
Research article

State-of-health prediction for lithium batteries based on feature decoupling and heterogeneous stacking ensemble learning framework

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Abstract: Accurate state-of-health (SOH) prediction of lithium batteries is vital for guaranteeing the safe operation of battery systems and extending their service life. However, previous data-driven models were usually established based on ideal laboratory environments, which would severely restrict their generalization ability in real-world applications. This paper develops an SOH prediction method based on feature decoupling and a heterogeneous stacking ensemble learning framework (HSELF). First, the validation dataset was constructed by using accelerated cycle aging data with three levels of gradient noise. Second, features based on incremental capacity analysis (ICA) were extracted from a selected charging voltage interval to capture underlying battery degradation characteristics. Then, a feature decoupling strategy based on noise robustness decay rate (NRDR) and the corresponding differentiated feature input spaces were constructed for the heterogeneous stacking model. Additionally, a nested inner leave-one-battery-out cross-validation (LOBOCV) strategy was developed to achieve an unbiased evaluation of generalization under small-sample conditions. Finally, the ridge regression method was adopted as the meta-learner to integrate the outputs of the base models in the HSELF, leveraging their complementary strengths for mitigating prediction errors. Experimental results based on the LISHEN dataset successfully demonstrated the effectiveness of the developed SOH prediction method based on feature decoupling and HSELF. Under noise-free and typical industrial noise ($\sigma \leq 10$ mV) conditions, the accuracy of the developed SOH prediction method would be significantly superior to that of individual base models. Furthermore, although the extreme noise ($\sigma = 20$ mV) causes severe performance degradation with individual base models, the

developed SOH prediction method can consistently maintain high prediction stability ($R^2 > 0.93$). In addition, experimental results based on an additional HNEI dataset also demonstrate that the developed SOH prediction method can achieve an effective balance among prediction accuracy, noise robustness, and cross-dataset robustness.

Keywords: lithium batteries; state-of-health prediction; incremental capacity analysis; heterogeneous stacking ensemble learning framework; feature decoupling

1. Introduction

The global energy structure is transitioning toward a low-carbon future, driving the development of the new energy industry [1,2]. Since lithium batteries are core energy carriers or storage devices in new energy applications, their operational performance directly determines the overall system safety and lifecycle. However, lithium battery systems are complex, nonlinear electrochemical systems. During long-term operation, they are subjected to the coupled effects of ambient temperature, charging/discharging power, and cutoff voltage. These coupled effects would trigger internal degradation reactions, including solid-electrolyte interphase thickening, lithium plating, active lithium-ion loss, and electrode degradation [3–5]. These mechanisms manifest as capacity or other performance decay. Therefore, state-of-health (SOH) prediction is essential for battery management systems, involving capacity fade, safe operation, and long service life. It serves as both a prerequisite for precise power control in battery management systems (BMS) and a key indicator for the second-life utilization of retired lithium batteries [6–8].

An obvious gap in SOH prediction exists between ideal laboratory and real-world conditions [9,10]. As is well-known, ideal laboratory applications generally feature constant temperature and strict charging/discharging protocols, whereas real-world operation conditions are highly dynamic. Recently, researchers have shifted the SOH prediction studies conducted on ideal laboratory tests toward real-world scenarios. For instance, researchers have used a deep learning framework and constructed multi-modal evaluation systems based on different charging voltage segments for the robust SOH prediction under actual road conditions in electric vehicle (EV) applications [10–12]. In these practical applications, BMSs should predict internal degradation of lithium batteries relying solely on limited external voltage/current signals with restricted computational resources under fluctuating operation conditions. Undoubtedly, these limited sampling signals, restricted computational resources, and fluctuating operation conditions would pose various challenges to existing SOH prediction technologies.

To address the above challenges, many advanced and intelligent methods have emerged for SOH prediction, including model-driven, mechanism-data hybrid-driven, and intelligent data-driven methods. Model-driven methods usually construct precise physical or equivalent circuit models to capture the internal degradation mechanisms of batteries [11–13]. For example, researchers proposed an electro-thermal aging model for the lithium battery, which used a filtering method to simultaneously predict its state-of-charge (SOC) and the resistance decay [14]. However, the pure mechanism-based method relies on solving complex differential equations, resulting in high computational load. Mechanism-data hybrid driven methods sufficiently excavate characteristics from the mechanism and operation data [15,16]. For instance, hybrid frameworks combining physical models with neural networks have achieved high-precision prediction and improved physical interpretability in battery

health or supercapacitor degradation assessment [17,18]. In addition, Bayesian optimization, bidirectional long short-term memory networks, and Kalman filter-based correction have also been combined to improve the accuracy and robustness of battery SOC estimation [19]. Although hybrid-driven methods possess many advantages, their prediction accuracy remains sensitive to initial parameter values, being difficult to achieve low-cost deployment in the embedded BMS.

To reduce model complexity, machine learning and intelligent data-driven methods with different advantages in feature interpretability, nonlinear representation, and small-sample adaptation have become mainstream in battery SOH prediction [20]. In these methods, researchers aimed to exploit the underlying correlations among battery aging features to improve model accuracy and generalization ability. Consequently, multi-indicator models, multi-model fusion methods, and ensemble learning frameworks have attracted much attention [21,22]. For example, multi-layer stacking ensemble models could effectively mitigate the overfitting of single models [23]. On the other hand, multi-feature strategies have been adopted for decision fusion, while feature extraction methods using convolutional neural networks have also demonstrated excellent performance [24]. However, pure data-driven methods are heavily dependent on full-cycle and high-quality data. In practical applications, onboard sensors inevitably exhibit measurement noise [25,26]. Contrary to this, most studies lack robustness validation against noisy environments. As a result, the SOH prediction performance and generalization ability of these pure data-driven models under real-world conditions obviously decay.

To deal with the data fragmentation issue for SOH prediction in practical applications, feature engineering methods based on partial charging data have emerged in recent years [27,28]. For example, a short charge curve was combined with long short-term memory networks to extract local and temporal aging information for battery health estimation [29]. The corresponding results effectively demonstrated the feasibility of extracting battery degradation information from limited charging data. For instance, incremental capacity analysis (ICA) and the corresponding extracted features can effectively reflect internal electrochemical phase transition mechanisms of lithium batteries. Previous studies successfully extracted health features or indicators from the charging voltage data [30]. Meanwhile, other researchers have also extracted the correlation coefficient of the SOH variation from partial charging curves as health features, utilizing the discrete wavelet packet transform for denoising and the Gaussian process regression (GPR) for prediction [31]. Partial charging curves have also been utilized to extract aging features with the dual GPR models [32]. In summary, previous studies have successfully confirmed the feasibility and physical validity of using fragmented data within specific charging voltage intervals for battery SOH prediction [33].

Although utilizing specific charging voltage intervals has been widely accepted for battery SOH prediction, the research related to ICA still faces a neglected challenge [29,30]. Because the computational essence of ICA involves numerical differentiation, it would amplify quantization noise from onboard voltage sensors [34–36]. Existing work primarily used back-end filtering to smooth data. However, the systematic and quantitative evaluation for the noise-resistant properties of front-end ICA features was lacking. This is problematic for the low-precision sampling of the onboard BMS in practical applications, where different ICA features exhibit different sensitivity properties. Therefore, comprehensive performance evaluation and precise voltage interval screening are crucial for battery SOH prediction [37]. If features are directly exploited for model training without proper and precise screening, the prediction performance of intelligent data-driven methods would greatly decay under real-world conditions. Additionally, traditional feature robustness evaluation methods usually analyze the correlation between each feature and the battery SOH under the clean or noise conditions [38], or

evaluate the model prediction performance based on comprehensive error metrics [39]. Different from traditional methods, we use the noise robustness decay rate (NRDR) strategy, which can quantify the relative change in the correlation between the selected feature and battery SOH under noise conditions. Undoubtedly, the NRDR strategy is an improved method for feature screening.

Based on the above-mentioned analyses, this study develops a robust SOH prediction method based on feature decoupling and a heterogeneous stacking ensemble learning framework (HSELF) to deal with the limited data fragmentation and high-frequency noise issues. The main contributions of this study are summarized as follows:

(1) A feature screening method based on the NRDR strategy is developed, which quantifies feature degradation under different noise levels and extracts high-fidelity health indicators from the selected charging voltage interval.

(2) The HSELF, including random forest (RF), extreme gradient boosting (XGB), and support vector regression (SVR) based on the ridge regression, is developed. Furthermore, a nested inner leave-one-battery-out cross-validation (LOBOCV) is designed for the HSELF, which can effectively ensure computational efficiency and unbiased evaluation for SOH prediction.

(3) The effectiveness and generalization ability of the developed SOH prediction method are systematically validated through gradient noise experiments, ablation analyses, and comparative analyses with the Light GBM-Cat Boost stacking framework.

This paper is organized as follows: Section 2 details the battery dataset construction, the selection of the partial voltage interval, and the multidimensional feature extraction via dual smoothing-filtering techniques. Section 3 elaborates on the feature decoupling mechanism based on the NRDR and the construction of the HSELF. Section 4 reports the ablation study, quantitative evaluations, benchmark comparison, and generalizability validation. Finally, Section 5 gives the conclusion.

2. Multidimensional feature extraction

2.1. Battery datasets

The dataset is derived from accelerated cycle aging experiments of eight commercial LISHEN 18650 lithium batteries conducted by Xi'an Jiaotong University [40]. These batteries feature a nickel-cobalt-manganese (NCM) positive electrode [41], with a nominal capacity of 2.0 Ah and a nominal voltage window from 2.5 to 4.2 V. To eliminate the impact of temperature fluctuations on electrochemical kinetics, all experimental tests are conducted inside a temperature chamber maintained at 25 ± 2 °C [11,42].

The experimental protocol is composed of initial performance calibration and accelerated cycle aging. During the initial performance calibration, the new batteries are charged at a constant current (CC) of 0.5 C until the voltage reaches 4.2 V. Then, a constant-voltage (CV) mode is conducted until reaching 0.02 C. After a 5-min resting period, they are discharged at 0.2 C until the voltage reaches 2.5 V to determine the initial baseline capacity. Furthermore, the accelerated aging test would simulate the fast-charging condition in EV applications [43,44]. The batteries are charged at 2.0 C to 4.2 V until the CV mode with the cutoff current (0.05 C) is reached. Then, the batteries are rested for 5 min and then discharged at 1.0 C to 2.5 V. This process is repeated continuously until the aging threshold is satisfied.

Figure 1 illustrates the capacity decay trajectories over the full battery lifecycles. Notice that

variations exist in degradation rates among individual batteries, stemming from internal manufacturing tolerances [45], which can provide a diverse sample space. This diversity enables a comprehensive and rigorous evaluation of the HSELF.

To further evaluate the generalization ability of the developed SOH prediction method, an additional validation dataset is constructed based on the public HNEI NMC-LCO battery dataset. Eight cells operated under the same CC–CV charging protocol are selected. To maintain consistency with the primary dataset, the same charging voltage interval (3.7–4.1 V) is selected. Additionally, the same feature extraction, noise injection, feature allocation, and model evaluation procedures are then applied to this additional validation dataset. This design enables an enhanced assessment of whether the developed HSELF can maintain robust SOH prediction performance with different battery chemistries.

