

Research Article

Improved 2RC-PNGV Modeling and Adaptive Sage-Husa H Infinity Filtering for Battery Power State Estimation Based on Multi-Parameter Constraints

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Abstract

With the transformation of the global energy landscape, lithium-ion batteries have become an important component in the field of new energy storage. Accurate assessment of battery status plays a crucial role in efficiently utilizing electrical energy and extending the battery's service life. The key parameters of battery status include charging state (SOC) and power state (SOP). This paper constructs an improved 2RC-PNGV battery equivalent circuit model and introduces an innovative method to enhance the dynamics of particle swarm optimization. At the same time, an adaptive H infinity (∞) filtering algorithm based on Sage-Husa and a temperature-constrained SOP estimation method for lithium-ion batteries is designed. Among them, the real-time dynamic particle swarm optimization algorithm adjusts the forgetting factor in each iteration; the adaptive H ∞ filtering algorithm based on Sage-Husa improves the accuracy of SOC estimation by adapting the noise covariance matrix. Moreover, the multi-parameter constrained state estimation method for lithium-ion batteries can effectively track the changes in state quantities with different durations and instantaneous values. The improved forgetting factor least squares method has an error of fewer than 0.02 volts in the voltage simulation test, with high accuracy. The adaptive H ∞ filtering algorithm based on Sage-Husa achieves higher estimation accuracy in three complex operating scenarios, ensuring that the state quantity estimation error remains below 2%. The maximum estimation error of the multi-parameter constrained state quantity estimation method is less than 84.00 watts. These research results provide a solid theoretical foundation for ensuring the safety and efficient operation of batteries.

Keywords

Lithium-ion Battery, Estimation Strategy of SOC, Power State Estimation Strategy, Dynamic Particle Swarm Optimization algorithm, H Infinity Filtering, State Joint Estimation

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1. Introduction

In recent years, with the development of clean energy, vehicle lithium-ion battery packs have become one of the core components of the power system of new energy vehicles [1, 2]. With the surge in market demand, the demand for high-performance, reliable, and efficient battery systems is increasing day by day. Accurately estimating the battery state (such as SOC and SOP) is crucial for improving energy utilization efficiency, alleviating "range anxiety", and optimizing charging and discharging strategies. The use of large-capacity battery packs requires high integration and the safety and real-time monitoring of systems with high energy density. The battery management system (BMS) plays a core role in this process, monitoring the health status, remaining power, and other parameters in real time, and estimating SOC and SOP [3, 4].

SOC is defined as the ratio of the current capacity to the rated capacity, reflecting the remaining battery power and the driving range [5]. However, it is susceptible to factors such as environmental temperature and the number of cycles, making real-time estimation difficult. Currently, Kalman filtering (KF) and its derivative algorithms (such as Extended Kalman Filtering, EKF) are the mainstream methods for state estimation. EKF solves the problem of nonlinear systems by optimizing KF, but it relies on high-precision models [6, 7].

SOP represents the instantaneous peak power output of the battery at a specific moment, and it includes two indicators: maximum power and rated power [7, 8]. The estimation methods mainly include the lookup table method based on characteristic functions and the method based on multi-parameter constraints. The latter requires comprehensive consideration of SOC, terminal voltage, and current limits. Accurate SOP estimation can improve battery efficiency and determine the vehicle's power demand [9, 10].

The precise estimation of lithium-ion battery state requires decoupling the coupling relationships of key parameters. The main methods include model analysis and data-driven approaches [11, 12]. The model analysis method predicts the internal state of the battery through multi-factor analysis, while the data-driven method combines the estimation of SOC and SOP by analyzing the coupling factors through big data [13, 14].

This paper focuses on the estimation of the SOC and SOP of lithium-ion batteries. It adopts the PNGV model with dual RC parallel connections for equivalent modeling. The parameters are identified online through the dynamic particle swarm optimization (DPSO)-improved forgetting factor least squares method (FFRLS), and the H_∞ filtering algo-

rithm is improved based on the Sage-Husa adaptive method for joint estimation.

