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An uncertainty-weighted Bayesian-fusion SVGMR framework for robust battery SOH estimation under partial charging conditions

Hongjie Lv[1], Xingchen Liu[2,*], Dong Wang[3,4], Bingchang Hou[5], Dong Zhen[1] and Jinzhen Kong[1,*]

[1] School of Mechanical Engineering, Hebei University of Technology, Tianjin 300401, People's Republic of China
[2] Department of Industrial and Systems Engineering, Hong Kong Polytechnic University, Hong Kong SAR, People's Republic of China
[3] Department of Industrial Engineering and Management, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, People's Republic of China
[4] State Key Laboratory of Mechanical System and Vibration, Shanghai Jiao Tong University, Shanghai, People's Republic of China
[5] State Key Laboratory of Mechanical Transmission for Advanced Equipment, Chongqing University, Chongqing, People's Republic of China

E-mail: xingchen.liu@polyu.edu.hk and jinzhenkong@hebut.edu.cn

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Abstract

Accurate state of health (SOH) estimation for lithium-ion batteries (LIBs) is essential to ensure operational safety and reliability. However, most of existing SOH estimation studies are conducted under the assumption of complete battery charging data, which are not applicable to practical applications. Partial charging conditions and cell-to-cell degradation variability bring significant challenges for accurate online SOH estimation for LIBs. To address these issues, this paper proposes an enhanced uncertainty-weighted Bayesian-fusion sequential variational Gaussian mixture regression (BF-SVGMR) framework to improve SOH estimation accuracy and robustness under partial charging conditions, integrating historical degradation priors and incomplete charging curves into consideration. Firstly, the probabilistic relationship between extracted partial-charging features and historical capacity information is modeled, and the current-cycle capacity prediction with its uncertainty is then obtained using SVGMR. A prior representing the historical capacity degradation trend is then constructed from the previously observed capacity sequence using a sliding-window strategy. To realize online updating of priors, an uncertainty-weighted Bayesian online correction method is presented. Comparison

* Author to whom any correspondence should be addressed.

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experiments are conducted on two different datasets to verify the efficiency of the proposed framework. Results indicate that the proposed BF-SVGMR framework is superior to baseline methods, presenting excellent performance under partial charging conditions

Keywords: Lithium ion battery, SOH estimation, Incomplete charging curve, SVGMR, Bayesian fusion, on-line correction

1. Introduction

With the rapid development of new energy transportation, electrochemical energy storage and smart grid, lithium-ion batteries (LIBs) are widely used in electric vehicles, energy storage systems, and ship power systems due to their high energy density, long cycle life and low self-discharge rate [1–3]. However, LIBs inevitably degrade during prolonged charge–discharge cycling. Internal electrochemical reactions, loss of active materials, impedance growth, and increased polarization gradually reduce the available capacity and power capability. Battery performance degradation will not only reduce the efficiency of the system, but also bring security risks. Therefore, accurate assessment of battery health status is of great significance for ensuring the safe operation of the battery system, prolonging the service life and optimizing maintenance decisions. Previous studies have pointed out that state of health (SOH) is an important indicator of battery health in battery management systems, which can usually be characterized by the ratio of current capacity to initial capacity [4].

In the battery management system (BMS), SOH estimation is an important basis for state estimation, life prediction and operation optimization. Accurate SOH estimation can provide a key basis for battery remaining usable capacity judgment, charge–discharge strategy optimization, remaining useful life (RUL) prediction and echelon utilization evaluation. Especially in electric vehicles and energy storage systems, the degree of battery degradation directly affects vehicle endurance, system economy and whether the battery needs to be replaced or decommissioned [5, 6]. Previous studies have shown that accurate estimation of SOH and RUL can improve battery safety, reliability and life management capabilities, which is one of the key functions of intelligent

BMS [2, 7].

At present, SOH estimation methods for LIBs mainly include direct test methods, model-driven methods, and data-driven methods [8–10]. Direct testing methods obtain battery-state information through standard capacity tests, cycling-aging tests, or disassembly analysis. Although accurate, these methods are time-consuming and costly, making them unsuitable for online applications. The model-driven method mainly describes the internal state of the battery through the equivalent circuit model, electrochemical model or empirical degradation model, and combines the parameter identification or filtering algorithm to estimate the SOH. For example, the method based on electrochemical impedance spectroscopy and equivalent circuit model can use impedance parameters to reflect battery degradation information, and combined with methods such as Gaussian process regression (GPR), high-precision SOH estimation can be achieved [11].

