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A Degradation-Aware SegRNN Method Optimized by ASHA for Lithium-Ion Battery SOH Prediction

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Abstract: To address the challenges of multi-step state-of-health (SOH) prediction for lithium-ion batteries under small-sample and noisy conditions, such as susceptibility to local fluctuations and insufficient continuity of predicted trajectories, this paper proposes a degradation-aware SegRNN prediction method optimized by the asynchronous successive halving algorithm (ASHA). First, reversible instance normalization (RevIN) is applied to the input samples to reduce local distribution discrepancies. Then, the historical window is divided into consecutive degradation segments, and a gated recurrent unit (GRU) is employed to encode the temporal evolution among segments, thereby extracting the current degradation state. At the prediction stage, a cumulative degradation increment prediction (CDIP) mechanism is designed to enhance the continuity of multi-step prediction trajectories. In addition, a degradation-aware training strategy (DATS) is introduced, in which weighted multi-step prediction errors and slope-consistency constraints are incorporated to improve trend consistency under noisy conditions. Finally, ASHA is adopted to adaptively optimize the key hyperparameters of the model. Experimental results on the NASA and CALCE battery datasets demonstrate that the proposed model achieves lower prediction errors and higher fitting accuracy. Ablation studies further verify the effective contribution of the proposed modules to

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performance improvement. These results indicate that the proposed method can effectively improve the performance of noisy multi-step SOH prediction for lithium-ion batteries.

Keywords: lithium-ion battery; state of health; multi-step prediction; SegRNN; ASHA

1. Introduction

With the rapid development of electric vehicles, distributed energy storage, and renewable-energy grid-integration systems, lithium-ion batteries have become key energy storage units due to their high energy density, long cycle life, and low self-discharge rate [1-2]. During long-term charge–discharge operation, lithium-ion batteries inevitably undergo capacity fading, internal resistance growth, and performance degradation, leading to a decline in the state of health (SOH) and consequently affecting the safety, reliability, and economic efficiency of energy storage systems [3-4]. Therefore, accurate SOH prediction is of great significance for lithium-ion battery maintenance decision-making and energy management.

In recent years, lithium-ion battery SOH prediction methods have generally been categorized into model-driven and data-driven approaches [5-6]. Model-driven methods are usually based on electrochemical models, equivalent circuit models (ECMs), or empirical degradation models, and estimate battery health by describing internal reaction mechanisms or external electrical characteristics [7]. Rodriguez-Cea et al. developed an SOH diagnostic method using data from the constant-voltage charging stage and an equivalent circuit model incorporating internal resistance, thereby estimating battery capacity and health status through variations in internal battery parameters [8]. Chen et al. further integrated a first-order equivalent circuit model with a data-driven method; by identifying the ECM internal resistance

and using it as an input to a neural network, their approach improved both SOH estimation accuracy and generalization capability [9]. Kong et al. proposed a joint state-of-charge (SOC)-SOH estimation framework based on a single-particle electrochemical model, in which mechanistic variables such as electrode overpotential and solid-phase surface lithium-ion concentration were used to characterize battery-state evolution under complex operating conditions [10]. These methods offer strong physical interpretability; however, they rely on complex model structures and accurate parameter identification, resulting in high modeling costs and limited adaptability in practical applications.

In contrast, data-driven methods have attracted considerable attention because they can extract degradation features from historical data [11]. Traditional machine learning methods exhibit a certain degree of stability in small-scale data scenarios; however, their predictive performance generally depends on handcrafted feature construction and parameter selection [12]. Qian et al. proposed an SOH estimation method based on equal-discharge-voltage-difference energy accumulation features and improved relevance vector regression. By integrating feature extraction, correlation-based feature screening, and model parameter optimization, their method improved estimation accuracy; nevertheless, its performance still depends on the construction and selection of health indicators [13]. Bao et al. combined electrochemical impedance spectroscopy features with temporal features and employed SHAP to interpret feature contributions, demonstrating the advantages of machine learning methods in terms of interpretability while further indicating that feature selection has a pronounced impact on model performance [14].

Compared with conventional machine learning methods, deep learning approaches can

effectively extract nonlinear degradation features and have demonstrated strong modeling capability in battery SOH prediction tasks [15]. Lin et al. proposed an LSTM network with an attention mechanism to extract key temporal information during the degradation process of lithium-ion batteries [16]. Li et al. further developed a BiLSTM-Transformer model for SOH estimation under fast-charging conditions, in which BiLSTM was used to capture local temporal dependencies, while Transformer was employed to enhance global feature modeling capability [17]. Huang et al. proposed an SOH estimation method combining CNN-LSTM with temporal pattern attention. In this method, CNN-LSTM was used to extract local degradation features and long-term dependencies, and an attention mechanism was introduced to improve the utilization efficiency of historical information [18].

The above studies indicate that deep learning methods have strong capabilities in nonlinear degradation feature extraction and complex operating-condition modeling. However, the number of battery samples in existing datasets remains limited, and complex deep models are therefore prone to overfitting. In addition, the selection of model parameters and window lengths can significantly affect prediction results. Moreover, most existing data-driven methods directly predict future SOH values without explicitly considering the continuous degradation characteristics of lithium-ion batteries. This may lead to unstable multi-step prediction trajectories or inconsistent local trends, thereby reducing the consistency between the predicted trajectory and the actual degradation trend.

To address the above issues, this paper proposes a degradation-aware Segment recurrent network (SegRNN) optimized by the asynchronous successive halving algorithm (ASHA) for multi-step SOH prediction of lithium-ion batteries. First, the original univariate SOH sequence

is transformed into supervised samples using a sliding-window strategy in chronological order, and each historical window is divided into multiple consecutive degradation segments. Then, a linear embedding layer is employed to extract local representations of each degradation segment, and a gated recurrent unit (GRU) is used to temporally encode the segment sequence, thereby capturing local degradation features and their dynamic evolution patterns. In addition, to characterize the degradation process of battery SOH, a cumulative degradation increment prediction (CDIP) mechanism is designed at the prediction stage. Specifically, the future SOH trajectory is reconstructed by predicting the degradation increment at each future step and cumulatively summing these increments. Furthermore, to enhance trend consistency under small-sample prediction scenarios, a degradation-aware training strategy (DATS) is developed to constrain the local variation trend of the predicted trajectory while maintaining point-wise prediction accuracy. Finally, ASHA is adopted to adaptively optimize the key hyperparameters of the model, thereby improving its adaptability to different battery degradation sequences.

The main contributions of this paper are summarized as follows:

1. A degradation-aware SegRNN model is proposed. By extracting local degradation segments from historical SOH sequences through segmented recurrent modeling and using GRU to model the temporal evolution relationships among segments, the proposed model enhances degradation-sequence modeling capability under small-sample conditions.
2. A CDIP mechanism is designed to enable the model to effectively characterize the continuous degradation process of battery health. Meanwhile, DATS is introduced to improve the trend consistency of multi-step prediction trajectories.
3. ASHA is employed to adaptively optimize both structural parameters and training

hyperparameters of the model. Comparative experiments are conducted on the NASA and CALCE datasets against several representative models, and ablation studies are further performed to analyze the contributions of the proposed modules.

2. Materials and methods

2.1 Dataset description

To verify the effectiveness of the proposed method in small-sample multi-step SOH prediction for lithium-ion batteries, this study conducts experimental analyses using the NASA battery aging dataset and the CALCE battery dataset. The basic information of the two datasets is summarized in Table 1 [19-20].