2. Theoretical Analysis

2.1. Improved Second-order PNGV Equivalent Circuit Model of Lithium-ion Battery

Compared with the Thevenin model, the second-order RC equivalent circuit model adds a set of RC circuits, which better describes the dynamic characteristics of lithium-ion batteries by utilizing different time constants [15]. The PNGV equivalent circuit model further covers polarization effects and ohmic internal resistance characteristics, with higher accuracy and moderate computational load [16, 17]. However, it does not consider the issue that the ohmic internal resistance varies due to the different current directions during charging and discharging. Therefore, this paper improves the PNGV model (Figure 1) to more accurately describe the dynamic characteristics of ternary lithium batteries.

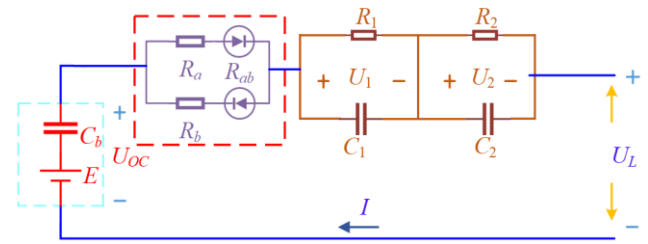


Figure 1. 2RC-PNGV model.

In the model, U_{OC} represents the open-circuit voltage, U_L denotes the load voltage, and E together with C_b reflects changes in U_{OC} . R_0 is the ohmic internal resistance, while R_1 and C_1 form a polarization loop to simulate the battery's fast polarization response. Additionally, R_2 and C_2 are introduced to model the slow electrochemical polarization response. The improved model replaces the original R_0 with discharge resistance R_a and charge resistance R_b and employs a dual-RC loop instead of a single-RC loop to more precisely characterize the dynamic behavior during charging and discharging [18, 19].

$$\begin{cases} U_L(t) = U_{OC}(t) - U_0(t) - U_1(t) - U_2(t) \\ I_L = C_1 \frac{dU_1}{dt} + \frac{U_1}{R_1} = C_2 \frac{dU_2}{dt} + \frac{U_2}{R_2} \\ U_{OC} = f[SOC(t)] \\ SOC(t) = SOC(0) - \eta \int_0^t \frac{i}{Q} dt \\ U_0 = R_0 I_L \end{cases} \quad (1)$$

$$\begin{cases} \begin{bmatrix} SOC(k+1) \\ U_1(k+1) \\ U_2(k+1) \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{T}{\tau_1}} & 0 \\ 0 & 0 & e^{-\frac{T}{\tau_2}} \end{pmatrix} \begin{bmatrix} SOC(k) \\ U_1(k) \\ U_2(k) \end{bmatrix} + \\ \begin{bmatrix} -\frac{\eta T}{Q_v} R_1 \left(1 - e^{-\frac{T}{\tau_1}}\right) R_2 \left(1 - e^{-\frac{T}{\tau_2}}\right) \end{bmatrix} I(k) + w(k) \\ U_L(k) = \left(\frac{\partial U_{OC}}{\partial SOC} \quad -1 \quad -1 \right) [SOC(k) \quad U_1(k) \quad U_2(k)]^T - \\ R_0 I(k) + v(k) \end{cases} \quad (2)$$

By integrating the model circuit equations with the SOC estimation derived from the ampere-hour integration method, the time-domain equations for lithium-ion batteries (Formula 1) and the state-space equations (Formula 2) can be derived. Here, η represents coulombic efficiency, K and k denote observation and state errors, respectively, Q_v is the current capacity, and τ_1 and τ_2 are the time constants for electrochemical reaction and polarization. Analysis shows that SOC estimation is influenced by multiple parameters, and its accuracy depends on precise modeling of battery characteristics.

2.2. Least Square Method of Forgetting Factor Based on Dynamic Particle Swarm Optimization

2.2.1. Real-Time Parameter Estimation via PSO-Enhanced Adaptive Forgetting Factor Least Squares

In engineering applications, the recursive least squares (RLS) online parameter identification method may accumulate errors with increasing iterations, ultimately reducing data accuracy. To mitigate this, a forgetting factor (λ) is introduced to diminish the influence of historical data during each iteration, thereby improving identification precision (Formula 3). However, a fixed λ value creates a trade-off between convergence speed and noise resistance: a smaller λ reduces anti-noise capability, while a larger λ slows convergence. To address this, this study employs a dynamic particle swarm optimization (PSO) algorithm to optimize λ in real-time, dynamically adjusting its value during iterations to enhance identification accuracy.