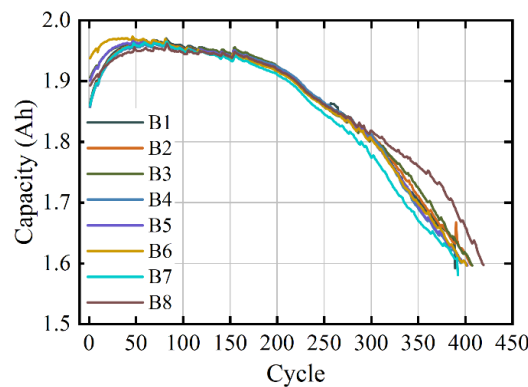


Figure 1. Capacity decay trajectories for commercial LISHEN 18650 lithium batteries.

2.2. Construction of validation dataset

Unlike ideal laboratory data, voltage signals collected by the BMS inevitably contain dynamic measurement noise and errors in real-world applications. To systematically evaluate model robustness against these practical interferences, a hierarchical noise injection protocol is applied to the high-precision baseline data. In this study, zero-mean Gaussian white noise is adopted as a controllable benchmark for high-frequency random voltage disturbances rather than an exhaustive representation of all BMS measurement uncertainties [46].

$$V_{\text{noisy}}(t) = V_{\text{clean}}(t) + \delta(t) \quad (1)$$

where the interference term $\delta(t)$ follows a normal distribution $\delta(t) \sim \mathcal{N}(0, \sigma^2)$.

To comprehensively cover various application scenarios, three graded noise levels are designed: 1) **Level A** ($\sigma = 5$ mV) simulates high-precision front-end applications; 2) **Level B** ($\sigma = 10$ mV) aligns with the typical measurement accuracy of industrial-grade BMSs, serving as the core engineering benchmark; and 3) **Level C** ($\sigma = 20$ mV) simulates severe sensor aging and electromagnetic interference for testing the model boundary limits. Figure 2 illustrates the impact of these graded noise levels on the voltage and corresponding ICA curves. It can be observed that the noise is significantly amplified in the differential domain [47]. With the **Level C** interference, the electrochemical phase transition peak is seriously distorted. If it is unfiltered, these sequences lead to erroneous feature extraction (e.g., capturing random peaks as H_{peak}). This visualization explicitly validates the necessity of the filtering strategy for the raw sampling data.

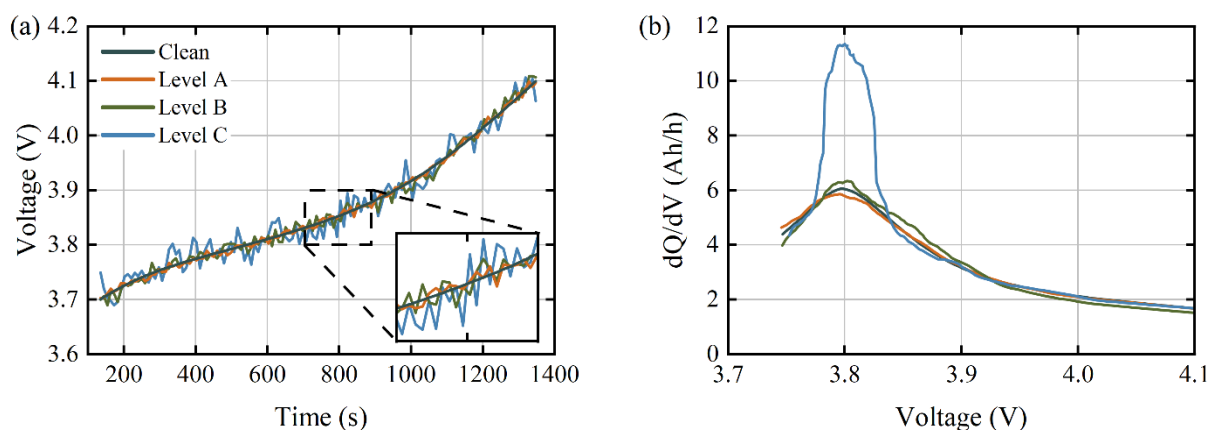


Figure 2. Impact of varying noise levels on the terminal voltage and ICA curves. (a) Voltage curves under various noise levels. (b) ICA curves under various noise levels.

2.3. Charging voltage interval selection and incremental capacity analysis

As illustrated in Figure 3, to reflect the noise interference of real-world data and avoid nonlinear polarization at the end of charging, the 3.7–4.1 V CC charging voltage interval is selected for feature extraction. From an electrochemical perspective, this CC charging voltage interval captures the core $\text{Ni}^{2+}/\text{Ni}^{3+}$ and $\text{Ni}^{3+}/\text{Ni}^{4+}$ redox reactions in the NCM electrode. Due to the acute redox reactions, the selected charging voltage interval exhibits a high initial signal-to-noise ratio [48]. On the macroscopic ICA curve, as shown in Figure 3(b), it manifests as an obvious main peak that is highly sensitive to lithium-ion and active material losses [48,49].

Although the charging voltage curves and ICA peak positions progressively shift along with battery aging, Figure 3 shows that the selected 3.7–4.1 V charging voltage interval consistently covers the principal electrochemical response region across the representative aging stages. In particular, the dominant ICA peak remains within this voltage window after 350 charge-discharge cycles, indicating that the voltage interval can continuously capture the phase transition characteristics associated with capacity degradation. Therefore, the selected charging voltage interval is suitable for feature extraction throughout the whole battery lifespan. It should be noted that the specific charging voltage interval might not be suitable for other lithium batteries with different chemistries, but the principle used to determine the charging voltage interval can be transferable. The selected charging voltage interval should be within the stable region of the CC charging stage, and avoid the initial ohmic effect caused by the current surge, the polarization effect at the end of charging, and the unchanged voltage limit with trickle charging on the CV stage. Meanwhile, it should cover ICA peaks. Therefore, for other batteries with different chemistries and operating conditions, the appropriate voltage interval should be re-identified based on the corresponding charging voltage change and ICA peaks instead of directly adopting 3.7–4.1 V.

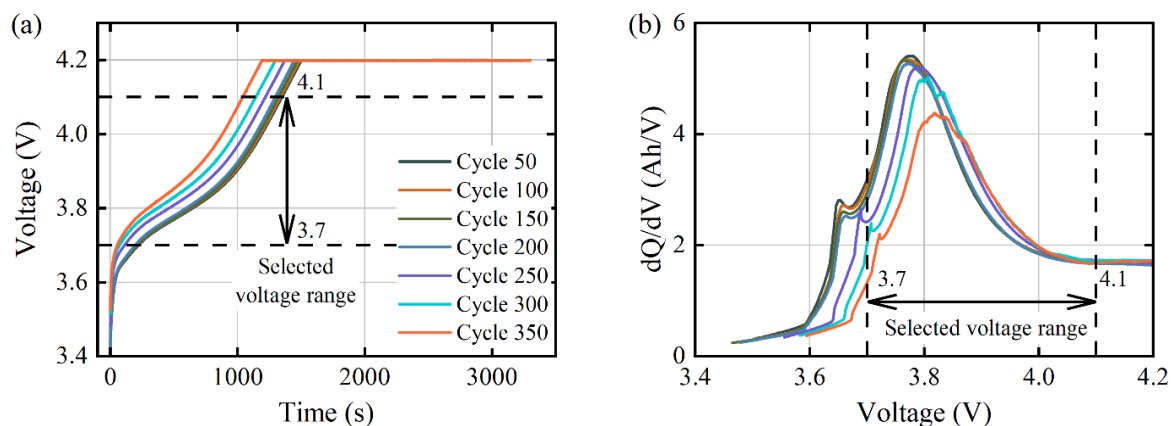


Figure 3. Evolution of charging voltage interval and incremental capacity curves. (a) Voltage interval. (b) ICA curves.

For the batteries investigated in this study, this voltage interval corresponds to approximately 30%–90% SOC of lithium batteries, which is consistent with frequent daily charging behaviors in practical applications [30]. Moreover, real-world charging and discharging records obtained from voltage and current sensors are often incomplete or fragmented under dynamic operating conditions. Using an accessible charging interval, therefore, provides a practical method for extracting degradation features from the incomplete or fragmented charging data.

Nevertheless, all experiments in this study are conducted under controlled temperature conditions. The applicability of the selected charging interval under varying temperatures and complex operating conditions requires further investigation.

To extract internal aging indicators, the ICA is employed to convert the CC curves into ICA curves. Because the numerical differentiation inherently amplifies the sensor quantization noise [28], a dual Savitzky–Golay (SG) filtering strategy is implemented, as illustrated in Figure 4.

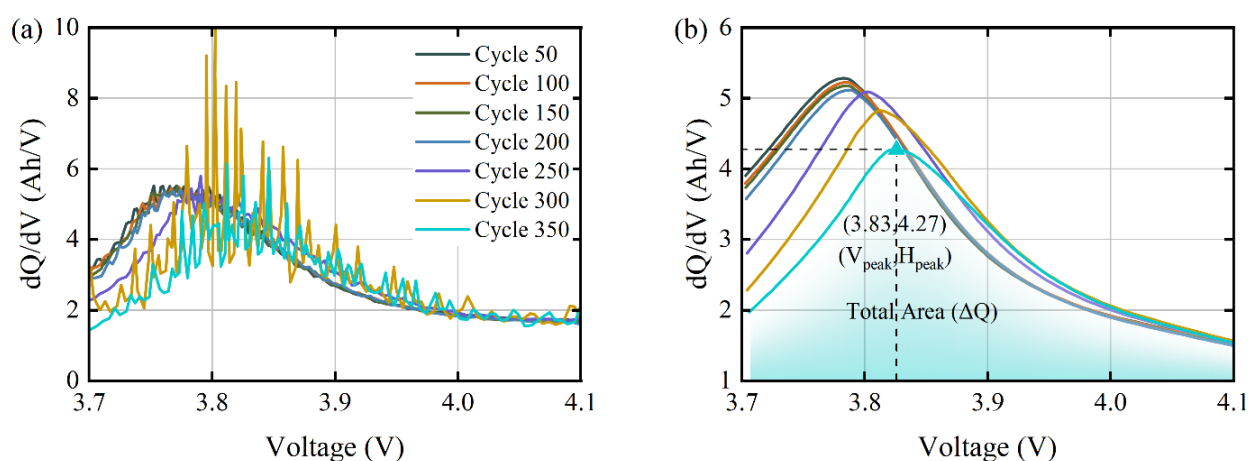


Figure 4. Incremental capacity curve denoising. (a) ICA curves with noise. (b) ICA curves after dual SG filtering.

The dual SG filtering strategy is adopted because it preserves ICA peak geometry better than the conventional moving-average filtering strategy [29]. Specifically, a smaller window size or an excessively high polynomial order may retain or overfit local noise, leading to an unstable peak position. In contrast, an excessively large window size or an overly low polynomial order may excessively flatten or shift the peak of the ICA curve, thereby discarding the key aging information. In this study, the first SG filter smooths the raw voltage–time sequence using a 51-point window size and a second-order polynomial, while the second SG filter smooths ICA curves using a 31-point window size and a first-order polynomial.

To further validate the above parameter selection, a quantitative sensitivity analysis is conducted for the dual SG filters. The first-stage window sizes are set to 41, 51, and 61, with polynomial orders of 1–3, while the second-stage window sizes are set to 21, 31, and 41, also with polynomial orders of 1–3. Therefore, it has 81 parameter combinations. For each combination, the mean absolute Spearman correlation ($\text{Mean } |r_{\text{Clean}}|$) between the three ICA features and the SOH under the **Clean** condition with the corresponding mean NRDR under the **Level C** noise condition are calculated. As shown in Figure 5, the adopted combination (51,2)/(31,1) achieves a mean absolute correlation of 0.9239 and a mean NRDR of 37.09%, which is the combination that achieves the best performance between degradation sensitivity and noise robustness among the other combinations. On this basis, the filtered ICA curves are then used to extract the peak position (V_{Peak}), peak height (H_{Peak}), and total area (A_{ICA}) [50].