B0006 and B0007 from the NASA dataset are selected as short-sequence experimental objects to evaluate the prediction stability of the model under small-sample degradation sequences. CS2-36 and CS2-38 from the CALCE battery dataset are selected as long-sequence experimental objects. Compared with the NASA dataset, the CALCE dataset contains longer degradation sequences and exhibits more pronounced local fluctuations and capacity regeneration phenomena during the degradation process. Therefore, it is used to evaluate the adaptability of the proposed model to complex degradation trajectories.

Table 1. Basic information of the datasets

Dataset	Battery ID	Number of Sequence Points	Sequence Characteristic
NASA	B0006	168	Short sequence
NASA	B0007	168	Short sequence
CALCE	CS2-36	936	Long sequence
CALCE	CS2-38	996	Long sequence

2.2 Noisy SOH sequence construction and waveform characteristics

To better reflect practical SOH observation scenarios and evaluate the prediction robustness of the model under noisy conditions, this study constructs noisy SOH sequences based on the original SOH sequences and uses them as both the model inputs and prediction targets. Figure 1 compares the original SOH curves with the corresponding noisy SOH curves.

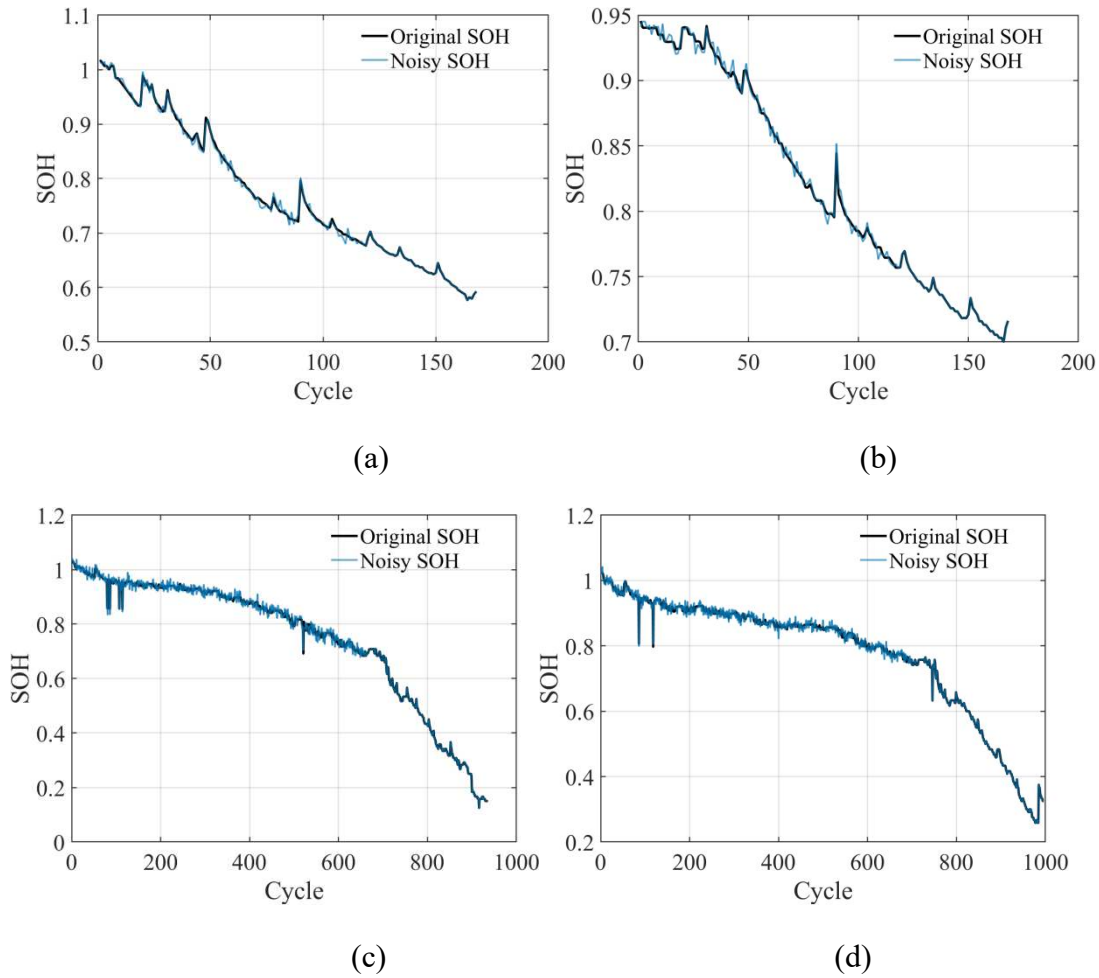


Figure 1. Comparison of SOH sequences: (a) B0006; (b) B0007; (c) CS2-36; (d) CS2-38.

As shown in Figure 1, after noise is introduced, the SOH curves retain their long-term degradation trends while exhibiting more pronounced local fluctuations. The NASA dataset is used to evaluate the robustness of the model under short-sequence and small-sample conditions, whereas the CALCE dataset is used to assess the adaptability of the model to complex

degradation trajectories.

2.3 Data preprocessing and sample construction

Considering the explicit temporal dependence of the battery degradation process, this paper adopts a chronological data-splitting strategy. Specifically, the first 70% of each SOH sequence is used for training, while the remaining 30% is used for testing. In addition, 20% of the training samples are further separated as the validation set for early-stopping control and hyperparameter selection.

To reduce the influence of differences in SOH value ranges among different batteries on model training, a standardization method based on the statistical characteristics of the training set is adopted:

$$\tilde{s}_t^{norm} = \frac{\tilde{s}_t - \mu_{train}}{\sigma_{train}}$$

Where $\tilde{s}_t$ denotes the noisy SOH corresponding to the t -th cycle, and μ_{train} and σ_{train} represent the mean and standard deviation of the noisy SOH sequence in the training set, respectively.

During the construction of supervised samples, a sliding-window strategy is adopted to transform the univariate noisy SOH sequence into multi-step prediction samples. Let the length of the historical input window be L and the prediction horizon be H . The t -th sample is then defined as:

$$X_t = [\tilde{s}_{t-L+1}, \tilde{s}_{t-L+2}, \dots, \tilde{s}_t]$$

$$Y_t = [\tilde{s}_{t+1}, \tilde{s}_{t+2}, \dots, \tilde{s}_{t+H}]$$

where X_t denotes the model input, representing a sliding window composed of L consecutive historical SOH points, and Y_t denotes the prediction target, representing the SOH

values over the next H cycles. The settings for data preprocessing and sample construction are summarized in Table 2.

Table 2. Parameter settings for data preprocessing

Parameter	Setting
Training set	70%
Validation set	20% Training set
Test set	30%
L_{NASA}	10
L_{CALCE}	40
H	5

2.4 ASHA-Optimized Degradation-Aware SegRNN Prediction Model

Based on the constructed noisy SOH samples, this section proposes an ASHA-optimized degradation-aware SegRNN framework for multi-step SOH prediction of lithium-ion batteries.

2.4.1 Degradation-aware SegRNN

2.4.1.1 Local degradation segment representation

For the noisy multi-step SOH prediction task, the historical window contains not only the overall trend of capacity degradation but also short-term variation information, such as local fluctuations, capacity regeneration, and measurement disturbances. Therefore, in this section, each window is represented as an ordered set of local degradation segments, and a GRU encoder is employed to extract the evolutionary relationships among these segments, thereby providing state inputs for subsequent multi-step trajectory prediction. First, to mitigate local scale differences among different degradation stages, reversible instance normalization (RevIN)

is performed within each input window [21]:

$$\bar{X}_t = \frac{X_t - \mu_t}{\sigma_t}$$

where μ_t and σ_t denote the mean and standard deviation of the SOH sequence within the window X_t , respectively. The model performs segment encoding and prediction in the normalized space, and the outputs are restored to the original SOH scale using the same statistics at the output stage.