$$\begin{cases} \theta(k) = \theta(k-1) + \gamma \cdot P(k-1)x(k) [y(k) - x^T(k) \\ \theta(k-1)] \\ \gamma = [x^T(k)P(k-1)x(k) + \lambda]^{-1} \\ P(k) = [I - \gamma \cdot P(k-1)x(k)x^T(k)]P(k-1)/\lambda \end{cases} \quad (3)$$

In the PSO algorithm, particle position (X_{id}) and velocity (V_{id}) are updated according to Formula 4:

$$\begin{cases} V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1 (P_{id}^k - X_{id}^k) + c_2 r_2 (P_{gd}^k - X_{id}^k) \\ X_{id}^{k+1} = X_{id}^k + V_{id}^k \end{cases} \quad (4)$$

Here, ω is the inertia weight, c_1 and c_2 are acceleration constants, and r_1 , r_2 are random numbers in $[0, 1]$. The fitness function is defined as the deviation between the actual terminal voltage $U(k)$ and the estimated voltage (Formula 5):

$$f = |U(k) - U_{OC}(k) - \varphi^T(k)\hat{\theta}(k-1)| \quad (5)$$

2.2.2. Dynamic Processing of Inertia Weight

The inertia weight ω influences the PSO algorithm's global and local search capabilities. This study adopts a dynamic adjustment strategy (Formula 6):

$$\omega(k) = \omega_a - (\omega_a - \omega_b) \left(\frac{k}{T_{max}} \right)^2 \quad (6)$$

Where $\omega_a = 0.9$ (initial value), $\omega_b = 0.4$ (final value), and T_{max} is the maximum number of iterations. This strategy nonlinearly decreases ω with iterations, balancing exploration and exploitation.

The steps of the particle swarm optimization algorithm are shown in Figure 2.

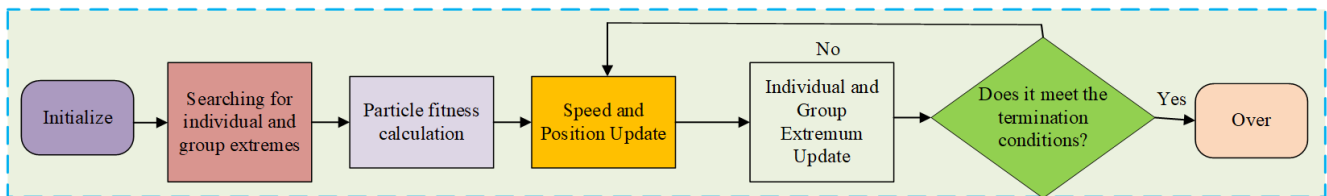


Figure 2. Step diagram of the particle swarm optimization algorithm.

2.3. Analysis of SOC Estimation Strategy Based on H^∞ Filtering Algorithm

2.3.1. Construction of Cost Function and Implementation of H^∞ Filtering Algorithm

The H^∞ filtering algorithm is an improved version of the EKF. Based on game theory, it constructs a cost function.

$$J = -\frac{1}{\delta} \|x(0) - \hat{x}(0)\|_{P^{-1}(0)}^2 + \sum_{k=0}^N [\|x(k) - \hat{x}(k)\|_{S(k)}^2 - \frac{1}{\delta} (\|w(k)\|_{Q^{-1}(k)}^2 + \|w(k)\|_{R^{-1}(k)}^2)] < 0 \quad (7)$$

$$x(k) = A(k)x(k-1) + B(k)I(k) + \omega(k) \quad (8)$$

$$P(k) = A(k-1)P(k-1)A^T(k-1) + Q(k-1) \quad (9)$$

$$K(k) = P(k) [I - \delta S(k)P(k) + C^T(k)R^{-1}(k)C(k)P(k)]^{-1} C^T(k)R^{-1}(k) \quad (10)$$

$$\hat{x}(k) = \hat{x}(k-1) + K(k) [y(k) - \hat{y}(k-1)] \quad (11)$$

$$P(k) = P(k-1) [I - \delta S(k)P(k-1) + C^T(k)R^{-1}(k)C(k)P(k-1)]^{-1} \quad (12)$$

