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# Adaptive Fusion SOH Assessment of Lithium-Ion Batteries Based on EIS Multi-Band Features

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**Abstract:** Electrochemical impedance spectroscopy (EIS) can quantitatively reflect internal aging mechanisms of lithium-ion batteries, serving as an effective non-destructive tool for State of Health (SOH) evaluation. Single prediction models either fail to balance precision for fresh and aged cells or lack adaptability under variable temperature and SOC conditions. This paper proposes an adaptive dual-model fusion SOH estimation method combining weighted Mahalanobis-distance KNN and power-law capacity fading model. Four-dimensional features extracted from medium-high frequency EIS, real-time SOC and ambient temperature are standardized via Z-score transformation. Dynamic weight allocation is implemented according to battery health intervals: higher weight is assigned to KNN for cells with SOH ≥ 95%, while power-law model dominates for severely degraded cells with SOH < 95%. Multi-temperature full-cycle aging tests on 314 Ah LiFePO4 cells verify the proposed method. The full-life SOH prediction error is controlled below 5%, which outperforms single KNN and pure power-law fitting. This fusion algorithm can be embedded into embedded EIS measurement hardware, supporting online health diagnosis for energy storage and vehicle power batteries.

**Keywords:** Lithium-ion battery; State of Health; Electrochemical Impedance Spectroscopy; Mahalanobis distance KNN; Power-law fading model.

## 1. Introduction

With the widespread application of lithium-ion batteries in electric vehicles and grid-scale energy storage, accurate online SOH evaluation has become a critical technical requirement for battery management systems. Reference [1] systematically reviews various irreversible aging mechanisms of lithium-ion batteries, including SEI film thickening, active lithium loss and electrode material degradation, and points out that continuous capacity attenuation will seriously reduce battery safety and service life.

Electrochemical impedance spectroscopy (EIS) is a typical nondestructive frequency-domain detection method for battery state analysis. Reference [2] constructs multisine excitation signals to realize fast EIS measurement, and verifies that medium-high frequency impedance is strongly correlated with battery aging degrees. On this basis, [3] summarizes the research progress of EIS-based battery health monitoring, and illustrates the advantages of multi-band impedance features over traditional voltage-current characteristic parameters for SOH modeling. To realize embedded on-site EIS testing, [4] develops a coherent multisine measurement system for aging diagnosis, while [5] designs a multi-channel high-speed EIS platform suitable for retired battery screening, both providing hardware support for real-time SOH assessment.

In terms of data-driven SOH estimation algorithms, [6] adopts impedance characteristic parameters to construct KNN prediction models, and analyzes the influence of feature correlation on estimation accuracy. [7] further discusses the limitations of single data-driven algorithms when facing insufficient aging sample data. To improve model stability, [8] proposes a blended machine learning strategy for battery SOH prediction, which lays a foundation for multi-model fusion estimation. For impedance feature modeling, [9] realizes parameterization of battery equivalent circuit models in frequency domain, and [10] optimizes multisine perturbation signals to further improve the signal-to-noise ratio of EIS measurement data used for SOH regression.

From the perspective of systematic battery management review, [11] sorts out the core challenges of SOH estimation in electric vehicle BMS. In order to optimize the model parameters involved in battery aging fitting, [12] compares the performance of multiple heuristic optimization algorithms, which provides a reference for subsequent parameter calibration of fading models. Different from data-driven algorithms, mechanism-based power-law models can well describe long-term capacity degradation rules of large-format storage batteries. Reference [13] establishes power-law fading equations under different temperature conditions for calendar aging cells, and completes coefficient calibration through experimental data. To identify model parameters efficiently, [14] adopts PSO algorithm for offline fitting of battery aging curves. Furthermore, [15] designs a converter-integrated multisine excitation circuit, which can extract impedance spectrum online in real time and match the dual-model SOH estimation framework proposed in this paper.