The normalized window $\bar{X}_t$ is then divided into multiple consecutive degradation segments. Let the segment length be l_s and the segment stride be r_s . The i -th segment is defined as follows:

$$P_t^i = [\bar{s}_{a_i}, \bar{s}_{a_i+1}, \dots, \bar{s}_{a_i+l_s-1}], i = 1, 2, \dots, M$$

where a_i denotes the starting position of the i -th segment. The number of segments is calculated as follows:

$$M = \left\lfloor \frac{L - l_s}{r_s} \right\rfloor + 1$$

Each segment is mapped into a hidden-space representation through a linear embedding layer as follows:

$$e_t^i = W_e P_t^i + b_e$$

where (W_e) and (b_e) are learnable parameters. Accordingly, the historical SOH window is decomposed into a sequence of segment embeddings:

$$E_t = [e_t^1, e_t^2, \dots, e_t^M]$$

This strategy compresses the continuous degradation information in the original window into ordered segment-level features, thereby providing inputs for subsequent temporal encoding. Based on this representation, the GRU encoder recursively updates the hidden state

along the segment order [22]:

$$h_t^i = GRU(e_t^i, h_t^{i-1}), i = 1, 2, \dots, M$$

As the local segments are sequentially fed into the encoder, the hidden state progressively integrates the degradation patterns of different segments within the window and their ordered variation information. The final hidden state is defined as the degradation state of the current historical window:

$$z_t = h_t^M$$

where the state vector z_t represents the overall degradation trend and local fluctuation characteristics within the current window, and serves as the basis for generating the future SOH trajectory.

2.4.1.2 Cumulative degradation increment prediction

After obtaining the degradation-state representation z_t , the model outputs the SOH increments over the next H steps through a fully connected prediction layer. Each increment represents the SOH variation between two adjacent prediction steps and is subsequently used to cumulatively reconstruct the future SOH trajectory. The predicted increment sequence is expressed as:

$$\Delta \hat{Y}_t = [\Delta \hat{s}_{t+1}, \Delta \hat{s}_{t+2}, \dots, \Delta \hat{s}_{t+H}]$$

where $\Delta \hat{s}_{t+h}$ denotes the SOH increment corresponding to the h -th prediction step. Taking the last observed value $\tilde{s}_t$ in the current window as the starting point of the trajectory, the predicted SOH value at the future h -th step is obtained by cumulatively summing the first h increments:

$$\hat{s}_{t+h} = \tilde{s}_t + \sum_{j=1}^h \Delta \hat{s}_{t+j}, \quad h = 1, 2, \dots, H$$

In this manner, SOH can be represented as a predicted trajectory that starts from the current observation point and is progressively accumulated through multiple consecutive increments. This mechanism preserves the temporal continuity of multi-step prediction results and helps characterize the gradual degradation process of battery health.

2.4.1.3 Degradation-aware training strategy

Training the model solely based on point-wise multi-step prediction errors cannot sufficiently constrain the local variation pattern of the predicted curve. Therefore, this study further develops a degradation-aware training strategy (DATS), enabling the model to learn future SOH values while maintaining consistency between the predicted trajectory and the true SOH sequence in terms of local variations.

First, a horizon-weighted mean squared error (MSE) is adopted to represent the point-wise error of multi-step prediction [23]:

$$\mathcal{L}_{wmse} = \frac{1}{H} \sum_{h=1}^H w_h (\hat{s}_{t+h} - \tilde{s}_{t+h})^2$$

where w_h denotes the error weight assigned to the h -th prediction step. By setting horizon-dependent weights, the model can more effectively characterize prediction errors at different future positions.

Furthermore, to further constrain the local variation of the predicted trajectory, this paper introduces a slope-consistency loss based on the differences between adjacent prediction points [24]. This loss is used to measure the discrepancy in local variations between the predicted trajectory and the true trajectory:

$$\mathcal{L}_{slope} = \frac{1}{H-1} \sum_{h=2}^H [(\hat{s}_{t+h} - \hat{s}_{t+h-1}) - (\tilde{s}_{t+h} - \tilde{s}_{t+h-1})]^2$$

where $\hat{s}_{t+h} - \hat{s}_{t+h-1}$ represents the variation of the predicted trajectory between two adjacent prediction steps, while, $\tilde{s}_{t+h} - \tilde{s}_{t+h-1}$ denotes the corresponding variation of the true SOH trajectory. In this way, the model is encouraged to focus on both the local variation direction and the variation magnitude of the predicted sequence.

Finally, the degradation-aware training objective is defined as:

$$\mathcal{L} = \mathcal{L}_{wmse} + \lambda \mathcal{L}_{slope}$$

where λ denotes the weighting coefficient of the slope-consistency loss, which is used to balance the point-wise prediction error and the trajectory-variation error. The above strategy ensures multi-step prediction accuracy through the point-wise error term and enhances the local variation consistency of the predicted trajectory through the differential error term, thereby improving the stability of multi-step prediction results for noisy SOH sequences.

2.4.2 Asynchronous Successive Halving Algorithm

The prediction performance of the proposed model depends on the configuration of key hyperparameters. Therefore, ASHA is employed in this paper to adaptively optimize the critical hyperparameters of the model, thereby improving its prediction performance across different battery degradation sequences.

2.4.2.1 ASHA

ASHA is a multi-fidelity hyperparameter optimization method designed for computationally expensive models, which can efficiently identify promising hyperparameter configurations under limited computational resources [25].

Let the hyperparameter search space be denoted as X , from which a set of candidate solutions is sampled:

$$\mathcal{C} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_Q\}$$

where $\mathbf{x}_q$ denotes the q -th candidate hyperparameter configuration, and Q is the number of candidate solutions. For each candidate solution, the model is trained under a given training budget r , and the objective function is calculated on the validation set:

$$J(\mathbf{x}_q, r) = RMSE_{val}(\mathbf{x}_q, r)$$

where r denotes the number of training epochs, and $RMSE_{val}$ represents the validation-set RMSE. In this study, minimizing $RMSE_{val}$ is used as the optimization objective.

Let the minimum number of training epochs be r_0 , the maximum number of training epochs be R , and the reduction factor be h . At the k -th screening stage, the number of training epochs can be expressed as:

$$r_k = r_0 \eta^k, k = 0, 1, \dots, K$$

where K denotes the maximum number of screening stages. At each stage, ASHA ranks the candidate solutions according to their validation errors under the current training budget and retains a subset of candidates with smaller errors for promotion to the next stage. The retention rule can be expressed as:

$$\mathcal{C}^{(k+1)} = \text{Top}_{1/\eta}(\mathcal{C}^{(k)}, J(\mathbf{x}_q, r_k))$$

where $\mathcal{C}^{(k)}$ denotes the candidate set evaluated at the k -th stage, and $\text{Top}_{1/\eta}$ indicates that the top $1/h$ proportion of candidate solutions is retained according to the objective function value. Candidate solutions that are not retained are terminated early at the current stage.

Finally, ASHA selects the configuration with the minimum validation error among all candidate solutions as the optimal hyperparameter combination:

$$\mathbf{x}^* = \arg \min_{\mathbf{x}_q \in \mathcal{X}} J(\mathbf{x}_q, r_q)$$

where r_q denotes the actual number of training epochs reached by the candidate solution $\mathbf{x}_q$. After the optimal solution is obtained, the corresponding model is saved and used for subsequent SOH prediction.

2.4.2.2 Integration of ASHA with the proposed model

In the proposed model, ASHA is employed to jointly optimize the model hyperparameters. The control parameter settings are listed in Table 3, and the hyperparameter search space is presented in Table 4.