2.3.2. Adaptive Noise Covariance Matrix Based on Sage-Husa Method

The Sage-Husa adaptive algorithm improves noise resistance by dynamically updating the statistical characteristics

J (Formula 7) and seeks the optimal estimation by minimizing J . Here, δ represents the performance boundary, and the iterative process is described by Formula 8-12. The H^∞ filter exhibits strong robustness, though its accuracy requires further enhancement.

of system and measurement noise (Formula 13). The forgetting factor σ (ranging from 0.9 to 1) adjusts data weighting, enabling high-precision and rapid SOC estimation even under complex noise conditions.

$$\begin{cases} Q(k) = (1 - d_k)Q(k-1) + d_k [K(k)e(k)e^T(k)K^T(k) \\ \quad + P(k) - A(k)P(k-1)A^T(k)] \\ R(k) = (1 - d_k)R(k-1) + d_k [e(k)e^T(k) - \\ \quad C(k)P(k)C^T(k)] \\ d(k) = \frac{1-\sigma}{1-\sigma^{k+1}} \end{cases} \quad (13)$$

2.3.3. Realization of SOC Estimation Algorithm Based on Noise Adaptive H^∞ Filtering

Conventional EKF and H^∞ filters require preset noise statistics, but real-world environmental noise (possibly colored noise) can lead to estimation errors or divergence. To address

the highly nonlinear nature of lithium-ion batteries, an Adaptive H^∞ Filter (AHIF) (Formula 14) is proposed, integrating the Sage-Husa method to dynamically adjust noise covariance matrices and improve SOC estimation accuracy. The algorithm is shown in Figure 3.

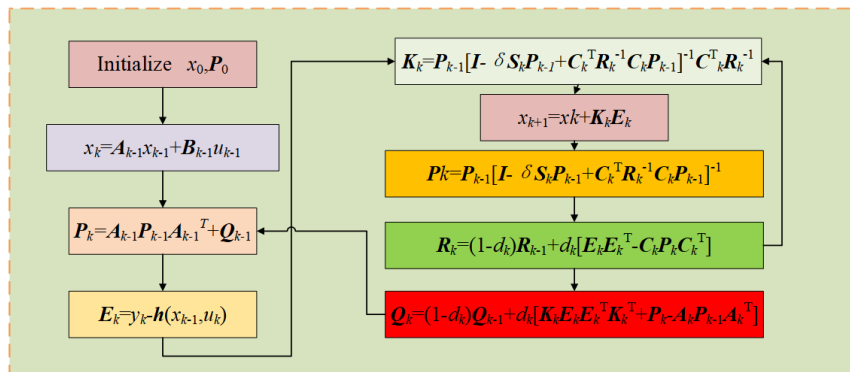


Figure 3. Adaptive H^∞ Algorithm Implementation Block Diagram.

$$\begin{cases} K(k) = P(k)[I - \delta S(k)P(k) + C^T(k)R^{-1}(k)C(k)P(k)]^{-1} \\ \quad C^T(k)R^{-1}(k) \\ x(k+1) = A(k)\hat{x}(k) + B(k)u(k) + \\ \quad K(k)[y(k) - \hat{y}(k)] \\ P(k+1) = A(k)P(k) \\ \quad [I - \delta S(k)P(k) + C^T(k)R^{-1}(k)C(k)P(k)]^{-1}A^T(k) \\ \quad + Q(k) \end{cases} \quad (14)$$

2.4. SOP estimation Strategy for Lithium-ion Batteries Based on Multi-parameter Constraints Figures

2.4.1. Power State Calculation and Analysis Based on Multi-constraints

To more accurately characterize the performance of power lithium-ion batteries, it is necessary to comprehensively consider constraints under different operating conditions. A single limitation cannot fully reflect battery performance, leading to significant discrepancies between measured power and theoretical values. Therefore, multiple constraints (voltage limits, SOC limits, and current cutoffs) must be employed to estimate the battery's SOP, improving estimation accuracy and reliability. Based on these constraints, the peak current equation under multi-parameter constraints (Formula 15) can be derived:

$$\begin{cases} I_m^{dis}(k+L) = \min\{I^{dis}, I_U^{dis}(k+L), I_{SOC}^{dis}(k+L)\} \\ I_m^{chg}(k+L) = \max\{I^{chg}, I_U^{chg}(k+L), I_{SOC}^{chg}(k+L)\} \end{cases} \quad (15)$$