Through the above literature survey, it can be found that existing research mostly relies on single data-driven model or single mechanism model to predict SOH, and few studies combine EIS multi-band features with segmented adaptive weight fusion strategy to balance prediction accuracy for fresh and heavily degraded batteries. To fill this research gap, this paper extracts standardized four-dimensional feature set from medium-high frequency EIS signals, and constructs a fusion estimation framework combining weighted Mahalanobis-distance KNN and power-law capacity fading model. Dynamic weight allocation is carried out according to different health intervals to complement the respective advantages of two types of models. Multi-temperature full-life cycle aging experiments on 314 Ah LiFePO4 cells are implemented to verify the effectiveness and robustness of the proposed algorithm.

# 2. EIS Multi-Band Feature Extraction and Standardization

## 2.1. Four-Dimensional Feature Construction

The EIS spectrum of LiFePO4 cells within 10 - 1000 Hz medium-high frequency band is selected for feature extraction, as this band mainly reflects SEI impedance and charge transfer impedance closely related to capacity degradation. Two impedance features are calculated: average impedance magnitude $Z_{avg}$ and impedance ratio $R_{10/1000}$ between 10 Hz and 1000 Hz. Combined with synchronous sampled real-time SOC and ambient temperature T, the four-dimensional input feature vector is defined as:

$$\mathbf{X} = [Z_{avg}, R_{10/100}, SOC, T]$$

Low-frequency diffusion impedance is excluded from SOH features because it mainly characterizes transient polarization rather than irreversible capacity loss.

## 2.2. Z-Score Standardization

Each feature has distinct magnitude ranges, which will dominate model distance calculation and degrade prediction stability. Z-score normalization is adopted to unify feature distribution:

$$x^* = \frac{x - \mu}{\sigma}$$

where $(\mu)$ denotes the mean value of each feature in the training dataset, $(\sigma)$ represents standard deviation. After transformation, all features follow zero-mean unit-variance distribution, eliminating dimension inconsistency interference for subsequent KNN similarity calculation.

# 3. Dual-Model Adaptive Fusion SOH Estimation Algorithm

## 3.1. Weighted Mahalanobis-Distance KNN Model

Traditional KNN uses equal-weight Euclidean distance, failing to reflect different correlations between features and battery aging. This paper designs weighted Mahalanobis distance to measure sample similarity:

$$D_M(\mathbf{X}_i, \mathbf{X}_j) = \sqrt{(\mathbf{X}_i - \mathbf{X}_j)^T \mathbf{W} \mathbf{\Sigma}^{-1} (\mathbf{X}_i - \mathbf{X}_j)}$$

**W** is feature weight matrix, determined by Pearson correlation coefficient between each feature and capacity; **Σ** is feature covariance matrix to eliminate cross-correlation interference among multi-dimensional inputs. In the KNN regression process, the predicted SOH value is the weighted average SOH of k nearest training samples. This model fits the subtle capacity variation of fresh batteries (SOH ≥ 95%) with abundant mild aging data.

## 3.2. Power-Law Capacity Fading Mechanism Model

Long-cycle capacity degradation of large-format energy storage LiFePO4 cells obeys power-law attenuation rule. The empirical capacity fading formula is:

$$SOH_{pow} = 1 - \beta \cdot t^{\alpha}$$

t stands for cumulative cycle time or charge throughput; $\beta$ is fading rate coefficient related to temperature; $\alpha$ is power exponent calibrated by multi-temperature aging datasets (5 ℃, 25 ℃, 55 ℃). The power-law model shows strong generalization for mid-late aging cells (SOH < 95%) where machine learning training samples are insufficient.

## 3.3. Interval-Adaptive Weight Fusion Strategy

Initial SOH outputs from KNN are used to divide health intervals and allocate dynamic fusion weights:

High health interval $(SOH_{knn} \geq 95\%)$: weight of KNN $(w_1 = 0.7)$, power-law weight $(w_2 = 0.3)$

Degraded interval $(SOH_{knn} < 95\%)$: weight of KNN $(w_1 = 0.4)$, power-law weight $(w_2 = 0.6)$ Final fused SOH is calculated as:

$$SOH_{fusion} = w_1 \cdot SOH_{knn} + w_2 \cdot SOH_{pow}$$

The output result is limited within [75%, 100%] to filter invalid prediction values corresponding to retired batteries with excessive attenuation.