Table 3. ASHA control parameter settings

Parameter	Setting
Q	100
r_0	60
R	180
h	4
opt_patience	30

Table 4. ASHA hyperparameter search space

Hyperparameter	NASA search range	CALCE search range
L	{4,6,8,10,12,14}	{16,24,32,40,48,56,62,70}
hidden size	{16,24,32,48,64,128}	{16,32,48,64,96,128}
number of layers	{1,2,3,4}	{1,2,3,4}
l_s	{2,3,4,5,6}	{3,4,5,8,10,12,16}
r_s	{1,2,3,4}	{1,2,3,4}
learning rate	$[10^{-4}, 10^{-2.3}]$	$[10^{-4}, 10^{-2.3}]$

weight decay	$[10^{-8}, 10^{-3}]$	$[10^{-8}, 10^{-3}]$
dropout	$[0, 0.25]$	$[0, 0.25]$
λ	$[10^{-2.3}, 1]$	$[10^{-2.3}, 1]$
w_H	$[1, 3]$	$[1, 3]$
noise level	$[0, 0.035]$	$[0, 0.035]$

During the optimization process, ASHA first samples 100 candidate configurations from the search space defined in Table 4 and evaluates them through multiple rounds of training. In the first round, all candidate models are rapidly evaluated using the initial training budget. The candidates are then ranked according to their validation RMSE, and the top 25% with lower errors are retained for further training with an extended budget of 180 epochs. Finally, the model with the lowest validation RMSE is selected as the optimal model. The detailed optimization procedure is presented in Algorithm 1.

Algorithm 1 : ASHA

Input : SOH sequence S , hyperparameter search space $\mathbf{X}$ and number of initial candidates Q

Output : Best hyperparameter configuration and optimized proposed model.

- 1 Sample Q candidate hyperparameter configurations from $\mathbf{X}$, and obtain the initial candidate set $C^{(0)}$
 - 2 Initialize the training budget $r=r_0$ and the stage index $k=0$
 - 3 **While** $r \leq R$
 - 4 **for each** candidate configuration $x_q \in C^{(k)}$ **do**
 - 5 Construct training and validation samples using the L in x_q
-

```

6      Build model using the segment length  $l_s$ , segment stride  $r_s$ , hidden size, and
      number of layers in  $x_q$ 

7      Set the training parameters, including learning rate, weight decay, dropout,
       $\lambda$ ,  $w_H$ , and noise level, according to  $x_q$ 

8      Train the candidate model using the current training budget  $r$ .

9      Generate multi-step SOH predictions on the validation set according to Eq.
      (X).

10     Compute the validation RMSE according to Eq. (X) as the objective value.

11     end for

12     Rank all candidate configurations in  $C^{(k)}$  in ascending order of validation
      RMSE.

13     Retain the top  $1/h$  candidate configurations with the lowest validation RMSE
      to form  $C^{(k+1)}$ .

14     Update the training budget  $r=\eta r$ 

15     Update the stage index  $k=k+1$ 

16 end while

17 Select the configuration with the lowest validation RMSE

18 Obtain the optimized proposed model

```

2.4.3 ASHA-Optimized Degradation-Aware SegRNN Model

The workflow of the proposed ASHA-optimized degradation-aware SegRNN model for multi-step SOH prediction of lithium-ion batteries is illustrated in Figure 2. The detailed procedure is described as follows.

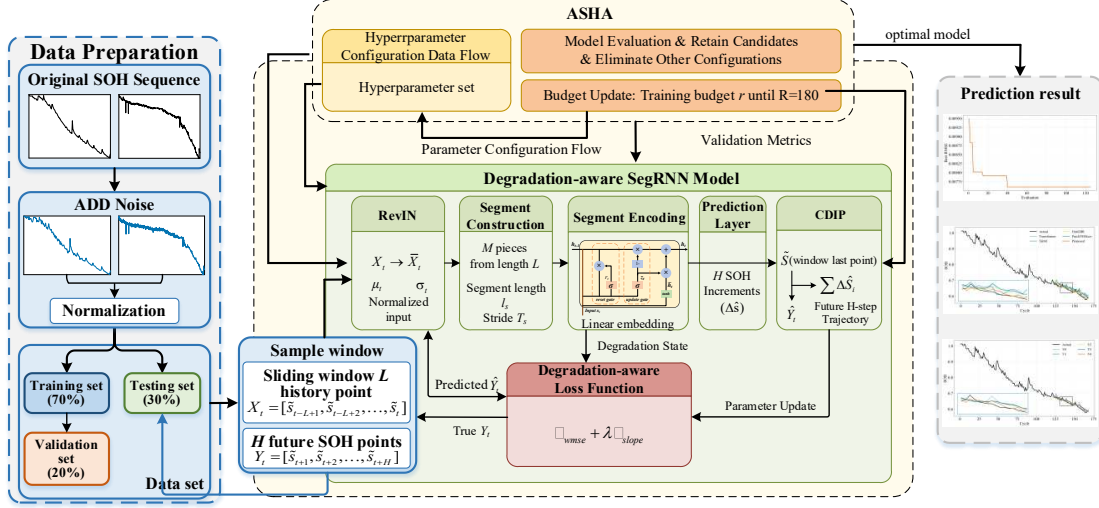


Fig.2 The workflow of the proposed ASHA-optimized degradation-aware SegRNN model

Step 1: Data preprocessing. Noise is added to the original SOH sequence to obtain a noisy SOH sequence. The dataset is then divided chronologically, with 70% of the data used for training and 30% used for testing. In addition, 20% of the training samples are further used as the validation set.

Step 2: Window-sample construction. Each input sample consists of L consecutive historical SOH points, and the prediction target consists of the next H SOH points. In this study, H is set to 5. The historical window length L , as a sample-construction parameter, is adaptively selected by ASHA.

Step 3: Candidate hyperparameter initialization. Candidate hyperparameter configurations are generated based on the predefined search space of ASHA. Each candidate configuration is defined according to Table 4, and each set of candidate parameters corresponds to a complete training scheme for the degradation-aware SegRNN model.

Step 4: RevIN-based local normalization and segment construction. For each candidate configuration, input windows are constructed according to its corresponding L . RevIN is then applied to perform local normalization within each window. Subsequently, the normalized

historical window is divided into local degradation segments according to the segment length l_s and segment stride r_s . These segments are further mapped into segment-level features through a linear embedding layer.

Step 5: GRU-based segment encoding and degradation-state extraction. The segment-feature sequence is fed into the GRU encoder in temporal order to recursively update the hidden state. The final hidden state is regarded as the degradation state of the current historical window and is used for subsequent future SOH trajectory prediction.

Step 6: CDIP-based multi-step SOH trajectory reconstruction. Based on the extracted degradation state, the prediction head outputs the SOH increments over the next H steps. Taking the last observed SOH value in the current window as the starting point, the CDIP mechanism cumulatively sums the predicted future increments step by step to reconstruct the future H -step SOH prediction trajectory.

Step 7: Model training. The proposed model is trained using the training samples. During training, a degradation-aware loss function is adopted by combining the horizon-weighted MSE and the slope-consistency loss, enabling the model to learn both the future SOH value levels and the local trajectory variations.

Step 8: ASHA-based optimization. ASHA uses the validation-set root mean square error (RMSE) as the evaluation metric for hyperparameter optimization. The candidate configuration with the lowest validation RMSE is selected as the optimal hyperparameter combination, yielding the final proposed model for lithium-ion battery SOH prediction.

Step 9: Performance evaluation. Based on the prediction results on the test set, the model performance is evaluated using mean absolute error (MAE), RMSE, mean absolute percentage

error (MAPE), and the coefficient of determination (R2).

3. Results and discussion

To verify the effectiveness of the proposed model in noisy multi-step SOH prediction for lithium-ion batteries, experimental validation is conducted in this section using the NASA and CALCE battery datasets.