Here, I^{dis} and I^{chg} denote the factory-set discharge and charge cutoff currents, $I_U^{chg/dis}$ represents the peak current under voltage constraints, and $I_{SOC}^{dis/chg}$ is the peak current under SOC constraints. Based on Formula 15, the continuous peak power state under multiple constraints (Formula 16) can be expressed as:

$$\begin{cases} P_m^{dis}(k+L) = U^{min} I_m^{dis}(k+L) \\ P_m^{chg}(k+L) = U^{max} I_m^{chg}(k+L) \end{cases} \quad (16)$$

This equation indicates that the battery's peak power state must be characterized jointly by voltage and current parameters.

2.4.2. Analysis of Joint Estimation Method for SOC and SOP of Lithium-ion Battery

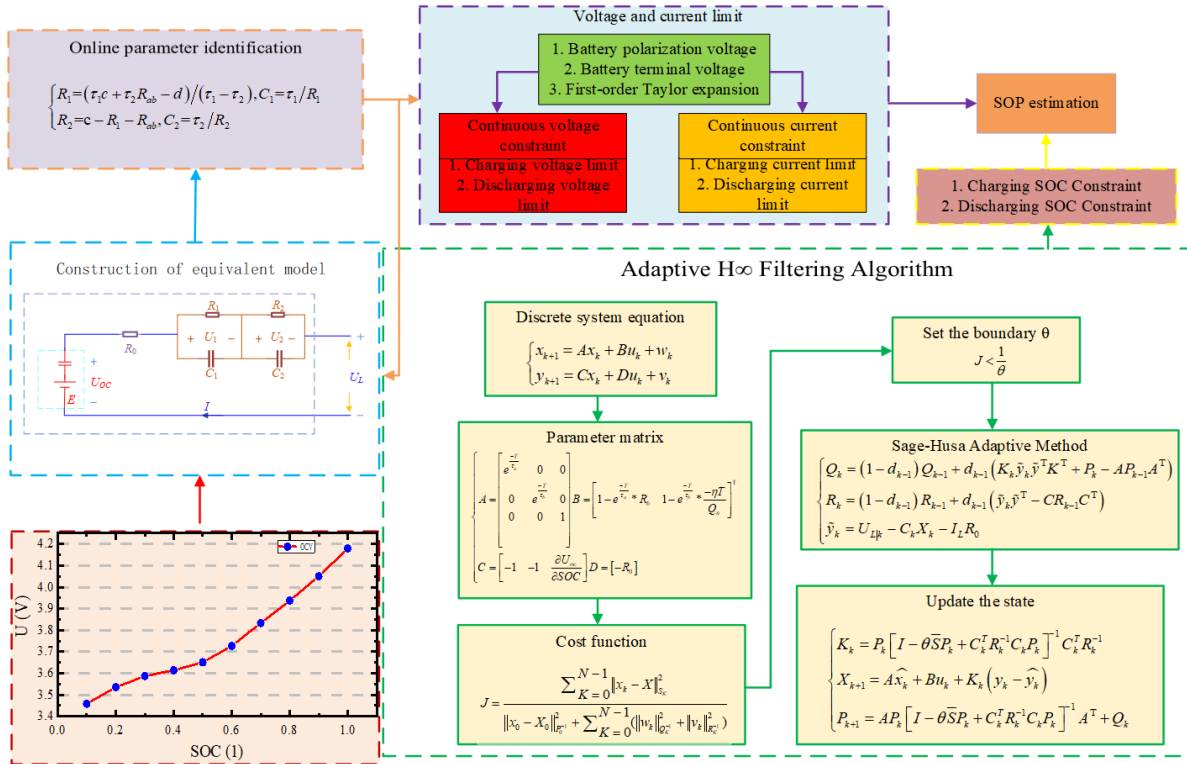


Figure 4. Block diagram of power state estimation under multiple constraints of parameters in online mode.