Compared with the model-driven method, the data-driven method does not need to establish a complex electrochemical mechanism model, but extracts health features from data such as voltage, current, temperature, SOH, incremental capacity curve or impedance spectrum, and uses machine learning or deep learning models to establish the mapping relationship between features and SOH [12, 13]. The commonly used methods include support vector regression (SVR), GPR, convolutional neural network (CNN) , long short-term memory (LSTM) and Transformer [14–16]. In recent years, deep learning methods have been widely used in SOH estimation, which can automatically extract nonlinear features from complex time series data. For example, some studies have used historical state information and future load information to construct attention-based multisource sequence-to-sequence models to predict SOH under different load conditions [17]; there are also studies that convert incremental capacity curves into image features and combine CNN-LSTM-eXtreme gradient boosting framework for SOH estimation [18].

However, most existing methods still have some shortcomings in practical applications. First of all, The charging process in practical applications is often affected by various factors such as user behavior, state of charge (SOC) at the beginning and end of charging, ambient temperature and working conditions [19, 20]. It is difficult to obtain a complete standard charging curve stably, which makes it difficult for many methods relying on complete charging and discharging data to be directly applied to online scenarios. Secondly, some data-driven methods mainly rely on the current cycle characteristics to predict, and the historical capacity degradation trend of the target battery is not fully utilized. In fact, the battery capacity degradation has obvious time continuity. The current SOH is not only related to the characteristics of the current charging curve, but also closely related to the capacity change trend of the previous cycles. Previous studies have also shown that historical state information plays an important role in SOH prediction [17, 21].

In addition, a single model is easily affected by sample size, working condition changes and individual differences of batteries in complex degradation processes and cross-battery applications, resulting in insufficient generalization ability. In recent years, methods such as physical information neural network, hybrid model, basic model and transfer learning have gradually attracted attention. Relevant research shows that introducing physical constraints, electrochemical mechanism or cross-domain knowledge into the model can help

improve the accuracy, interpretability and generalization ability of SOH estimation [22–24]. However, these methods are usually complex in structure and have high requirements on data scale, computing resources or model design.

Therefore, developing an SOH estimation method that can effectively use limited charging-curve information and historical degradation trends while enabling online correction remains an important research topic, particularly when prediction stability and model interpretability are both required. SVGMR provides a probabilistic regression framework for battery SOH estimation under incomplete charging conditions. By jointly modeling the charging-curve features and battery capacity, SVGMR can infer the capacity distribution even when part of the charging information is unavailable [25]. However, the original SVGMR framework mainly relies on the current-cycle charging features, while the historical degradation trajectory of the target battery is not explicitly incorporated into the prediction process. To address this limitation, this study introduces a historical capacity degradation trend prior into the SVGMR framework and adaptively fuses the current-cycle prediction with the historical trend prediction through an uncertainty-weighted Bayesian fusion mechanism. In this way, the proposed method improves the accuracy, stability, and generalization ability of SOH estimation under partial charging conditions.

In view of above problems, this study takes the SOH estimation of LIB under the condition of incomplete charging curve as the research object. Based on the original SVGMR method, a Bayesian fusion online correction method based on historical capacity degradation trend prior is proposed. This method uses the modeling ability of SVGMR to incomplete charging curve, and first obtains the observation and prediction results of the current cycle based on characteristics of the charging curve. Then, the degradation trend prior is constructed according to the historical capacity sequence of the target battery. Finally, the observation prediction and historical prior are adaptively weighted by Bayesian fusion mechanism, so as to realize the online correction of SOH prediction results. The main research content of this paper are as follows:

Firstly, the SOH estimation mechanism of the original SVGMR method under the condition of incomplete charging curve is studied. This paper analyzes the three models of SVGMR-C, SVGMR-A and SVGMR-O, and points out that although they can make use of incomplete samples and online update mechanism, the explicit utilization of the historical capacity degradation trend of the target battery is still insufficient.

