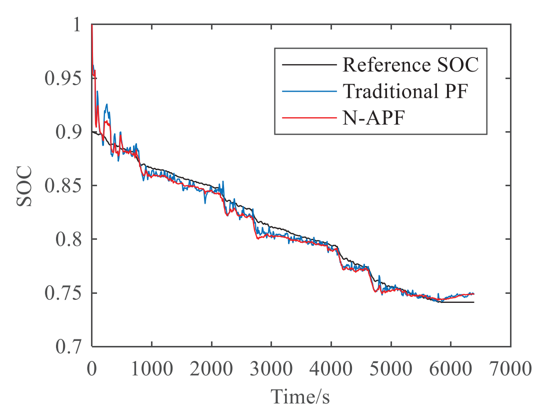

Fig 10. Estimation results of laboratory verification

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The estimation error is shown in Figure 11. It can be clearly seen that the N-APF method can effectively enhance the stability of state tracking while ensuring the rapid convergence of the initial error.

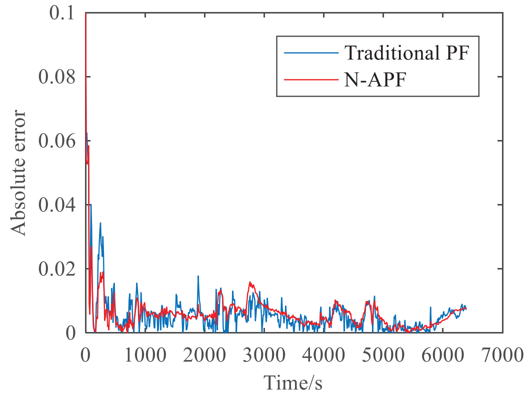

Fig 11. Estimation error comparison

Figure 12 shows the change of σ during the process of estimating SOC based on the N-APF method, and the red line represents the mean value of σ in the whole process. It can be seen that N-APF can adaptively reduce the variance of process noise during the estimation process, and thereby reduce the volatility of the particles to ensure the estimation effect.

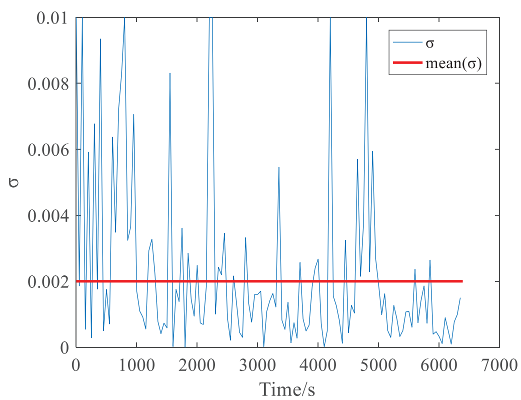

Fig 12. Adaptive process noise during estimation

4. REAL VEHICLE VERIFICATION AND CONCLUSION

4.1 Real Vehicle Verification

In order to verify the estimation effect of the noise adaptive particle filter algorithm on the actual vehicle data, about two days of battery information from the cloud platform is selected here. And the recording period of the cloud data is 10s. Since the battery pack in real vehicle is composed of 90 cells in series, the cell whose voltage is often the lowest is selected as the characteristic one, and the voltage and current of which are chosen as the input of the algorithm. The original vehicle speed and current information are shown in Figure 13. The discharge current is positive and the charge current is negative. So the data contains various working conditions such as normal driving, rapid acceleration, braking, parking, and charging. Taking the estimated value of the vehicle-mounted BMS as the reference SOC and taking the absolute time as abscissa, the SOC estimation effect based on the noise adaptive particle filter algorithm is shown in Figure 14. It can be seen that the N-APF algorithm can rapidly decrease the SOC initial error and maintain stable state prediction during the different driving conditions.