SOC and SOP are closely interrelated: real-time SOP prediction relies on SOC characterization, while changes in SOP also affect SOC. Since the estimation of both depends on model accuracy and parameter identification effectiveness, this study employs the DPSO-FFRLS online parameter identification method to rapidly identify key model parameters in conjunction with an equivalent circuit model. These parameters are then input into an adaptive H^∞ filtering algorithm to estimate SOC. Subsequently, the multi-parameter constrained SOP estimation strategy is applied to calculate SOP, achieving joint estimation of SOC and SOP. Figure 4 illustrates the workflow of the multi-constraint SOP estimation strategy.

3. Experimental Analysis

3.1. Experimental Platform Construction

A 70Ah ternary lithium battery was selected as the re-

$$U_{OC}(k) = 4.625 * SOC^5(k) - 14.9 * SOC^4(k) + 19.38 * SOC^3(k) - 10.77 * SOC^2(k) + 2.947 * SOC(k) + 3.251 \quad (17)$$

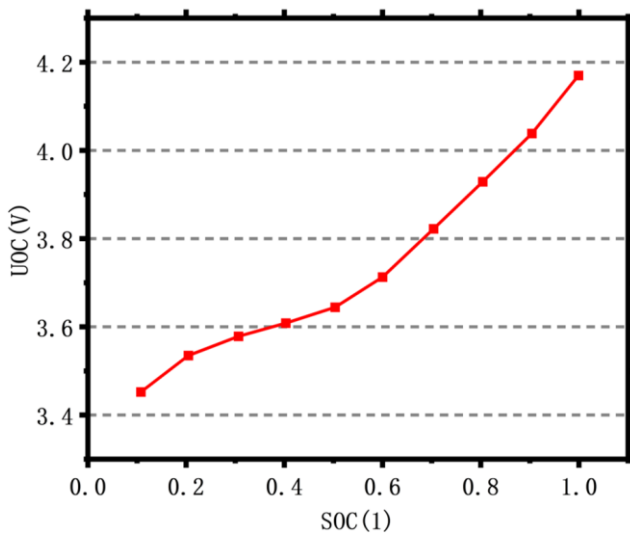


Figure 5. SOC-OCV fitting curve.

3.2.2. Voltage Verification Under HPPC Conditions

Comparing RLS, FFRLS, and DPSO-FFRLS algorithms, DPSO-FFRLS exhibited the smallest voltage error (<0.02 V), validating its high-precision parameter identification capability (Figures 6-7).

search object, with an experimental temperature range of -5°C to 15°C . An experimental platform was constructed to study the variation patterns of battery characteristics under different operating conditions. The traditional PNGV model was optimized by adding an RC parallel circuit, proposing a 2RC-PNGV equivalent circuit model. Combined with the Forgetting Factor Recursive Least Squares (FFRLS) method based on Dynamic Particle Swarm Optimization (DPSO) and the AHIF algorithm, joint estimation of SOC and SOP under complex operating conditions was achieved.

3.2. Parameter Identification and Verification Based on DPSO-FFRLS

3.2.1. SOC-OCV Curve Fitting

Using HPPC test data, a fifth-order polynomial in MATLAB was employed to fit the SOC-OCV relationship (Formula 17), with results shown in Figure 5.

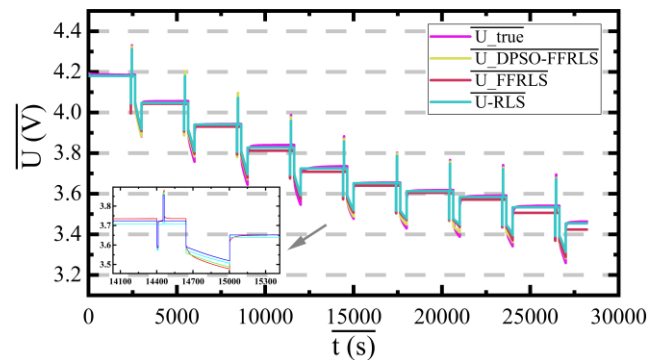


Figure 6. Voltage tracking and comparison of each algorithm under HPPC working conditions.