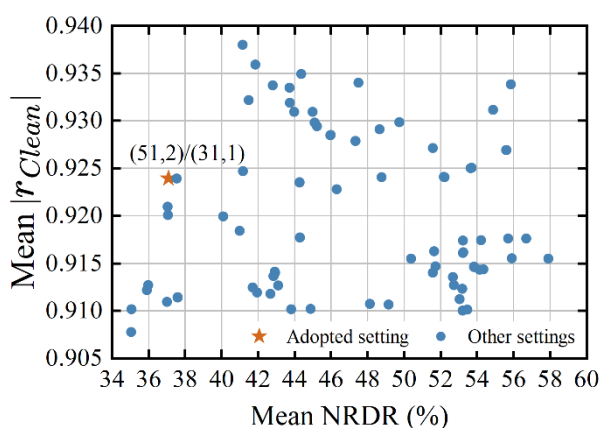


Figure 5. Quantitative sensitivity analysis for dual SG filtering parameters.

2.4. Extraction of multidimensional aging features

Because single-dimensional features are often insufficient to characterize complex degradation processes [51], nine features are extracted based on the selected charging voltage interval, i.e., 3.7–4.1 V. These multidimensional aging features would effectively capture both the microscopic electrochemical thermodynamic state derived from ICA curves and the macroscopic evolution of the voltage–time curve.

At the microscopic level, three features are extracted from the smooth ICA curves, including V_{Peak} , H_{Peak} , and A_{ICA} . The peak voltage and peak height are defined as

$$V_{\text{Peak}} = \operatorname{argmax}_V \left(\frac{dQ}{dV} \right) \quad (2)$$

$$H_{\text{Peak}} = \max \left(\frac{dQ}{dV} \right) \quad (3)$$

where dQ/dV denotes the rate of capacity change with respect to voltage during charging.

To prevent feature mislocalization caused by local polarization oscillations under dynamic and complex application conditions [50], the selected regions for V_{Peak} and H_{Peak} are restricted to 3.75–3.95 V. Additionally, A_{ICA} is calculated through global trapezoidal integration over the selected 3.7–4.1 V charging voltage interval:

$$A_{\text{ICA}} = \int_{V_{3.7}}^{V_{4.1}} \left(\frac{dQ}{dV} \right) dV \quad (4)$$

The global integration operation provides an inherent low-pass filtering effect, thereby enhancing the noise robustness of A_{ICA} .

At the macroscopic level, six aging features are extracted to characterize the geometric, temporal, statistical, and dynamic evolution of the charging voltage curve. Among them, the area under the voltage–time curve (A_{VT}) and the charging time interval (Δt) are obtained from the voltage region of 3.75–3.80 V. The two features are defined as:

$$A_{\text{VT}} = \int_{t_{3.75}}^{t_{3.80}} V(t) dt \quad (5)$$

$$\Delta t = t_{V3.8} - t_{V3.75} \quad (6)$$

The average voltage rise rate ($\bar{k}$) is determined through the first-order polynomial fitting:

$$V_i = \beta_0 + \bar{k}t_i + \varepsilon_i \quad (7)$$

where $\bar{k}$ is the fitted slope coefficient, β_0 is the intercept, and ε_i denotes the fitting residual. The delta mean voltage ($\Delta\bar{V}$) and voltage standard deviation (σ_V) are calculated as

$$\Delta\bar{V} = \bar{V}_{\text{current}} - \bar{V}_{\text{initial}} \quad (8)$$

$$\sigma_V = \sqrt{\frac{1}{(N-1)} \sum_{i=1}^N (V_i - \bar{V})^2} \quad (9)$$

where $\bar{V}_{\text{current}}$ and $\bar{V}_{\text{initial}}$ denote the mean voltages of the current and initial cycles, respectively; V_i is the i -th voltage sample; $\bar{V}$ is the corresponding mean voltage; and N is the number of voltage samples.

The conventional maximum operator used to calculate the maximum voltage rise rate (k_{max}) is highly sensitive to transient spikes in the voltage gradient sequence. Therefore, a percentile-based representation is employed to mitigate the impact of outliers [52]:

$$k_{\text{max}} = P_{98} \left(\left\{ \frac{V_{i+1} - V_i}{t_{i+1} - t_i} \right\}_{i=1}^{N-1} \right) \quad (10)$$

where $P_{98}(\cdot)$ denotes the 98th percentile of the voltage-gradient sequence.

To justify that the 98th percentile is an optimal threshold, the 95th, 98th, and 99th percentiles are selected for comparison. As shown in Figure 6, the 95th percentile achieves the lowest NRDR, but its correlation coefficient with the SOH under the **Clean** noise condition is only 0.37, indicating the weakened degradation sensitivity. In contrast, although the correlation coefficient with the SOH of the 99th percentile is equal to the highest value, it exhibits the highest NRDR value of 48.31%. As a comparison, the 98th percentile can maintain a relatively high correlation coefficient of 0.62 and limit the NRDR value to 38.37%. Therefore, the 98th percentile is selected for $k_{\max}$.

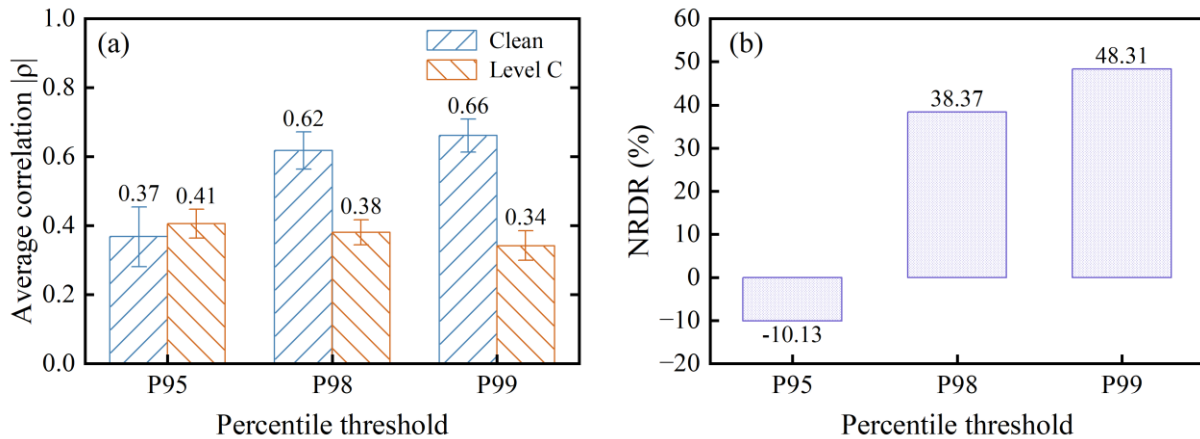


Figure 6. Sensitivity analysis based on different percentiles.

The six macroscopic voltage–time features, together with the three ICA features, constitute the initial pool of nine aging features for subsequent noise-robustness evaluation and feature decoupling.

3. Feature decoupling and heterogeneous stacking ensemble learning framework

3.1. Feature decoupling based on the NRDR

High-frequency quantization noise from onboard sensors in real-world applications can cause severe distortion of ICA curves within the nonlinear feature space. To overcome this limitation, this study develops a quantitative evaluation method based on the NRDR after the dual SG filtering and initial multidimensional feature extraction. This metric aims to systematically quantify the stability boundaries of various health features under extreme interference conditions. Considering the complex nonlinear correlations between battery aging features and capacity degradation, the Spearman rank correlation coefficient (r) is selected to measure their relationship. For a sample size of n , the rank variables corresponding to the feature and the actual SOH are defined as x_i and y_i , respectively. r is defined as:

$$r = 1 - \frac{6\sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad (11)$$

where $d_i = x_i - y_i$ indicates the rank difference of the i -th sample between the two variable sequences.

Subsequently, the rank correlation coefficients under the **Clean** condition (r_{clean}) and the **Level C** noise condition (r_{noise}) are calculated. The NRDR of a feature (η) is defined as the relative

percentage loss of the absolute correlation coefficient.

$$\eta = \frac{|r_{\text{clean}}| - |r_{\text{noise}}|}{|r_{\text{clean}}|} \times 100\% \quad (12)$$

Features exhibit distinct characteristics depending on their mathematical extraction logic. The macroscopic statistical features, based on global integration and mean calculations, inherently possess a low-pass filtering effect. This effect effectively neutralizes the zero-mean normally distributed noise, maintaining high robustness in capacity mapping. Conversely, the microscopic dynamic features, such as local differences or extremum retrievals, are highly sensitive to noise.

Furthermore, indiscriminately feeding all multidimensional parameters into a single model inevitably introduces multicollinearity and exacerbates the amplification of errors from highly sensitive features, which would significantly increase the overfitting risk. Hence, the NRDR metric is first used to screen invalid features and quantify the noise-robustness level of each retained feature. Correlation analysis is subsequently performed to identify highly redundant feature pairs. Based on the screening results, model-specific feature subspaces are finally constructed. This feature decoupling strategy not only eliminates information redundancy but also establishes the theoretical foundation for the HSELF.

3.2. Heterogeneous stacking ensemble learning framework

To enhance the generalization ability and overcome the structural limitations of individual base models, this study proposes a two-stage HSELF based on feature decoupling. This two-stage HSELF is illustrated in Figure 7. The traditional ensemble learning framework often relies on global input features, which frequently leads to overfitting in sensitive base models. To address this issue, this study proposed a differentiated feature allocation strategy based on the NRDR evaluation for the feature decoupling described in Section 3.1. Because the radial basis function kernel of the SVR is extremely sensitive to dimensional differences in Euclidean distance, its input features undergo strict standard normalization prior to training. This step focuses on minimizing the adverse effects of high-frequency noise on nonlinear spatial mapping.

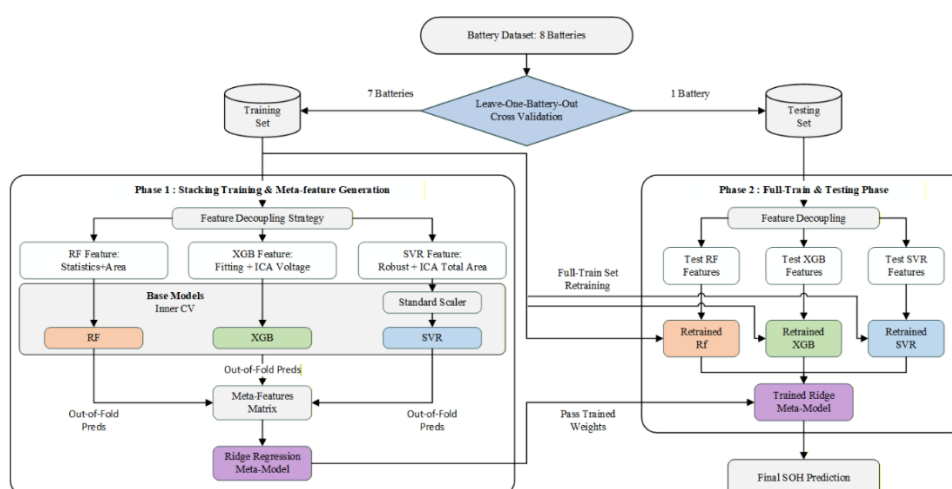


Figure 7. Flowchart of the two-stage HSELF.