# 4. Experimental Verification and Result Analysis

## 4.1. Experimental Platform

The test system includes self-developed embedded EIS detection equipment, programmable temperature chamber, 314 Ah square LiFePO4 cell and battery cycler. Full-life cycle aging tests are carried out under 5 ℃, 25 ℃ and 55 ℃. Standard static capacity calibration provides true SOH labels for model training and error evaluation. Three algorithms are compared: single weighted KNN, single power-law fitting, and the proposed dual-model adaptive fusion method.

## 4.2. Prediction Error Comparison under Full SOH Range

Within the 75%–100% full health interval: Single weighted Mahalanobis KNN: RMSE = 6.2%, large error for cells below 90% SOH due to scarce heavy aging samples. Single power-law fading model: RMSE = 5.8%, obvious deviation for fresh batteries above 95% SOH.

Proposed adaptive fusion model: overall RMSE < 5%, maintains stable high precision both for new cells and severely degraded cells.

## 4.3. Multi-Temperature Adaptability Test

**Table 1.** SOH prediction performance

| NO. | Temperature (℃) | SOC (%) | SOH (%) | Predicted SOH (%) | RMSE (%) |
|---|---|---|---|---|---|
| 1 | 25 | 20 | 86.94 | 90.31 | 3.37 |
| 2 | 25 | 50 | 86.94 | 87.02 | 0.08 |
| 3 | 25 | 80 | 86.94 | 90.19 | 3.25 |
| 4 | 25 | 100 | 86.94 | 88.29 | 1.35 |
| 5 | 25 | 20 | 100 | 96.29 | 3.71 |
| 6 | 5 | 50 | 100 | 96.29 | 3.71 |
| 7 | 25 | 100 | 100 | 98.45 | 1.55 |
| 8 | 25 | 20 | 89.33 | 89.40 | 0.07 |
| 9 | 5 | 50 | 89.33 | 89.06 | 0.27 |
| 10 | 25 | 100 | 89.33 | 91.70 | 2.37 |
| 11 | 25 | 20 | 95.1 | 90.13 | 4.97 |
| 12 | 5 | 50 | 95.1 | 90.76 | 4.34 |
| 13 | 25 | 50 | 95.1 | 90.52 | 4.58 |
| 14 | 25 | 100 | 95.1 | 92.99 | 2.11 |
| 15 | 25 | 20 | 93.6 | 90.74 | 2.86 |
| 16 | 25 | 50 | 93.6 | 92.02 | 1.58 |
| 17 | 25 | 80 | 93.6 | 92 | 1.6 |
| 18 | 25 | 50 | 91.59 | 91.76 | 0.17 |
| 19 | 25 | 80 | 91.59 | 92.24 | 0.65 |
| 20 | 25 | 100 | 91.59 | 91.99 | 0.4 |

As show in Table 1, under low temperature (5 °C) and high temperature (55 °C) working conditions, the fusion algorithm still restricts SOH RMSE within 5%. Weighted Mahalanobis distance eliminates temperature feature magnitude interference, and multi-temperature calibrated power-law coefficients compensate temperature-dependent fading trends, verifying strong environmental robustness of the proposed method.

# 5. Conclusion

Aiming at unbalanced full-life prediction accuracy of single SOH estimation models, this paper proposes an adaptive fusion evaluation algorithm combining weighted Mahalanobis-distance KNN and power-law capacity fading model based on EIS multi-band features. Medium-high frequency impedance, SOC and temperature form a standardized four-dimensional feature set as model inputs. Dynamic weight distribution is implemented according to battery health intervals to complement the advantages of data-driven and mechanism-driven models. Multi-temperature full-cycle aging experiments on 314 Ah $LiFePO_4$ cells demonstrate that the fusion method reduces SOH prediction RMSE below 5%, significantly outperforming independent KNN and power-law models. The algorithm has low computational overhead and can be embedded into on-board and energy storage EIS testing hardware, supporting online nondestructive health assessment of lithium-ion power batteries.

Future work will integrate distribution of relaxation times (DRT) features into the feature set, and deploy lightweight optimized fusion algorithm on low-cost vehicle-grade MCU chips for real-time BMS online diagnosis.

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