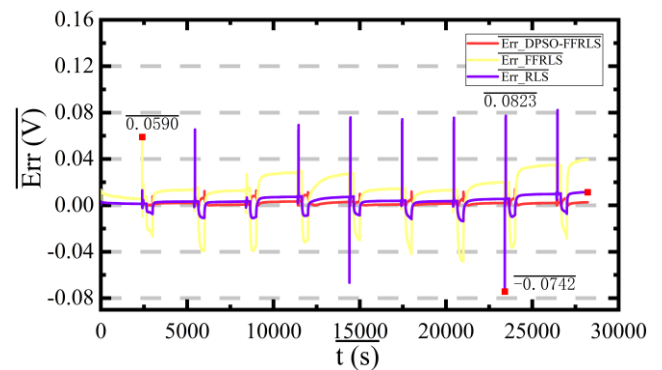


Figure 7. Voltage tracking error of each algorithm under HPPC working conditions.

3.2.3 Voltage Verification Under DST Conditions

In Dynamic Stress Test (DST) conditions, DPSO-FFRLS still performed optimally, with a maximum error <0.018 V (Figures 8-9).

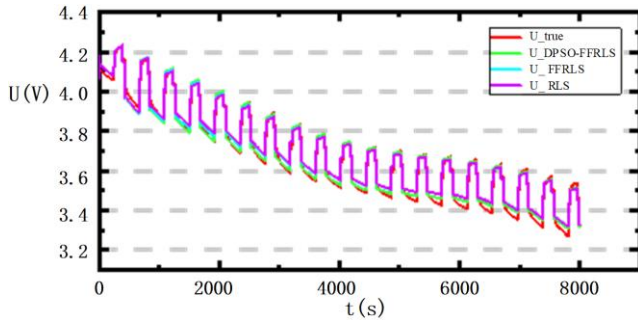


Figure 8. Voltage tracking and comparison of each algorithm under DST conditions.

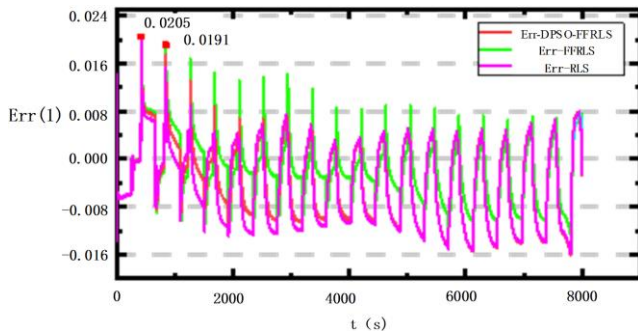


Figure 9. Voltage tracking error of each algorithm under DST conditions.

3.3. Validation and Analysis of SOC and SOP Estimation Strategies

To evaluate the performance of the AHIF under complex operating conditions, this study systematically validated the algorithm using three typical test conditions (HPPC, DST, and BBDST) at different temperatures (-5°C , 5°C , and 15°C).

In the HPPC condition validation, by comparing the parameter identification effectiveness between the fixed forgetting factor FFRLS and DPSO-FFRLS algorithms, it was found that DPSO-FFRLS demonstrated superior identification accuracy. Simultaneously, the SOC estimation results of the EKF, HIF, and AHIF algorithms indicated that the AHIF algorithm exhibited the best tracking capability and estimation accuracy, with a mean absolute error (MAE) of only 0.919% and a root mean square error (RMSE) of 0.984%. During the DST test, which simulated actual dynamic current conditions, the DPSO-FFRLS algorithm showed faster convergence, while the AHIF algorithm maintained stability throughout the estimation process, with the maximum error

consistently controlled below 0.02. The more complex BBDST condition test further verified the superiority of the AHIF algorithm. Even under conditions of intense current fluctuations, its MAE and RMSE remained at low levels of 0.571% and 0.660%, respectively, significantly outperforming the traditional EKF algorithm.

For evaluating the SOP of lithium-ion batteries, this study designed a multi-parameter constrained SOP estimation strategy. Under the low-temperature DST condition at -5°C , the estimation error of instantaneous discharge power was less than 90 W, and the charging power error was below 70 W. When the test condition was switched to the more stringent BBDST condition, the maximum discharge power error was controlled within 110 W, while the charging power error was further reduced to 45 W. Notably, the estimation accuracy for short-duration conditions (1 s and 5 s) was significantly better than that for long-duration conditions (15 s), a pattern consistently observed across different temperatures (5°C and 15°C). Test data indicated that lower temperatures led to a slight increase in estimation errors, but the multi-parameter constrained strategy maintained overall stability.