The training and evaluation of this framework rely on a nested LOBOCV strategy. In each outer loop, seven batteries are partitioned as the training set, while the extra battery is reserved as the unbiased test set. During **Phase 1**, features are extracted and decoupled from the seven training batteries before being fed into the corresponding base models.

To prevent data leakage, both hyperparameter selection and meta-feature generation are performed exclusively within the seven training batteries. Specifically, the hyperparameters of the RF, XGB, and SVR would be determined through grid search based on the inner LOBOCV under the **Level C** noise condition. For each candidate configuration, six batteries are used for model fitting, and the remaining battery is used for validation. A candidate configuration is acceptable only when $R^2 > 0.93$ can be achieved for every inner validation battery. Furthermore, the acceptable configuration with the highest mean R^2 across the inner folds is selected. The optimal hyperparameter configurations are shown in Table 1. In addition, the random state is set to 42 for the RF and the XGB. These hyperparameter configurations are subsequently fixed for the meta-feature generation, model fitting, and evaluation under all noise conditions.

Table 1. Optimal hyperparameter configurations of base learners.

Model	Hyperparameter	Candidate values	Optimal hyperparameter configurations
RF	n_estimators	5, 7, 10, 20	7
	max_depth	4, 6, 8, 10	8
XGB	n_estimators	50, 100, 150, 200	100
	learning_rate	0.01, 0.03, 0.05, 0.10	0.05
	max_depth	2, 3, 4, 5, 6	4
SVR	Kernel	RBF	RBF
	C	1, 10, 30, 50, 100	50
	Epsilon	0.005, 0.010, 0.015, 0.020, 0.050	0.015
	Gamma	scale, auto	scale

After hyperparameter selection, the base learners perform the inner LOBOCV to generate unbiased out-of-fold predictions for the seven training batteries. Their out-of-fold prediction results are then concatenated to construct a new meta-feature matrix.

For the i th sample, the meta-feature vector is defined as

$$Z_i = [\hat{y}_{RF,i}, \hat{y}_{XGB,i}, \hat{y}_{SVR,i}]^T \quad (13)$$

where $\hat{y}_{RF,i}$, $\hat{y}_{XGB,i}$, and $\hat{y}_{SVR,i}$ denote the out-of-fold predictions generated by the RF, XGB, and SVR models, respectively.

For the second-layer input based on the RF, XGB, and SVR, the ordinary least squares (OLS), Lasso regression, and ridge regression are selected to study the non-regularization, L1 regularization, and L2 regularization, respectively. As shown in Table 2, the three meta-learners can achieve good prediction performance under all noise conditions. Nevertheless, the OLS cannot constrain coefficient instability arising from base-model predictions, whereas the Lasso regression may shrink some fusion coefficients to zero and consequently discard complementary information from individual base learners. In contrast, the ridge regression constrains the fusion coefficients through L2 regularization

while retaining contributions of all three base learners. Finally, the ridge regression shows the best performance among the three meta-learners.

Table 2. Comparison of prediction performance among different meta-learners.

Noise level	Model	MAPE	RMSPE	R^2
Clean	OLS	0.4236	0.5089	0.9905
Clean	Lasso regression	0.4301	0.5152	0.9904
Clean	Ridge regression	0.4236	0.5083	0.9905
Level A	OLS	0.4329	0.5366	0.9894
Level A	Lasso regression	0.4398	0.5417	0.9897
Level A	Ridge regression	0.4328	0.5365	0.9897
Level B	OLS	0.4878	0.6028	0.9870
Level B	Lasso regression	0.4911	0.6058	0.9872
Level B	Ridge regression	0.4875	0.6024	0.9874
Level C	OLS	0.5642	0.7454	0.9809
Level C	Lasso regression	0.5702	0.7485	0.9810
Level C	Ridge regression	0.5640	0.7451	0.9810

Therefore, ridge regression is selected as the meta-learner in this study. The penalty function of the L2 regularization is defined as $\lambda \sum_{j=1}^p \beta_j^2$ [53,54]. Correspondingly, the ridge regression predictor can be written as:

$$\hat{\beta}_{ridge} = \underset{\beta}{\operatorname{argmin}} \left[\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2 \right] \quad (14)$$

where $\hat{\beta}_{ridge}$ indicates the minimum value of the loss function with the regularization, β_j indicates the coefficients, y_i indicates the target value, x_{ij} indicates the j -th feature value, n is the number of samples, p indicates the number of features, and λ indicates the coefficient of the penalty term, $\lambda > 0$. In this study, λ is designed as 0.1 and remains unchanged across all noise conditions and outer LOBOCV folds.

By imposing the L2 penalty, the ridge regression meta-learner mitigates coefficient instability caused by correlated base-model predictions and limits the risk of an individual learner excessively dominating the final prediction. After the meta-model training, the RF, XGB, and SVR undergo full retraining with the full seven-battery training set, ensuring optimal fitting for the underlying feature space.

During **Phase 2**, the data from the reserved single battery is split into three independent feature subsets, following the established feature decoupling rules. Each feature subset is individually injected into its corresponding fully retrained base model from **Phase 1**. Consequently, the three sets of primary prediction results are calculated. These primary prediction results serve as fresh inputs and are passed

to the trained ridge regression meta-model for the decision fusion. Ultimately, the predicted SOH of batteries is obtained. This strategy, characterized by underlying data decoupling and algorithmic integration, allows the final stacking model to maintain high-precision fitting ability under low noise conditions. Furthermore, through the regularized fusion of complementary base-model predictions, it inherits the high robustness of tree-based models to deal with extreme high-frequency noise interference.

4. Experimental results and discussion

4.1. Performance evaluation metrics

To comprehensively evaluate the model performance for the lithium battery SOH prediction, three core performance metrics are adopted: the coefficient of determination (R^2), mean absolute percentage error ($MAPE$), and root mean square percentage error ($RMSPE$).

The metric R^2 is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (15)$$

where y_i indicates the true value, $\hat{y}_i$ indicates the model-predicted value, $\bar{y}$ indicates the average of true values of all samples, and n is the sample number.

Second, to directly reflect the relative accuracy, the metric $MAPE$ is introduced.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{(y_i - \hat{y}_i)}{y_i} \right| \times 100\% \quad (16)$$

By normalizing the absolute error into a percentage format, the metric $MAPE$ provides an intuitive error level that does not depend on the magnitude of the original data. Compared to the traditional mean absolute error, the metric $MAPE$ more clearly demonstrates the proportion of the prediction deviation.

Furthermore, the metric $RMSPE$ is employed to further describe the dispersion and stability of the prediction errors. It is defined as follows:

$$RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{y_i - \hat{y}_i}{y_i} \right)^2} \times 100\% \quad (17)$$

The advantage of the metric $RMSPE$ lies in its high sensitivity to large-scale deviations, as it squares the relative errors. This characteristic makes the metric $RMSPE$ critical for evaluating model robustness. Particularly during the last stages of battery capacity degradation, or when large prediction deviations occur due to the noise interference, this metric can effectively highlight severe prediction errors under extreme operating conditions.

4.2. Balance for prediction performance and computational efficiency

By considering the time cost of full-lifecycle battery aging experiments, the dataset used in this study exhibits typical small-sample characteristics. Under these restricted conditions, selecting the

optimal resampling validation strategy is critical for constructing a highly reliable HSELF that balances the unbiased evaluation of model generalization ability and computational efficiency. Therefore, this study uniformly adopts the LOBOCV as the outermost independent testing standard. On this basis, two inner resampling frameworks for base model validation and meta-feature generation are systematically compared, including the nested inner LOBOCV and the combinatorial inner leave-two-batteries-out cross-validation (LTBOCV), as shown in Figure 8.

As illustrated in Figure 8(a), the two inner cross-validation strategies share a consistent overall architecture. Both strictly utilize out-of-fold predictions from the internal validation set to train the meta-model, thereby successfully preventing data leakage. However, their fundamental divergence lies in the splitting logic of the inner loop. Specifically, the nested inner LOBOCV extracts one battery as the validation set, leaving the remaining six batteries as the inner training set. Thus, a single outer iteration requires executing seven inner loops, such that the meta-model ultimately receives a meta-feature matrix constructed from seven validation segments. In contrast, the combinatorial inner LTBOCV employs a combinatorial mechanism ($\binom{7}{2} = 21$), extracting two batteries as the validation set each time and leaving the remaining five batteries as the inner training set. With this strategy, the number of inner loops increases to 21. By integrating the dual-battery prediction results from each round, the meta-model ultimately generates a significantly larger meta-feature matrix containing 42 validation segments.

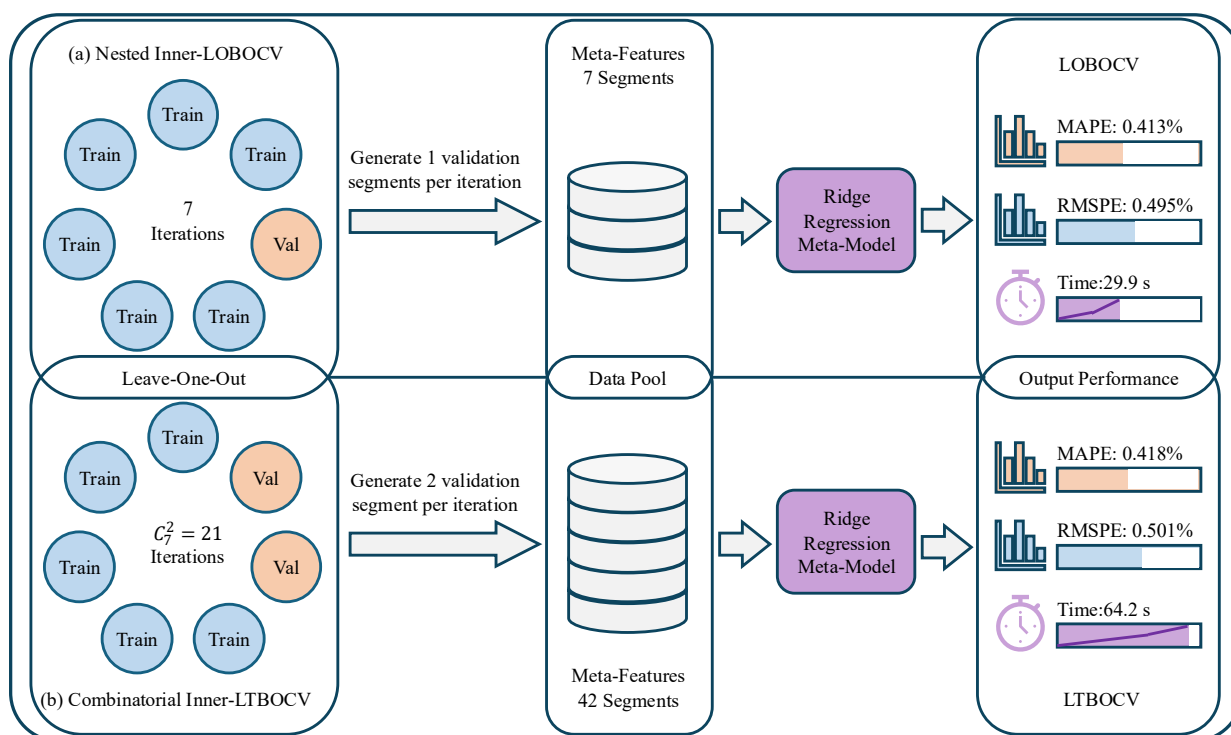


Figure 8. Performance trade-offs of the two inner cross-validation strategies. (a) Nested inner LOBOCV. (b) Combinatorial inner LTBOCV.