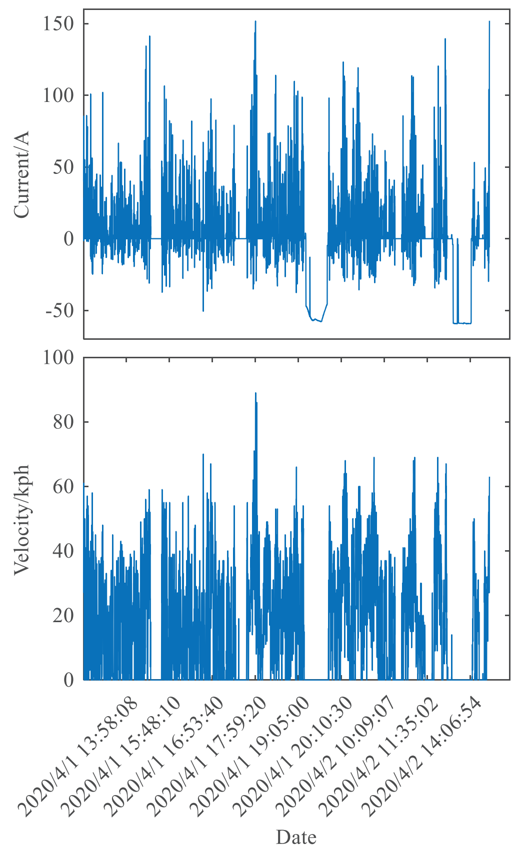

Fig 13. Current and velocity of real vehicle

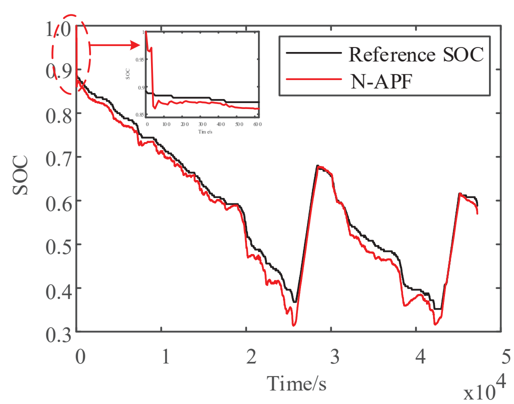

Fig 14. Estimation results based on cloud data

The SOC estimation error curve is shown in Figure 15. It can be seen that the SOC estimation error during the stable phase is less than 3%, while the estimation error will reach

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5% during the high-current discharge phases. And it is clear that this estimation method can get the stable convergence value of SOC during the charging. The results show that the proposed N-APF method can effectively estimate the SOC for connected vehicle.

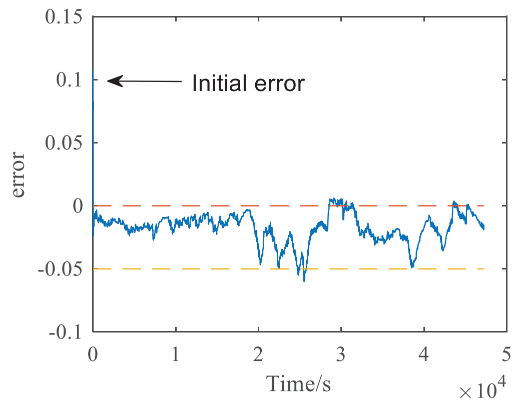

Fig 15. Estimation error based on cloud data

4.2 Conclusion

In order to achieve the accuracy remote SOC estimation through the cloud data with large sampling period, a model-based noise adaptive particle filter estimation method is proposed in this paper. Firstly, several cells are connected in series under the laboratory environment to simulate the grouping of battery packs in real vehicle. Then, the Thevenin model is established and the recursive least square algorithm is used for parameter identification. The reliability of online model parameter identification with 10s interval sampling is proved. Besides, the effect for enhancing the stability of SOC tracking and ensuring the rapid convergence of the initial error is proved based on FTP operating current in laboratory environment. Finally, the reliability of the N-APF method for the connected vehicle is verified based on the cloud data. The result shows that SOC estimation error during the stable phase is less than 3%, while the estimation error will reach 5% during the high-current discharge phases. The proposed method is expected to achieve the reliable remote SOC estimation while the estimated value of the vehicle-mounted BMS getting a large deviation during the continuous driving condition.

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