In summary, the SOC estimation method combining DPSO-FFRLS and AHIF proposed in this study demonstrated outstanding accuracy and robustness across various operating conditions. Meanwhile, the multi-parameter constrained SOP estimation strategy effectively addressed the challenges posed by dynamic conditions and temperature variations, providing a reliable technical solution for the state evaluation of lithium-ion batteries. These achievements establish a solid theoretical foundation for the practical application of battery management systems.

4. Results

The experimental results show that the constructed DPSO-FFRLS online parameter identification method can effectively identify the key parameters of the model, and the voltage error of the model is less than 0.02 V, with better performance than the RLS and FFRLS algorithms. The constructed adaptive H_{∞} filtering algorithm was verified under multiple working conditions, and through comparison with the EKF and H_{∞} filtering algorithms, it was proved that the adaptive H_{∞} filtering algorithm has high reliability, with an overall SOC estimation error of less than 2%. For the SOP estimation strategy with multiple parameter constraints, the effectiveness was verified through DST and BBDST working conditions, and comparative experiments were designed under different temperatures and different durations. The overall SOP error is less than 84 W.

5. Discussion

This paper enhances battery state estimation through lithium-ion battery modeling, parameter identification, and joint

estimation strategies. Key contributions include:

(1) A dynamic particle swarm optimization-based forgetting factor least squares method to balance convergence speed and noise resistance.

(2) An H_∞ filtering algorithm with Sage-Husa adaptive noise covariance for robust SOC estimation under mismatched noise conditions.

(3) A multi-parameter-constrained SOP estimation strategy, integrating DPSO-FFRLS online identification with battery current, SOC, and voltage limits for reliable performance.

6. Conclusions

In the lithium-ion battery management system, the state of charge and power state are crucial parameters. The accurate state of charge estimation can provide a reliable reference for the battery management system, and accurate state of power estimation is related to the safety and reliability of the whole electric vehicle. In this study, the focus is on estimating the state of charge and power of lithium-ion batteries. To achieve this, a double RC parallel circuit model based on the PNGV model is employed to represent the battery equivalently. The improved model is then identified online using the FFRLS optimized by DPSO. Additionally, an enhanced H_∞ filtering algorithm based on the Sage-Husa adaptive method is utilized for estimating the state of charge of lithium batteries. An SOP estimation strategy for lithium-ion batteries based on multi-parameter constraints is constructed. These improvements greatly improve the accuracy. Although this study has achieved certain results in the parameter identification and state estimation of ternary lithium battery cells, due to time and experimental conditions constraints, there are still several issues that need to be further addressed. Firstly, the current research only verified the algorithm for individual cells and has not examined the applicability of the constructed algorithm in complex operating conditions of battery packs. This needs to be improved in subsequent work. Secondly, in the research on the SOP estimation strategy of batteries, the algorithm's effectiveness in a constant temperature environment was mainly investigated. It neither evaluated the algorithm's performance under time-varying temperature conditions nor examined the situation under high-temperature operating conditions. In response to these limitations, the subsequent research will focus on two aspects: on the one hand, extend the algorithm verification to the battery pack level; on the other hand, focus on studying the influence of environmental temperature time-varying characteristics on the algorithm and improve its reliability in practical applications through algorithm improvement and experimental verification.

Abbreviations

SOC State of Charge

SOP	State of Power
BMS	Battery Management System
KF	Kalman Filter
EKF	Extended Kalman Filter
FFRLS	Forgetting Factor Least Squares Method
DPSO	Dynamic Particle Swarm Optimization
AHIF	Adaptive H-infinity Filter
HIF	H-infinity Filter
PSO	Particle Swarm Optimization

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Author Contributions

Xinyu Yan: Methodology, Software, Methodology, Writing – review & editing

Shunli Wang: Conceptualization, Resources, Formal Analysis, Supervision, Methodology, Writing – original draft, Writing – review & editing

Tao Xu: Writing – review & editing

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Data Availability Statement

The data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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