From the perspective of statistical learning theory, the combinatorial inner LTBOCV essentially introduces an implicit data augmentation mechanism. It attempts to enhance the robustness of the

meta-model weight allocation by expanding the meta-feature sample size by a factor of six. Nevertheless, the trade-off results between prediction error and computation time shown in Figure 8(b) indicate that increasing the overlap of internal validation data cannot yield the expected improvement in generalization ability. Quantitative results show that the *MAPE* and the *RMSPE* of nested inner LOBOCV are 0.413% and 0.495%, respectively. Conversely, errors of the combinatorial inner LTBOCV do not decrease or increase significantly. Instead, the corresponding values slightly increase to an *MAPE* of 0.418% and an *RMSPE* of 0.501%, respectively. The primary reason for this phenomenon is that, within a small-sample context, the stringent testing conditions lead the inner training set to further shrink to five batteries. This sharp reduction significantly increases the potential risk of underfitting for the underlying base models. The estimation variance introduced by the insufficient fitting of the base models is further amplified when propagated to the meta-model. Ultimately, this amplified variance offsets and overshadows the theoretical benefit anticipated from the implicit data augmentation mechanism.

Furthermore, the absence of this theoretical gain is accompanied by a disproportionate sacrifice in computational efficiency. In Figure 8, due to the sharp increase in inner iterations, the time consumption for a single round of outer evaluation in the combinatorial inner LTBOCV significantly increases from 29.9 to 64.2 s, meaning a more than doubled time cost. Since this study requires extensive hyperparameter optimization and repeats training under three graded noise levels with the multiple heterogeneous model architecture, adopting the combinatorial cross-validation strategy would cause the overall computation time to increase substantially. This severely reduces the iteration efficiency of the algorithm.

The comparative analysis demonstrates that nested inner LOBOCV can achieve an optimal balance among computational efficiency, base model fitting accuracy, and meta-model evaluation stability. Therefore, this study ultimately established nested inner LOBOCV as the core validation protocol. While maximizing data utilization, this strategy effectively ensures the statistical rigor for model performance evaluation.

4.3. Evaluations of feature noise resistance and differentiated allocation effects

To construct a highly reliable HSELF, this study extracts nine initial battery health features. Furthermore, the Spearman rank correlation coefficient (r) is introduced to systematically evaluate their evolution patterns under the noise-free baseline condition and the **Level C** noise condition. Figure 9 presents the correlation heatmaps of the candidate feature pools considered for the SVR, XGB, and RF during the screening and decoupling process. Additionally, Figure 10 and Table 3 systematically summarize the absolute values of correlation coefficients and the quantitative decay of each feature under extreme noise interference.

By jointly analyzing the right-column heatmaps in Figure 9(b), (d), and (f) and the high-noise performance in Figure 10, it can be observed that the extreme measurement noise significantly disrupts the distributional validity of specific dynamic features. Because the numerical differentiation inherently amplifies high-frequency measurement noise, features highly dependent on local extrema and discrete timestamps experience severe distortion under the **Level C** noise condition. Quantitative data show that the correlation coefficient between the Δt and the SOH decays sharply from 0.93 to 0.31 under the **Level C** noise condition. Similarly, the ICA peak height H_{Peak} and the maximum voltage rising rate k_{max} decrease from 0.89 to 0.37 and from 0.62 to 0.38, respectively. Because the

absolute correlation coefficients of these features drop below the effective threshold value, i.e., 0.5, they lose their validity in representing the true aging performance of the battery. Consequently, this study directly eliminates them in the initial screening stage, which effectively avoids uncontrollable prediction variance.

Table 3. Quantitative decay of correlation coefficients of each feature under extreme noise interference.

Conditions	$\Delta\bar{V}$	A_{VT}	σ_V	$\bar{k}$	$k_{\max}$	Δt	V_{Peak}	A_{ICA}	H_{Peak}
Clean Data	0.98	0.84	0.95	0.53	0.62	0.93	0.96	0.87	0.89
Level C	0.89	0.84	0.69	0.54	0.38	0.31	0.61	0.65	0.37
Drop rate	0.09	0	0.27	-0.02	0.38	0.67	0.36	0.25	0.58

After eliminating the invalid features, the noise-free heatmaps in the left column of Figure 9(a), (c), and (e) reveal a significant risk of multicollinearity among the initial features. For example, the correlation coefficient between $\Delta\bar{V}$ and σ_V is 0.96, while that between A_{ICA} and A_{VT} reaches 0.99. If such highly collinear feature clusters are simultaneously input into the single model, it inevitably introduces severe information redundancy and increases the risk of overfitting.

For the remaining features with collinearity decoupling, this study further evaluates their noise-robustness boundaries based on the corresponding NRDR values listed in Table 3. They are strictly classified into two robustness levels. The first level is comprised of strongly robust features (i.e., the noise-resistant core), including A_{VT} , $\bar{k}$, and $\Delta\bar{V}$. As quantified in Table 3, A_{VT} , $\bar{k}$, and $\Delta\bar{V}$ are exceptionally low, and the corresponding values are 0, -0.02, and 0.09, indicating that their correlation with the SOH remains virtually intact even under **Level C** noise. This robustness is visually corroborated by the stable bar heights in Figure 10. In terms of physical mechanisms, integral or mean operations based on global time periods inherently possess a low-pass filtering effect. This effect effectively filters random high-frequency noise.

The second level is composed of moderately sensitive features, including V_{Peak} , σ_V , and A_{ICA} . The corresponding NRDR values are 0.36, 0.27, and 0.25. Although their correlation with the SOH exhibits noticeable decay under the **Level C** noise, their absolute correlation coefficients remain above the effective threshold value (i.e., 0.5). Moreover, they retain critical electrochemical information regarding internal phase transitions. Therefore, they are preserved as informative but noise-sensitive features.

Based on the above NRDR classification and the mathematical rationale of retained features, this study establishes differentiated input spaces for the three heterogeneous base learners, as summarized in Table 4. In the HSELF, the RF model should serve as the robustness base learner. However, the corresponding random sampling, random feature selection, and ensemble averaging reduce the tree correlation and prediction performance. Therefore, it needs global features to suppress noise interference. Considering that the mean and integral calculations can effectively suppress local fluctuations, $\Delta\bar{V}$ and A_{VT} are selected as the RF model inputs.

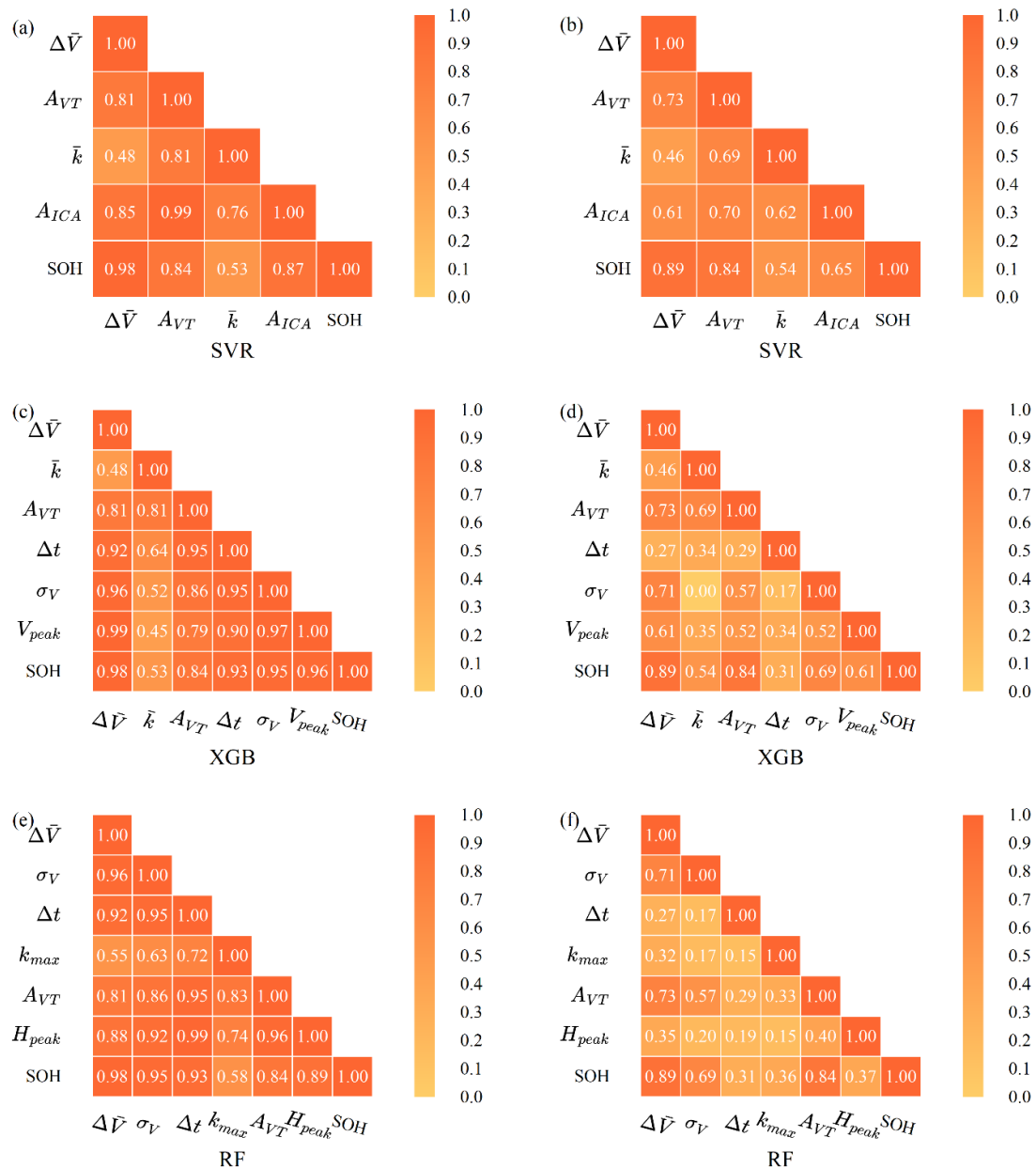


Figure 9. Correlation heatmaps between battery health features and SOH under various noise levels. (a), (c), and (e): Correlation heatmaps under clean data. (b), (d), and (f): Correlation heatmaps under **Level C** noise.

For the XGB model, its tree structure enables each tree to partition the feature space through a sequence of threshold splits, thereby identifying regions with distinct degradation characteristics and capturing nonlinear interactions among heterogeneous features. To support this modeling role, a multidimensional mixed feature space is constructed, based on global and robust descriptors ($\bar{k}$ and A_{VT}), informative distributional feature (σ_V), and local variation feature (V_{Peak}). Specifically, $\bar{k}$ and A_{VT} characterize the overall charging evolution, whereas σ_V and V_{Peak} provide complementary information on changes in the voltage distribution and shifts in electrochemical phase transitions, respectively.

The SVR model is used to establish a continuous nonlinear mapping within a compact feature space. Because its radial basis function kernel relies on distances among samples, the input space

should remain low-dimensional, low-redundancy, and insensitive to local random fluctuations. Accordingly, $\Delta\bar{V}$ and $\bar{k}$ are selected as its global features. Their Spearman correlation coefficient of 0.48 indicates that the two global features are not strongly collinear and contain limited information redundancy. Moreover, the two global features characterize the global voltage deviation and average charging dynamics through mean statistics and linear fitting, respectively, thereby reducing the influence of local measurement fluctuations.