3.1 Evaluation metrics

In this study, MAE, RMSE, MAPE, and R2 are used to evaluate the prediction performance of the model [26-27]. Since this study focuses on multi-step prediction, the evaluation metrics are calculated jointly over all prediction windows and all prediction horizons in the test set.

Let the test set contain N_{tes} prediction windows. The true value and predicted value at the h -th prediction step of the n -th test window are denoted as $y_{n,h}$ and $\hat{y}_{n,h}$, respectively. The evaluation metrics are defined as follows:

$$\begin{aligned}
 MAE &= \frac{1}{N_{\text{test}} H} \sum_{n=1}^{N_{\text{test}}} \sum_{h=1}^H |y_{n,h} - \hat{y}_{n,h}| \\
 RMSE &= \sqrt{\frac{1}{N_{\text{test}} H} \sum_{n=1}^{N_{\text{test}}} \sum_{h=1}^H \frac{|y_{n,h} - \hat{y}_{n,h}|^2}{y_{n,h}}} \\
 MAPE &= \frac{100\%}{N_{\text{test}} H} \sum_{n=1}^{N_{\text{test}}} \sum_{h=1}^H \left| \frac{y_{n,h} - \hat{y}_{n,h}}{y_{n,h}} \right| \\
 R^2 &= \frac{\sum_{n=1}^{N_{\text{test}}} \sum_{h=1}^H (y_{n,h} - \hat{y}_{n,h})^2}{\sum_{n=1}^{N_{\text{test}}} \sum_{h=1}^H (y_{n,h} - \bar{y})^2}
 \end{aligned}$$

where $\bar{y}$ denotes the mean value of all true SOH samples in the test set.

3.2 Experimental Results on NASA Batteries

This subsection presents the experimental results of the proposed model on the NASA dataset, including the ASHA optimization results, prediction performance comparisons among different models, and ablation analysis. By comparing the multi-step prediction performance of different models on short-sequence batteries, the effectiveness of the proposed model under small-sample and noisy SOH conditions can be intuitively evaluated.

3.2.1 Analysis of Hyperparameter Optimization Results

This section first presents the ASHA-based hyperparameter optimization results of the proposed model on the NASA dataset. For the two short-sequence batteries, B0006 and B0007, ASHA searches the predefined hyperparameter space to optimize the parameters of the proposed model. The optimization objective is the overall RMSE on the validation set, and the candidate configuration with the lowest validation RMSE is finally selected as the optimal hyperparameter combination for each battery.

Table 5 lists the optimal hyperparameter configurations obtained by ASHA for B0006 and B0007.

Table 5. Hyperparameter configuration results on the NASA dataset.

Hyperparameter	B006	B007
L	10	8
hiddensize	48	64
numberoflayers	1	4
l_s	5	3
r_s	2	2
learningrate	1.43×10^{-3}	9.19×10^{-4}
weightdecay	7.21×10^{-5}	7.63×10^{-7}

dropout	0.0236	0.1967
λ	0.0379	0.0274
w_H	1.3328	2.0621
noiselevel	0.0287	0.0120

To demonstrate the effectiveness of the hyperparameter search strategy, Figure 3 presents the convergence curves during the ASHA optimization process. These curves reflect the variation in validation-set RMSE of candidate hyperparameter configurations under successive training budgets, thereby verifying the effectiveness of the proposed optimization method.

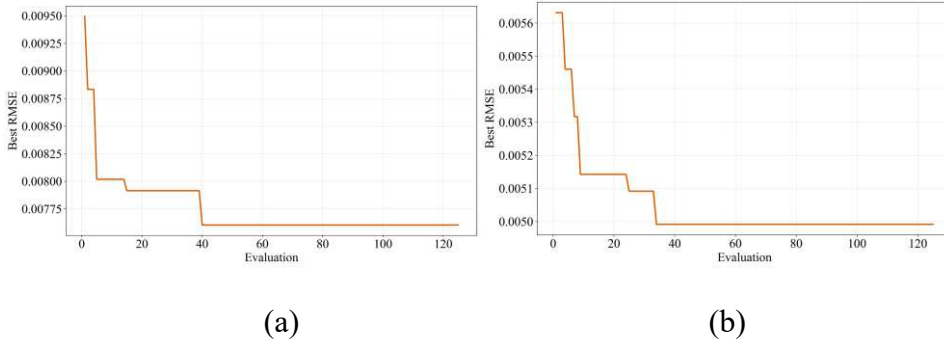


Figure 3. ASHA optimization curves (a) B0006; (b) B0007.

The results in Table 5 and Figure 3 demonstrate the advantage of ASHA in adaptively selecting the key parameters of the proposed model. After the optimal hyperparameters are obtained, the corresponding model weights are saved. All subsequent experimental results are generated based on this optimal configuration for test-set prediction and performance evaluation.

3.2.2 Analysis of Experimental Results

After completing ASHA-based hyperparameter optimization, this paper compares the proposed model with Transformer, TabM [28], HistGBR [29], and PatchTSMixer [30] on the B0006 and B0007 datasets for multi-step SOH prediction.

Figure 4 presents the comparison results of the prediction curves for batteries B0006 and B0007.

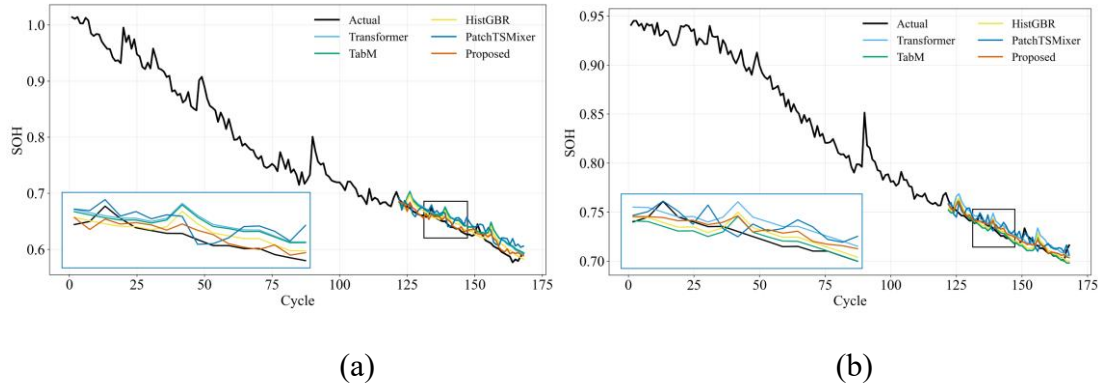


Figure 4. Comparison of multi-step prediction curves (a) B0006; (b) B0007.

As shown in Figure 4, the prediction trajectories of different models exhibit considerable differences in the test interval, particularly in regions with local fluctuations and near the late degradation stage. In comparison, the proposed model demonstrates better trajectory-tracking capability on both B0006 and B0007, with its predicted curves being generally closer to the true SOH curves. This indicates that the proposed model can effectively capture SOH degradation characteristics under short-sequence and noisy conditions.

Figure 5 presents the prediction scatter plots for the NASA batteries, which are used to evaluate the consistency between the predicted values and the true values.

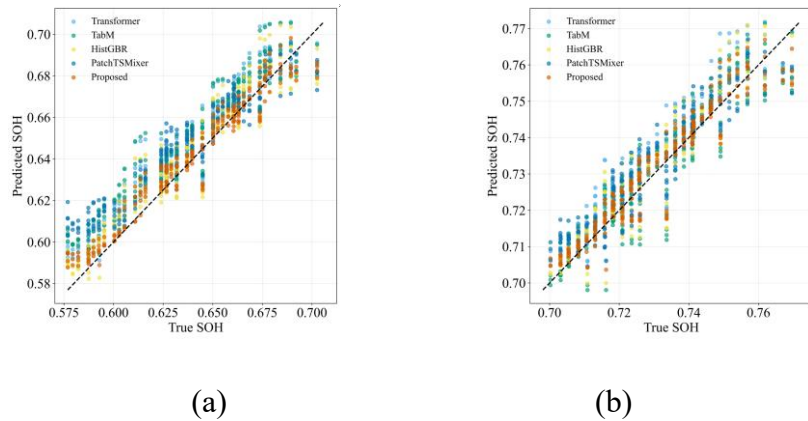


Figure 5. Scatter plots of multi-step prediction results (a) B0006; (b) B0007.

As shown in Figure 5, the scatter points of the proposed model are generally more concentrated and closer to the reference line, indicating relatively smaller prediction errors and better consistency between the predicted values and the true SOH values. This further demonstrates that the proposed method achieves favorable fitting stability in noisy multi-step SOH prediction tasks.

In addition, Table 6 summarizes the evaluation results of different models, providing a quantitative assessment of the multi-step prediction performance of the proposed model.

Table 6. Prediction metrics for NASA batteries

Battery	Models	MAE	RMSE	MAPE	R2
B0006	Transformer	1.25E-02	1.41E-02	1.98E+00	0.801
	TabM	1.34E-02	1.51E-02	2.13E+00	0.774
	HistGBR	8.54E-03	1.03E-02	1.34E+00	0.893
	PatchTSMixer	1.24E-02	1.48E-02	1.98E+00	0.781
	Proposed	5.75E-03	7.60E-03	9.05E-01	0.942
B0007	Transformer	6.65E-03	7.54E-03	9.10E-01	0.807
	TabM	4.95E-03	6.50E-03	6.75E-01	0.856
	HistGBR	5.30E-03	6.45E-03	7.23E-01	0.859

			03	
		6.56E-		
PatchTSMixer	5.65E-03		7.76E-01	0.854
		03		
		4.99E-		
Proposed	3.76E-03		5.13E-01	0.915
		03		

As shown in Table 6, for B0006, the proposed model achieves an R2 value of 0.942. Compared with HistGBR, the RMSE of the Proposed model is reduced by approximately 26.2%, the MAE is reduced by approximately 32.7%, and the MAPE decreases from 1.34 to 0.905. These results demonstrate that the proposed model can effectively reduce the overall prediction error and improve the fitting degree of the SOH degradation trajectory in short-sequence prediction tasks.

For B0007, the Proposed model also achieves the best overall prediction performance. Compared with the other models, the Proposed model maintains the lowest values across all error metrics. Specifically, compared with HistGBR, the RMSE of the Proposed model is reduced by 22.6%. Compared with TabM, which achieves the lowest MAE among the baseline models, the MAE of the Proposed model is further reduced by approximately 24.0%. Meanwhile, the Proposed model obtains a higher R2 than all comparison models, further confirming its superior fitting capability.

3.2.3 Ablation Analysis

To verify the contribution of each component of the proposed model to multi-step prediction performance, ablation experiments are further conducted on batteries B0006 and B0007. The key modules considered in the ablation study include RevIN, CDIP, DATS, and ASHA. The module configurations of different ablated variants are listed in Table 7.

Table 7. Model configurations for the ablation study

Variant	SegRNN	RevIN	CDIP	DATS	ASHA
V0	√	×	×	×	×
V1	√	√	×	×	×
V2	√	√	√	×	×
V3	√	√	√	√	×
V4	√	√	√	√	√

Figure 6 presents the prediction curves of the ablation experiments on the NASA batteries, and Table 8 reports the corresponding evaluation metrics.

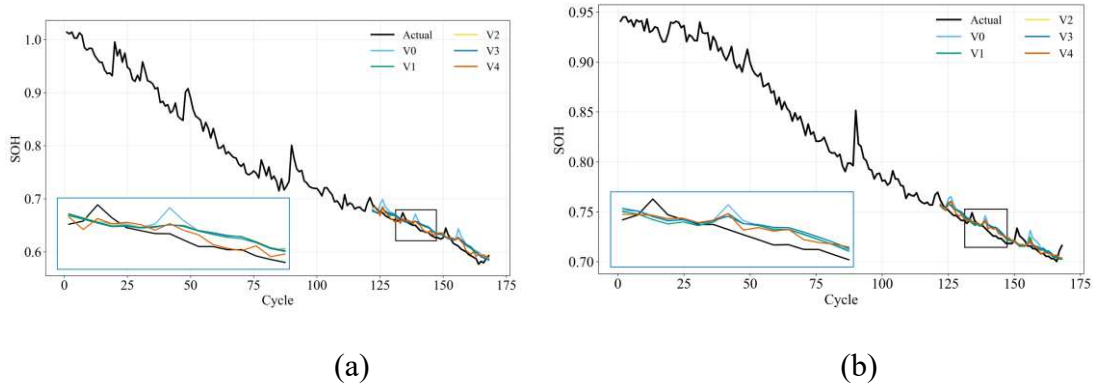


Figure 6. Comparison of prediction curves in the ablation experiments (a) B0006; (b) B0007.

Table 8. Prediction results of the ablation experiments on NASA batteries

Battery	Models	MAE	RMSE	MAPE	R2
B0006	V0	9.37E-03	1.12E-02	1.47E+00	0.876
	V1	7.57E-03	9.12E-03	1.19E+00	0.917
	V2	7.42E-03	8.99E-03	1.17E+00	0.919
	V3	7.34E-03	8.87E-03	1.16E+00	0.922
	V4	5.75E-03	7.60E-03	9.05E-01	0.942
B0007	V0	4.96E-03	6.23E-03	6.77E-01	0.868

V1	4.24E-03	5.36E-03	5.78E-01	0.903
V2	4.25E-03	5.32E-03	5.81E-01	0.904
V3	4.25E-03	5.30E-03	5.80E-01	0.905
V4	3.76E-03	4.99E-03	5.13E-01	0.915

Figure 6 shows the prediction results of different ablated models. SegRNN can capture the main degradation trend; however, under noisy short-sequence conditions, its prediction curves still exhibit certain deviations in regions with local fluctuations. After introducing RevIN, the model exhibits improved adaptability to input windows from different degradation stages, resulting in more stable prediction curves overall. With the further incorporation of CDIP, the multi-step prediction results are obtained by cumulatively summing consecutive degradation increments, thereby enhancing the temporal continuity of the predicted trajectory. As DATS and ASHA-based optimization are subsequently introduced, the curve-tracking capability of the model in the test stage is further improved. The complete Proposed model achieves better local fitting performance on both B0006 and B0007.

3.3 Experimental Results on CALCE Batteries

Furthermore, to verify the applicability of the proposed model to long-sequence prediction, experiments are conducted in this section on the CS2-36 and CS2-38 batteries from the CALCE dataset. Compared with the NASA batteries, the CALCE batteries contain longer SOH sequences and exhibit more pronounced local fluctuations and capacity regeneration phenomena during degradation. Therefore, they can further evaluate the multi-step prediction capability of the proposed model for complex degradation trajectories.

3.3.1 Analysis of Hyperparameter Optimization Results

This section presents the ASHA-based hyperparameter optimization results of the

proposed model on the CALCE dataset. Table 9 lists the optimal hyperparameter configurations obtained by ASHA for CS2-36 and CS2-38. Different from the short-sequence NASA batteries, the CALCE batteries have longer cycling sequences. Therefore, ASHA selects the historical window length from a larger search space of L to better adapt to the temporal information contained in the longer degradation process.