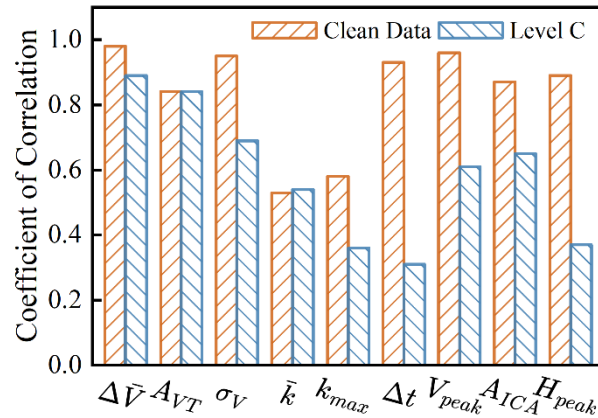


Figure 10. Comparison of correlation coefficients between extracted features and the SOH.

It should be noted that the moderately noise-sensitive feature A_{ICA} is obtained through global trapezoidal integration rather than local peak searching. This global trapezoidal integration averages local perturbations and reduces the dependence on precise peak localization, making A_{ICA} more suitable for the noise-sensitive SVR model compared with the local peak voltage indicator (V_{Peak}). Moreover, because its integration interval covers the main electrochemical phase-transition region, A_{ICA} possesses aging or capacity degradation information that complements the other two features ($\Delta\bar{V}$ and $\bar{k}$) of the SVR model. Previous studies have also demonstrated the reliability and effectiveness of the SVR model with the moderately noise-sensitive feature A_{ICA} [50,55].

Table 4. Feature allocation scheme for base learners in the HSELF.

Model	Feature allocation
RF	$\Delta\bar{V}$ and A_{VT}
XGB	$\bar{k}$, A_{VT} , σ_V , V_{Peak}
SVR	$\Delta\bar{V}$, $\bar{k}$, A_{ICA}

4.4. Ablation study on feature allocation based on the NRDR

To further verify the independent contribution of the feature allocation strategy based on the NRDR, an ablation study is conducted with three different feature input strategies. Specifically, the three feature input strategies are conducted under the same nested LOBOCV protocol and noise levels: 1) Conventional all-feature stacking strategy, i.e., nine initial features are simultaneously fed into the RF, XGB, and SVR models; 2) Conventional unclassified feature stacking strategy, which uses the screened features to feed all base learners without distinguishing models; and 3) the proposed

HSELF, where differentiated feature subsets are assigned to heterogeneous base learners according to the feature allocation rule based on the NRDR.

As shown in Figure 11(a) and (b), the proposed HSELF can achieve the lowest MAPE and RMSPE among the three strategies under the **Clean**, **Level A**, and **Level B** noise conditions. Meanwhile, Figure 11(c) shows that the HSELF can maintain the highest R^2 values under the three conditions. These results indicate that the feature allocation strategy based on the NRDR can effectively improve both prediction accuracy and fitting stability under the noise-free, low-noise, and typical industrial noise conditions. This improvement can be attributed to differentiated input subsets constructed for heterogeneous base learners. Specifically, noise-sensitive and redundant features are prevented from being indiscriminately injected into all models, while different base learners exploit complementary degradation information from their corresponding feature subsets.

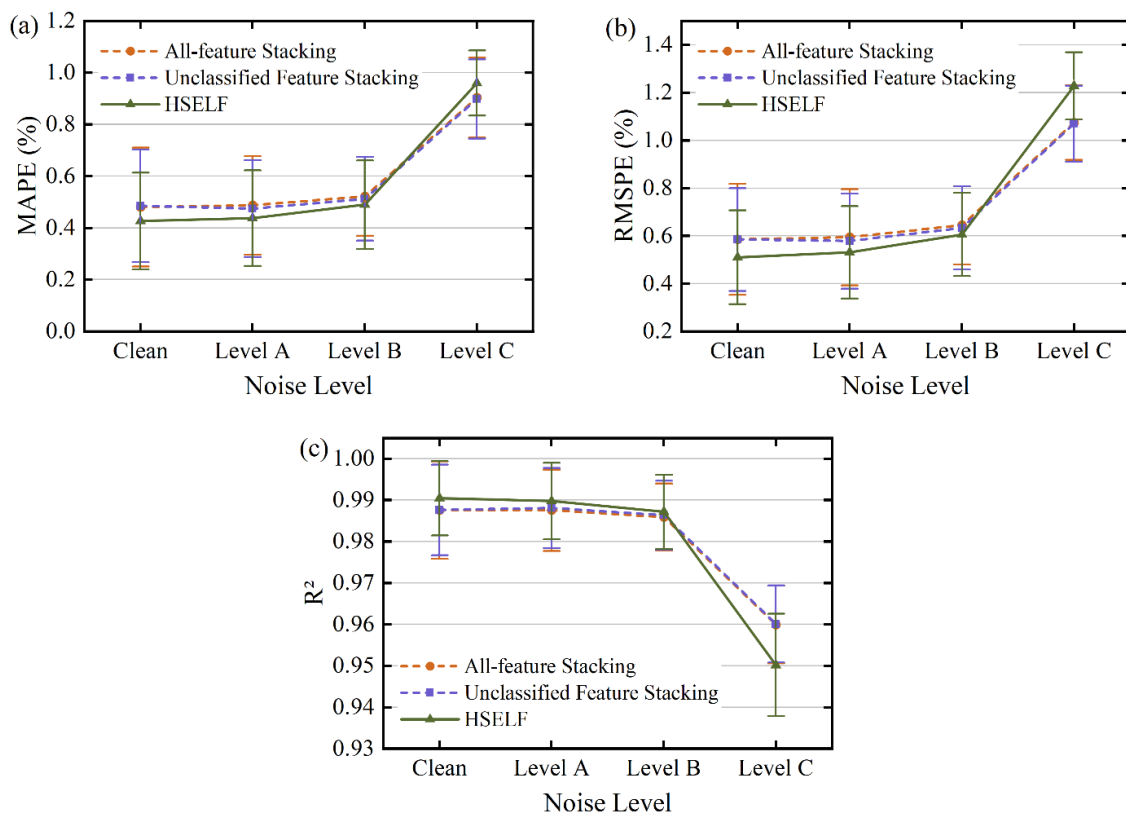


Figure 11. Ablation study for different feature input strategies under four noise levels. (a) MAPE. (b) RMSPE. (c) R^2 .

It should be noted that the performance gap among the three strategies becomes smaller under the **Level C** noise condition. This phenomenon suggests that extremely severe interference may exceed the stable boundary of the designed feature allocation rule. However, the **Level C** noise condition is designed as an extreme or special test condition. Therefore, the consistent advantage of the HSELF from the **Clean** condition to the **Level B** noise condition demonstrates that the proposed feature decoupling strategy is very effective under typical engineering noise conditions. The ablation results demonstrate that the performance improvement of the HSELF is not only derived from the stacking fusion but also from the feature allocation strategy based on the NRDR.

4.5. Quantitative results and generalization evaluation

Based on the feature allocation scheme developed in Section 4.3 and the ablation verification in Section 4.4, this section further evaluates the developed SOH prediction method based on feature decoupling and HSELF across different operating conditions. All experiments use the nested inner LOBOCV strategy to provide an unbiased estimation of model generalization capability. The quantitative results are detailed in Tables 5–8.

Table 5. SOH prediction performance of each model under the **Clean** data condition.

Battery	MAPE				RMSPE				R^2			
	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF
1	0.284	0.288	0.274	0.269	0.350	0.411	0.345	0.335	0.996	0.994	0.996	0.996
2	0.338	0.297	0.293	0.298	0.466	0.451	0.394	0.415	0.993	0.994	0.995	0.995
3	0.522	0.382	0.385	0.442	0.657	0.446	0.468	0.548	0.986	0.994	0.993	0.990
4	0.372	0.274	0.306	0.297	0.451	0.440	0.381	0.359	0.994	0.994	0.996	0.996
5	0.428	0.465	0.456	0.398	0.538	0.544	0.541	0.474	0.992	0.991	0.991	0.994
6	0.347	0.345	0.347	0.308	0.426	0.417	0.430	0.379	0.995	0.995	0.994	0.996
7	0.616	0.603	0.610	0.592	0.681	0.684	0.700	0.648	0.987	0.987	0.987	0.988
8	0.872	0.751	0.919	0.808	0.971	0.877	1.031	0.923	0.965	0.973	0.962	0.969

Table 6. SOH prediction performance of each model under the **Level A** noise condition.

Battery	MAPE				RMSPE				R^2			
	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF
1	0.290	0.411	0.320	0.296	0.362	0.598	0.412	0.370	0.995	0.987	0.994	0.995
2	0.336	0.405	0.343	0.315	0.464	0.606	0.453	0.440	0.993	0.988	0.994	0.994
3	0.520	0.511	0.445	0.455	0.659	0.632	0.547	0.566	0.986	0.987	0.991	0.990
4	0.373	0.375	0.307	0.301	0.465	0.599	0.388	0.377	0.993	0.988	0.995	0.995
5	0.432	0.489	0.454	0.394	0.556	0.626	0.546	0.485	0.991	0.988	0.991	0.993
6	0.360	0.443	0.338	0.326	0.449	0.570	0.431	0.408	0.994	0.990	0.995	0.995
7	0.626	0.649	0.618	0.592	0.700	0.790	0.724	0.664	0.986	0.982	0.986	0.988
8	0.915	0.731	0.923	0.820	1.029	0.914	1.054	0.938	0.960	0.970	0.960	0.968

Under the **Clean** and **Level A** noise conditions, all models can maintain high precision for the SOH prediction, with R^2 values consistently exceeding 0.960, as shown in Tables 5 and 6. However, the individual base models exhibit varying degrees of sample dependency. For instance, although the SVR model achieves low errors on Battery 1 and Battery 2, it demonstrates increased fitting errors on Battery 7, i.e., the corresponding *MAPE* is 0.610%. Battery 8 emerges as a hard-to-predict sample. Since its aging behavior deviates substantially from the typical degradation pattern observed in the other batteries (see Figure 1), the corresponding *MAPE* values are between 0.75% and 0.92% across all individual base models. The prediction difficulty of Battery 8 can be further explained by shifts in the feature distribution shown in Figure 12. Compared to the one standard deviation range based on the mean value of Batteries 1–7, Battery 8 exhibits systematic deviations, particularly in the lower SOH region. Specifically, its $\Delta\bar{V}$, $\bar{k}$, and V_{Peak} are generally higher, whereas A_{VT} , σ_V , and A_{ICA} are

significantly lower than the one standard deviation region. Therefore, the relationships between these features and the SOH learned from Batteries 1–7 cannot fully transfer to Battery 8, which leads to a large prediction error under the LOBOCV. However, the proposed HSELF can effectively mitigate this prediction error, thereby maintaining a high R^2 value and achieving low error across test batteries.