Table 9. Hyperparameter configuration results on the CALCE dataset

Hyperparameter	CS2-36	CS2-38
L	62	48
hidden size	48	96
number of layers	1	2
l_s	5	5
r_s	2	3
learning rate	3.69×10^{-4}	2.43×10^{-3}
weight decay	3.25×10^{-4}	9.23×10^{-6}
dropout	0.1719	0.0273
λ	0.839	0.1329
WH	2.0075	2.705
noise level	0.0117	0.0274

To demonstrate the effectiveness of the hyperparameter search strategy, Figure 7 presents the convergence curves during the ASHA optimization process. These curves show the changes in validation-set RMSE of candidate hyperparameter configurations under successive training budgets, thereby verifying the effectiveness of the proposed optimization method.

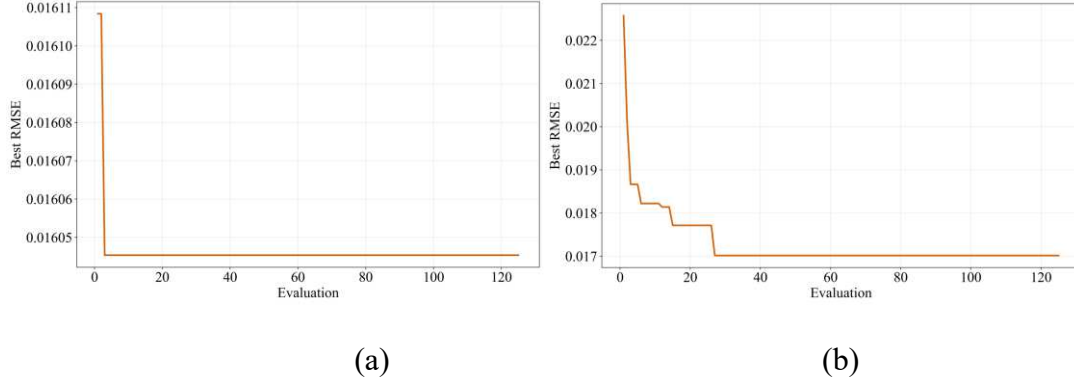


Figure 7. ASHA optimization curves (a) CS2-36; (b) CS2-38.

The results in Table 9 and Figure 7 demonstrate the advantage of ASHA in adaptively selecting the key parameters of the Proposed model. All subsequent experimental results are obtained based on this optimal configuration for test-set prediction and performance evaluation.

3.3.2 Analysis of Experimental Results

After completing ASHA-based hyperparameter optimization, the multi-step SOH prediction performance of the Proposed model is compared with that of Transformer, TabM, HistGBR, and PatchTSMixer on the CS2-36 and CS2-38 battery datasets.

Figure 8 presents the comparison results of the prediction curves for batteries CS2-36 and CS2-38.

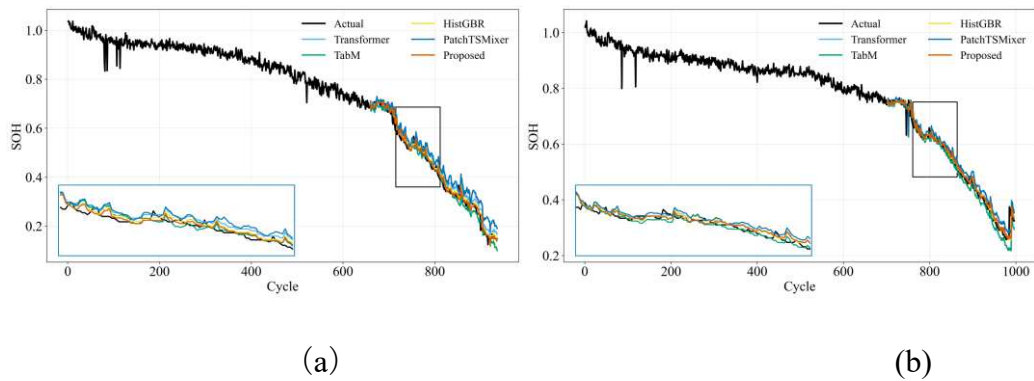


Figure 8. Comparison of multi-step prediction curves (a) CS2-36; (b) CS2-38.

As shown in Figure 8, the CALCE batteries exhibit more pronounced local fluctuations

and capacity regeneration phenomena. Although Transformer and PatchTSMixer are able to capture part of the temporal variations, they are prone to prediction deviations in regions with strong local fluctuations. TabM and HistGBR can maintain relatively good accuracy in some intervals, but their ability to characterize the continuous degradation process remains limited. In contrast, the Proposed model can follow the true SOH curves more closely on both batteries, indicating that the proposed degradation-aware SegRNN still possesses strong trajectory-modeling capability in long-sequence noisy SOH prediction tasks.

Figure 9 further presents the scatter plots, which reflect the consistency between the predicted values and the true values.

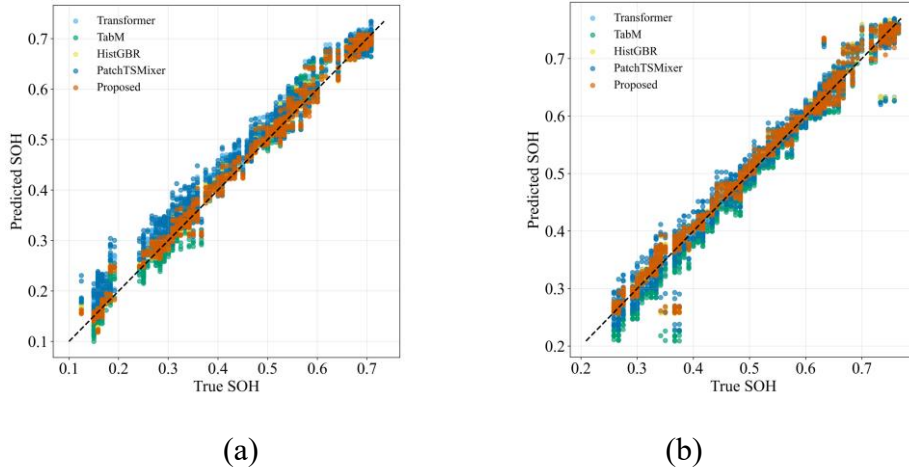


Figure 9. Scatter plots of multi-step prediction results (a) CS2-36; (b) CS2-38.

As shown in Figure 9, the scatter points of the Proposed model are generally closer to the reference line and exhibit a relatively smaller degree of dispersion, indicating good consistency between the predicted values and the true SOH values. For long-sequence data, the scatter distribution reflects not only point-wise prediction errors but also the stability of the model across different SOH intervals. The concentrated distribution of the Proposed model over different SOH ranges suggests that it has strong adaptability to degradation-stage variations in

long-sequence prediction tasks.

Finally, Table 10 summarizes the evaluation results of different models, providing a quantitative assessment of the multi-step prediction performance of the proposed model.

Table 10. Prediction metrics on the CALCE dataset

Battery	Models	MAE	RMSE	MAPE	R2
CS2-36	Transformer	2.44E-02	2.84E-02	7.296	0.973
	TabM	1.61E-02	2.06E-02	4.620	0.986
	HistGBR	1.25E-02	1.76E-02	3.474	0.990
	PatchTSMixer	2.44E-02	3.13E-02	7.912	0.967
	Proposed	1.12E-02	1.60E-02	3.062	0.991
CS2-38	Transformer	1.12E-02	1.88E-02	2.346	0.985
	TabM	1.96E-02	2.74E-02	4.593	0.968
	HistGBR	1.10E-02	1.86E-02	2.281	0.985
	PatchTSMixer	1.47E-02	2.18E-02	3.225	0.980
	Proposed	1.04E-02	1.70E-02	2.179	0.988

As shown in Table 10, for CS2-36, compared with HistGBR, which is the best-performing baseline model, the Proposed model reduces RMSE by 9.1% and MAE by 10.4%. This effectively demonstrates that, in the long-sequence prediction task on CS2-36, the proposed model can further reduce the overall prediction error while maintaining a high degree of fitting accuracy. For CS2-38, the Proposed model also achieves the best overall performance. Compared with HistGBR, the RMSE of the Proposed model is reduced by 8.6%, and the MAPE decreases from 2.281 to 2.179. Meanwhile, the Proposed model achieves a higher R2 than all baseline models, indicating its superior fitting capability for SOH variations in CS2-38.

Compared with the short-sequence experiments on the NASA dataset, the prediction difficulty of the CALCE dataset mainly lies in its longer sequences, more frequent local fluctuations, and more complex degradation stages. Nevertheless, the results in Figure 8, Figure 9, and Table 10 collectively demonstrate that the proposed model maintains stable prediction performance on long-sequence CALCE batteries.

3.3.3 Ablation Analysis

To verify the contribution of each component of the proposed model to multi-step prediction performance in long-sequence prediction tasks, ablation experiments are further conducted in this study. The module configurations of different ablated variants are listed in Table 7.

Figure 10 presents the prediction curves of the ablation experiments on the CALCE batteries, and Table 11 summarizes the evaluation metrics of different ablated variants.

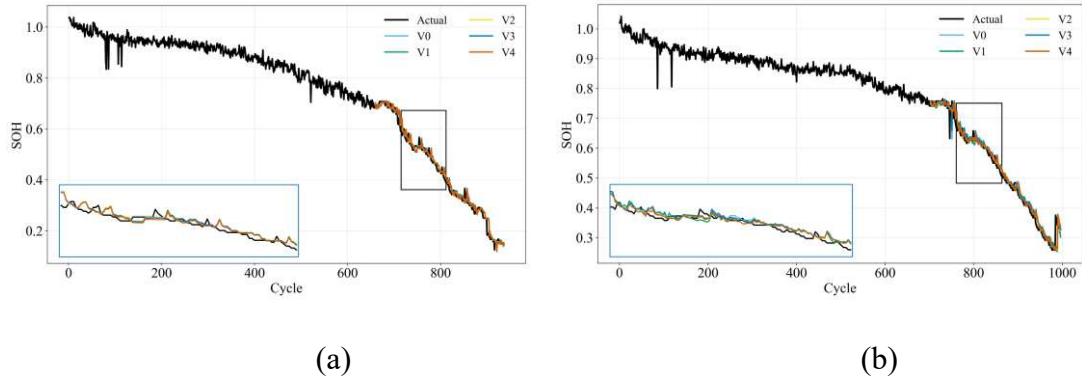


Figure 10. Comparison of prediction curves in the ablation experiments(a) CS2-36; (b) CS2-38.

As shown in Figure 10, V0 is already able to learn the main decreasing trend of long-sequence SOH. However, in regions with local fluctuations and capacity regeneration, its predicted trajectory still exhibits certain deviations. For long-sequence SOH data, the SOH

level and fluctuation amplitude vary significantly across different cycling stages. RevIN can mitigate such local scale discrepancies at the window level, enabling the model to extract segment-level degradation features more stably. With the further incorporation of CDIP, the model generates future multi-step prediction results by cumulatively summing degradation increments, thereby endowing the predicted trajectory with stronger temporal continuity.

Table 11. Prediction results of the ablation experiments on the CALCE dataset

Battery	Models	MAE	RMSE	MAPE	R2
CS2-36	V0	1.13E-02	1.65E-02	3.106	0.9908
	V1	1.14E-02	1.65E-02	3.134	0.9909
	V2	1.14E-02	1.63E-02	3.136	0.9911
	V3	1.12E-02	1.61E-02	3.054	0.9913
	V4	1.12E-02	1.60E-02	3.062	0.9914
CS2-38	V0	1.20E-02	1.91E-02	2.521	0.9846
	V1	1.11E-02	1.84E-02	2.330	0.9858
	V2	1.14E-02	1.81E-02	2.364	0.9863
	V3	1.06E-02	1.79E-02	2.199	0.9865
	V4	1.04E-02	1.70E-02	2.179	0.9878

As shown in Table 11, the contribution of each module differs between CS2-36 and CS2-38.

For CS2-36, since SegRNN is already able to capture the main degradation trend of this long sequence relatively well, the subsequent modules mainly further improve local variation modeling and prediction stability. Therefore, the performance gains brought by each module on CS2-36 are relatively moderate. In contrast, the improvements achieved by the modules on

CS2-38 are more pronounced. Compared with V0, after introducing RevIN, the RMSE of V1 decreases to 1.84×10^{-2} , indicating that window-level normalization has a clear positive effect on handling local distribution variations in CS2-38. After further incorporating CDIP, the RMSE of V2 decreases to 1.06×10^{-2} , demonstrating that the cumulative degradation increment mechanism helps improve the continuity of multi-step prediction trajectories. With the introduction of DATS in V3, the MAE decreases to 1.06×10^{-2} , indicating that the degradation-aware training strategy can further improve local variation consistency. Finally, V4 reduces the RMSE to 1.70×10^{-2} and increases R2 to 0.9878, achieving the best overall performance.

In summary, the experimental results on the CALCE dataset further verify the generalization and adaptability of the proposed model. The model not only achieves favorable prediction performance on short-sequence NASA batteries but also adapts well to the more complex local fluctuations and capacity regeneration phenomena in long-sequence CALCE batteries. These results demonstrate that the proposed model has strong applicability to noisy multi-step SOH prediction tasks involving different sequence lengths and degradation patterns.

4. Conclusions

This paper proposes an ASHA-optimized degradation-aware SegRNN method for multi-step SOH prediction of lithium-ion batteries. Experimental validation is conducted on the NASA and CALCE battery datasets. The main conclusions are as follows:

1. In the short-sequence experiments on the NASA dataset, the proposed model achieves the best prediction performance compared with Transformer, TabM, HistGBR, and PatchTSMixer. Specifically, the RMSE values on B0006 and B0007 are $7.60\text{E-}03$ and $4.99\text{E-}03$, respectively. These results indicate that the proposed method has a clear accuracy

advantage in noisy SOH prediction tasks under small-sample conditions.

2. In the long-sequence experiments on the CALCE dataset, the proposed model also maintains favorable prediction performance. The RMSE values on CS2-36 and CS2-38 are (1.60E-02) and (1.70E-02), respectively, outperforming all comparison models. This demonstrates that the proposed model is not only suitable for short-sequence prediction on the NASA dataset but can also adapt to the more complex local fluctuations and capacity regeneration phenomena observed in long-sequence CALCE batteries.

3. The ablation experiments further verify the effectiveness of each component of the proposed model. With the progressive introduction of RevIN, CDIP, DATS, and ASHA, the overall prediction error decreases and the fitting performance improves. In particular, the complete V4 model achieves the best overall performance on both the NASA and CALCE datasets, indicating that these modules can synergistically enhance noisy multi-step SOH prediction performance.

Overall, the proposed ASHA-optimized degradation-aware SegRNN model can achieve stable and accurate prediction results in noisy multi-step SOH prediction tasks, providing an effective approach for lithium-ion battery health-state assessment. However, the current study mainly uses SOH sequences as model inputs, and multi-source information such as voltage, current, temperature, and charge–discharge process features has not yet been fully considered. In addition, the generalization capability of the model under different battery material systems and complex operating conditions still requires further validation, and the ASHA-based optimization process may increase computational cost. Future work will focus on incorporating multi-source operating features, integrating physical constraints and uncertainty estimation,

and improving SOH prediction under cross-battery, cross-condition, and online updating scenarios.

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