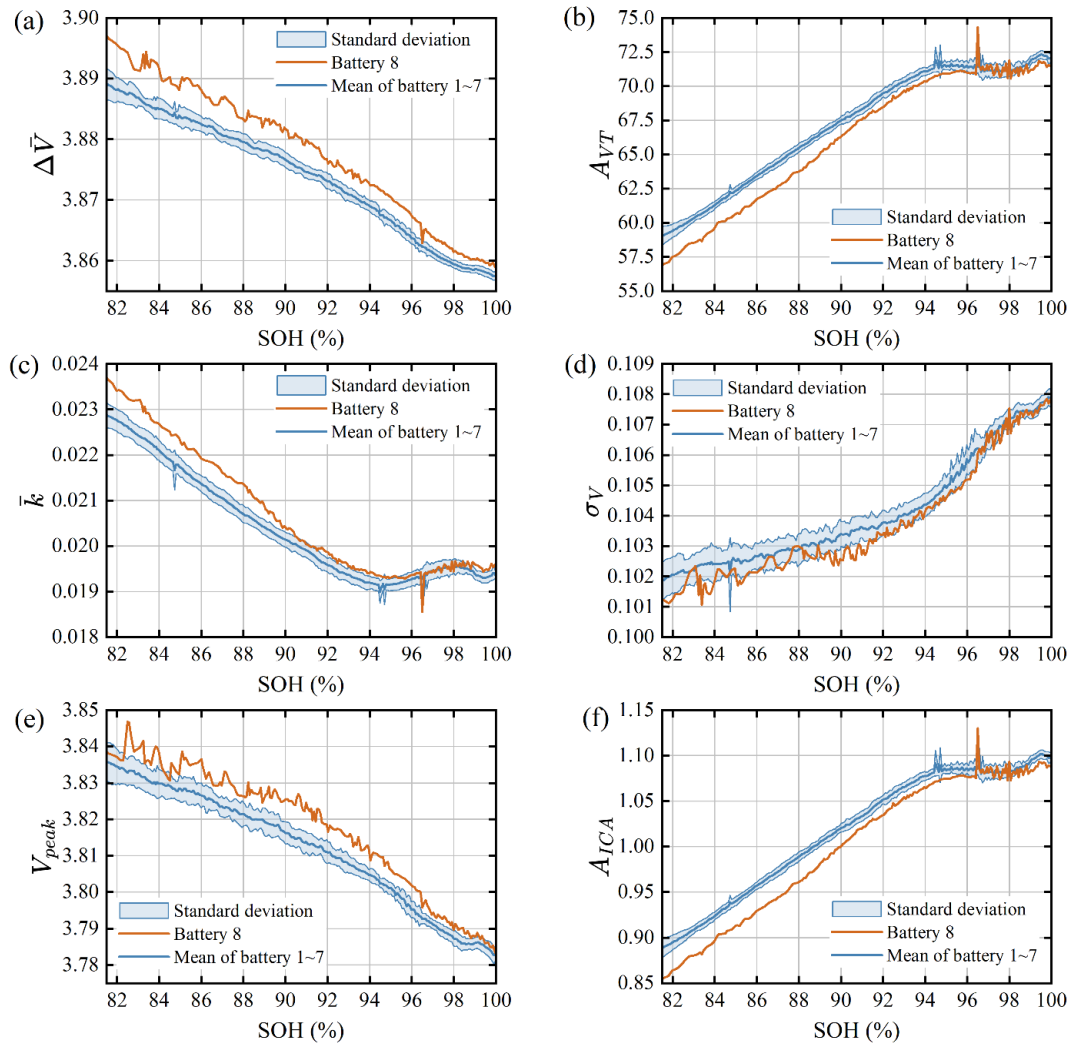


Figure 12. Comparison of the selected feature trajectories among Battery 8 and Batteries 1–7. (a), (c), and (e): Features of $\Delta\bar{V}$, $\bar{k}$, and V_{Peak} . (b), (d), and (f): Features of A_{VT} , σ_V , and A_{ICA} .

As the environmental noise increases to **Level B** and **Level C**, the performance gap among the individual base models widens considerably. The distance metric–based SVR model exhibits the most significant performance degradation for the SOH prediction compared with other models. As listed in Table 7, the $MAPE$ on Battery 3 is 0.761% under **Level B** noise condition. Under **Level C** noise conditions, the SVR model yields unreliable predictions. The corresponding $MAPE$ exceeds 2.7% across most samples, and the corresponding R^2 for Battery 8 decreases to 0.148, as shown in Table 8.

Table 7. SOH prediction performance of each model under the **Level B** noise condition.

Battery	MAPE				RMSPE				R^2			
	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF
1	0.346	0.613	0.586	0.387	0.451	0.914	0.744	0.497	0.992	0.968	0.981	0.991
2	0.378	0.583	0.532	0.396	0.526	0.892	0.741	0.531	0.991	0.974	0.984	0.991
3	0.527	0.692	0.761	0.534	0.668	0.878	0.930	0.668	0.986	0.975	0.973	0.986
4	0.420	0.533	0.427	0.340	0.540	0.848	0.539	0.445	0.991	0.976	0.991	0.994
5	0.487	0.624	0.474	0.433	0.658	0.829	0.592	0.563	0.988	0.979	0.990	0.991
6	0.379	0.638	0.440	0.357	0.474	0.915	0.587	0.452	0.993	0.975	0.990	0.994
7	0.639	0.874	0.733	0.636	0.731	1.066	0.865	0.736	0.985	0.967	0.979	0.985
8	0.961	0.792	0.930	0.833	1.090	1.027	1.105	0.955	0.955	0.960	0.956	0.967

Table 8. SOH prediction performance of each model under the **Level C** noise condition.

Battery	MAPE				RMSPE				R^2			
	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF	RF	XGB	SVR	HSELF
1	0.448	0.993	3.279	1.008	0.640	1.563	4.165	1.255	0.984	0.909	0.362	0.942
2	0.483	0.905	3.190	0.937	0.715	1.491	4.461	1.250	0.984	0.930	0.367	0.951
3	0.655	1.196	3.548	1.085	0.862	1.738	4.236	1.386	0.976	0.905	0.431	0.939
4	0.587	1.035	2.704	0.768	0.788	1.699	3.501	0.961	0.980	0.907	0.596	0.970
5	0.660	1.127	2.176	0.814	0.927	1.694	3.349	1.102	0.975	0.916	0.661	0.963
6	0.495	0.981	3.540	0.905	0.700	1.547	4.395	1.203	0.985	0.931	0.424	0.957
7	0.745	1.296	3.258	1.118	0.912	1.711	4.124	1.366	0.976	0.915	0.477	0.944
8	1.110	1.023	3.672	1.042	1.293	1.447	4.603	1.299	0.935	0.920	0.148	0.935

As shown in Figure 13, although the tree-based models in this study demonstrate higher inherent noise resistance, they produce step-like oscillations or excessive fluctuations in partial smooth intervals due to the discretized characteristics of their leaf nodes. These error distributions and trajectory deviations across different noise levels are illustrated in Figure 14. In contrast, the HSELF demonstrates a consistent fault-tolerant effect throughout the stress tests. By dynamically adjusting the fusion weights via the L2 regularization of the ridge regression meta-learner, the framework isolates the high-bias outputs from the SVR under the elevated noise level. For Battery 5 under the **Level B** noise condition, the HSELF yields an *MAPE* of 0.433%, which is lower than that of the RF (0.487%), XGB (0.624%), and SVR (0.474%) models. Under the **Level C** noise condition, where individual base models experience a significant performance reduction, the HSELF can maintain a stable predictive result. The corresponding R^2 values are maintained between 0.935 and 0.970, and the *MAPE* is confined within 0.70%–1.12%.

These quantitative findings are supported by the SOH prediction results in Figures 13 and 14. Specifically, the magnified insets in Figure 13 indicate that the SVR model exhibits a phase lag at nonlinear inflection points, while the tree-based models display discretized, step-like local deviations. Moreover, Figure 14 demonstrates that under high noise conditions, the SVR model produces pronounced numerical oscillations, as illustrated in Figure 14(e) and (f). In contrast, the HSELF can maintain a continuous prediction curve and align with the true capacity values across all tested conditions. The results confirm that the developed SOH prediction method can achieve a satisfactory

balance between fitting accuracy in routine applications and stability in dynamic operation environments.

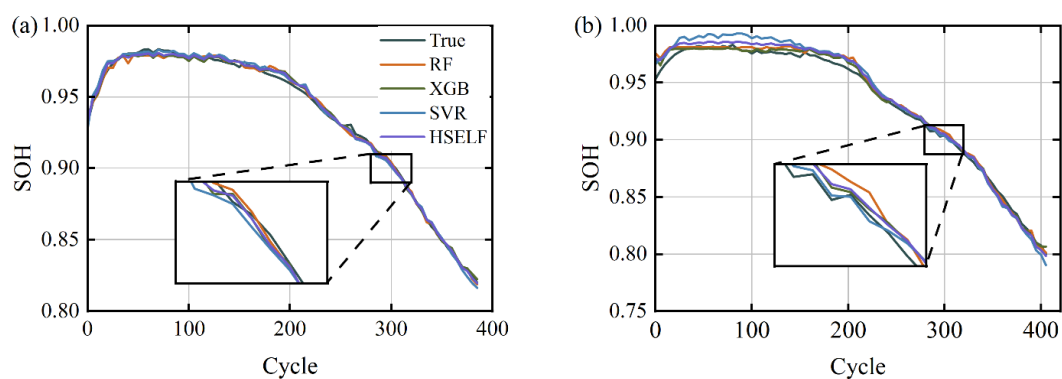


Figure 13. SOH prediction curves. (a) Battery 1. (b) Battery 3.

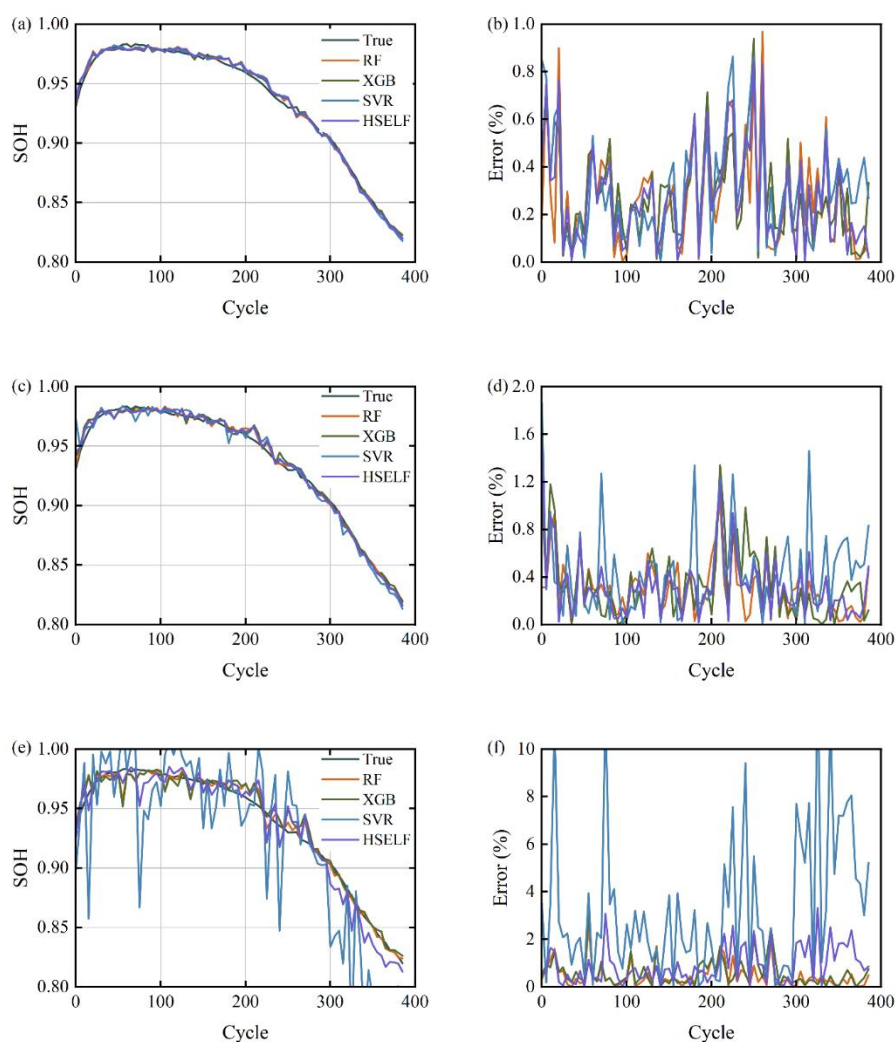


Figure 14. SOH prediction trajectories and error distributions under the three measurement noise levels. (a), (c), and (e): Prediction results under **Level A**, **Level B**, and **Level C** noise conditions. (b), (d), and (f): Corresponding error distributions.

It should be noted that graded noise conditions are designed to evaluate the robustness of the proposed method against high-frequency random disturbances. However, in practical BMSs, measurement errors may also arise from the sensor drift, quantization effect, and calibration deviation. Specifically, the sensor drift usually introduces fixed voltage or current offsets due to sensor aging or environmental variation, while the quantization effect generates step-like measurement fluctuations because of the finite resolution. In addition, the calibration deviation may cause a systematic offset in terms of voltage or current acquisition. In real-world applications, most measurement errors can be partly mitigated by dual SG filtering or other filtering methods. However, the inherent sensor error and severe systematic deviations should be corrected through sensor calibration or repeated measurements for practical battery management.

To further evaluate the competitiveness of the developed HSELF, an additional comparison is conducted based on the Light GBM-Cat Boost stacking framework. For a fair comparison, this framework adopts the same dataset, training strategy, and nested inner LOBOCV protocol as the developed HSELF. In this framework, the Light GBM and the Cat Boost are adopted as the first-layer base learners, and ridge regression is used as the second-layer meta-learner.

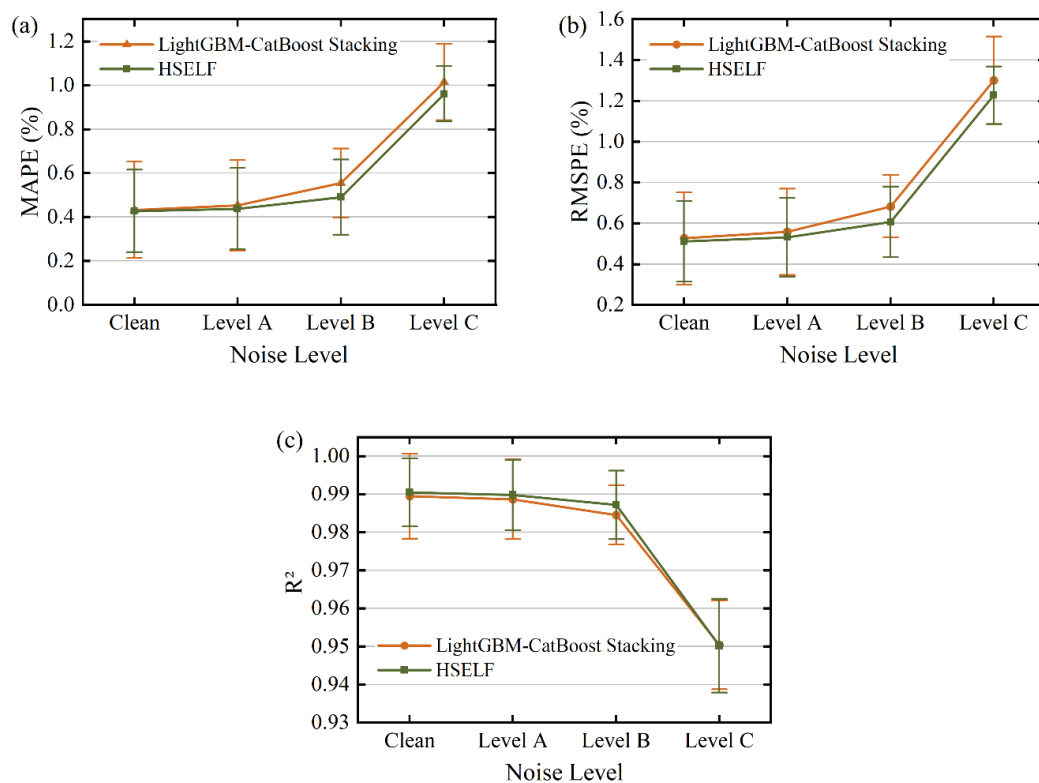


Figure 15. Comparison between the HSELF and the Light GBM-Cat Boost stacking framework under different noise levels. (a) *MAPE*. (b) *RMSPE*. (c) R^2 .

As shown in Figure 15, both stacking frameworks can achieve high prediction accuracy under the **Clean** and **Level A** noise conditions, indicating that the selected aging features have strong capacity prediction capability under low-noise environments. However, as the noise level increases, the performance difference between the two frameworks is obvious. Under the **Level B** and **Level C** noise conditions, the HSELF achieves lower values for the *MAPE* and the *RMSPE* than the Light GBM-Cat

Boost stacking framework. Meanwhile, the HSELF can also maintain comparable R^2 values compared with the Light GBM-Cat Boost stacking framework.

The superior robustness of the HSELF can be attributed to its feature decoupling strategy based on the NRDR. Unlike the Light GBM-Cat Boost stacking framework, which uses the same global feature space for different base learners, the HSELF allocates differentiated feature subsets to heterogeneous learners based on model characteristics and the physical and mathematical rationale behind assigning specific features. This allocation strategy reduces the direct propagation of noise-sensitive feature disturbances into all base learners. Therefore, the comparison results further confirm the performance improvement of the developed HSELF.

To further examine the cross-dataset robustness of the developed SOH prediction method based on feature decoupling and HSELF, the public HNEI dataset is employed as an additional validation. This dataset differs from the primary LISHEN dataset in cell chemistries, therefore providing an extra scenario for evaluating whether the proposed feature decoupling and heterogeneous fusion strategy remain effective beyond the original dataset. To ensure a fair comparison, the same feature extraction, model structure, hyperparameter settings, and evaluation strategy are implemented. Table 9 summarizes the prediction performance of the RF, XGB, SVR, and developed HSELF models over the eight HNEI cells under different noise levels. Under the **Clean** condition, the developed HSELF can achieve the lowest *MAPE* and *RMSPE*, with values of 0.780% and 0.944%, respectively. When the noise level increases from the **Clean** condition to **Level C** noise condition, the average *MAPE* of the developed HSELF only increases from 0.780% to 0.853%, and its R^2 decreases slightly from 0.965 to 0.961. In contrast, the SVR model exhibits obvious degradation and presents the worst indicators. The *MAPE* of the SVR model increases from 0.914% to 1.205%, while the corresponding R^2 decreases from 0.952 to 0.925. These results indicate that the prediction performance of the SVR model is vulnerable to noise interference, whereas the developed HSELF can effectively mitigate such instability through the differentiated feature allocation and heterogeneous fusion.

Table 9. SOH prediction performance over the public HNEI dataset under different noise levels.

Noise level	Model	MAPE	RMSPE	R^2
Clean	RF	0.821	1.015	0.959
Clean	XGB	0.820	1.046	0.966
Clean	SVR	0.914	1.113	0.952
Clean	HSELF	0.780	0.944	0.965
Level A	RF	0.824	1.023	0.959
Level A	XGB	0.832	1.058	0.966
Level A	SVR	0.935	1.150	0.951
Level A	HSELF	0.782	0.948	0.965
Level B	RF	0.832	1.048	0.958
Level B	XGB	0.877	1.120	0.963
Level B	SVR	0.988	1.225	0.947
Level B	HSELF	0.798	0.986	0.964
Level C	RF	0.879	1.142	0.955
Level C	XGB	1.037	1.316	0.953
Level C	SVR	1.205	1.557	0.925
Level C	HSELF	0.853	1.071	0.961

It should be noted that the developed HSELF can still achieve the lowest *MAPE* and *RMSPE* among all models under the severe **Level C** noise condition. Moreover, it can maintain the highest value of R^2 . Compared with the best individual base model under the severe **Level C** noise, the developed HSELF can reduce the *MAPE* and the *RMSPE* by 2.96% and 6.22%, respectively. These additional validation results further demonstrate that the developed HSELF is not only effective over the primary LISHEN dataset but also exhibits robust predictive performance over the other battery aging dataset with different battery chemistries.

5. Conclusions

To address the challenges of data fragmentation and high-frequency noise interference for the SOH prediction of lithium batteries in real-world applications, this paper developed a SOH prediction method through feature decoupling and HSELF. Considering the aging characteristics of NCM lithium batteries, this study selected the charging voltage interval 3.7–4.1 V for feature extraction. Furthermore, we utilized the dual SG filtering technique to extract health features. On this basis, the feature decoupling strategy and the HSELF were designed for the SOH prediction of lithium batteries. Finally, we successfully demonstrated that the developed SOH prediction method based on feature decoupling and HSELF can achieve a balance between fitting accuracy in routine applications and generalization ability in dynamic operation environments. The core conclusions are as follows:

(1) Proposal of the NRDR and differentiated feature allocation strategy for feature decoupling and HSELF construction. The NRDR analysis indicated that features with different mathematical properties exhibited significant differences under different levels of noise. Accordingly, this study adopted the NRDR and differentiated feature allocation strategy to replace the traditional global feature input mode. It constructed exclusive feature subspaces for the underlying heterogeneous base models, thereby effectively mitigating the multicollinearity and the amplification of errors within nonlinear mappings.

(2) Establishment of a nested inner LOBOCV ensuring computational efficiency and unbiased evaluation for the HSELF. Experiment results showed that the nested inner LOBOCV could provide a good generalization ability and avoid excessive computational overhead. This strategy reduces the number of inner-loop iterations by approximately 67%, including hyperparameter optimization and multi-level noise testing. Consequently, it successfully achieved an optimal balance between computational resource limitations and the accuracy of the SOH prediction.

(3) Achievement of fault-tolerant defense and high-precision prediction for the lithium battery SOH across diverse operating conditions. The HSELF achieves an effective balance among prediction accuracy, noise robustness, and cross-dataset robustness. On the LISHEN dataset, it achieves average *MAPE*, *RMSPE*, and R^2 values of 0.489%, 0.606%, and 0.987 under the **Level B** noise condition, respectively. Even under the **Level C** noise condition, the value of R^2 can be maintained in the region of 0.935–0.970. Additionally, it also achieved a better performance in terms of *MAPE*, *RMSPE*, and R^2 compared with the Light GBM–Cat Boost stacking framework. In addition, on the external HNEI dataset, the HSELF also achieved satisfactory *MAPE*, *RMSPE*, and R^2 under different noise conditions, demonstrating good SOH prediction accuracy and generalization ability.

In summary, the developed SOH prediction method based on feature decoupling and HSELF can effectively reduce the reliance on complete charge-discharge data and high-precision sensors. However, because all experiments were conducted under controlled temperature conditions, the applicability of

the selected charging voltage interval under variable temperature conditions remains to be verified. Future work will further evaluate the effect of temperature-induced charging voltage selection and ICA peak shifts for battery SOH prediction.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

This work is supported by the Major Science and Technology Innovation Project of Xianyang City, China (Grant No. L2025-ZDKJ-ZDCGZH-008), the Key Scientific and Technological Projects of Henan Province, China (Grant No. 252102220091), the Research and Practice Project of Higher Education Teaching Reform of Henan Province (Grant No. 2026SJGLX219), and the National Natural Science Foundation of China (Grant No. 51907160).

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Yongxun Liu: Writing—Methodology, Modeling, Original draft. Penglong Sun: Data curation, Review & editing. Ke Zhao: Methodology, Software, Original draft. Feng Zhao: Visualization, Funding acquisition. Bin Wang: Validation, Supervision, Review & editing and Funding acquisition.

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