Secondly, a prior of historical capacity degradation trend is constructed, and a Bayesian fusion online correction method is proposed. This paper uses the historical capacity sequence of the target battery to estimate the current cycle capacity change trend, and combines the SVGMR prediction results and their uncertainties for Bayesian fusion, so that the final prediction results take into account the current charging curve information and historical degradation trend information.

Thirdly, experimental verification is carried out on NASA and CALCE datasets. In this paper, the prediction accuracy, stability and generalization ability of the proposed method are systematically evaluated by prediction curve comparison, root mean square error (RMSE) analysis, absolute error trend analysis, ablation experiment, leave-one-cell cross-validation, traditional machine learning model comparison.

The main contribution of this study are summarized as follows:

(1) A historical degradation trend prior is introduced into the SVGMR framework. By using the previously observed capacity sequence of the target battery, the proposed method explicitly incorporates temporal degradation information into current-cycle SOH estimation.
(2) An uncertainty-weighted Bayesian fusion strategy is developed to combine the SVGMR observation prediction and the historical degradation prior. The fusion weights are adaptively determined according to predictive uncertainties of the two information sources, thereby improving the robustness of online SOH estimation.
(3) The proposed Bayesian-fusion sequential variational Gaussian mixture regression (BF-SVGMR) framework is systematically validated under incomplete charging conditions. Experiments on NASA and CALCE datasets, together with ablation studies and comparison with baseline models, demonstrate the effectiveness and generalization ability of the proposed method.

The remainder of this paper is organized as follows. Section 2 introduces theoretical basis and the original SVGMR method, including the relationship between charging curve characteristics and capacity degradation, the basic idea of SVGMR, and the three model forms of SVGMR-C, SVGMR-A and SVGMR-O, which lays a foundation for the improvement of subsequent methods. Section 3 proposes a Bayesian fusion online correction method based on the historical capacity degradation trend prior, focusing on the historical trend prior construction, Bayesian fusion mechanism and the overall algorithm flow. Section 4 introduces the experimental design and evaluation indicators, including the description of NASA and CALCE datasets, data preprocessing and feature construction, experimental settings, comparison methods, RMSE, mean absolute error (MAE) and other evaluation indicators. Section 5 gives experimental results and analysis, mainly based on the prediction curve, error index, ablation experiment, cross validation, machine learning model comparison and CALCE generalization verification to evaluate the effectiveness of the proposed method. Section 6 summarizes this paper and discusses the shortcomings and possible future research directions.

2. Theoretical basis and SVGMR method

2.1. Relationship between charging-curve features and capacity degradation

LIBs will gradually age during recycling, showing a decrease in available capacity. At the same time, the charging voltage curve will also shift with the battery degradation, so the

charging curve contains SOH-related information. The original SVGMR method uses the charging curve to estimate the degradation state of the battery.

From a physical point of view, as a battery degrades, its internal polarization and impedance will change, which will be reflected in the shape, slope, and voltage plateau of the charging curve. Therefore, the charging curves under different cycles can be used as an important source of information to describe the health status of the battery. The subsequent method of this paper is also based on the characteristics of the charging curve, and further combines the historical capacity degradation trend to achieve SOH online estimation.

2.2. Original SVGMR method

The core idea of the original SVGMR method is to jointly model the charging curve feature ($\mathbf{x}$) and capacity (c), rather than directly establish a simple input–output regression relationship. Its joint distribution can be expressed as:

$$p(\mathbf{x}, c) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}, c \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \tag{1}$$

where K is the number of Gaussian components, π_k is the mixed weight, and $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ represent the mean vector and covariance matrix of the kth Gaussian component, respectively. After the model training is completed, the current cycle capacity can be estimated by the conditional distribution $p(c \mid \mathbf{x})$, and the estimation uncertainty can be obtained. Since this method adopts a probabilistic modeling framework, even if the charging curve is partially missing, the capacity can be inferred based on the observed curve segments.

The original SVGMR method mainly includes three variants: SVGMR-C, SVGMR-A, and SVGMR-O. SVGMR-C uses complete charging-curve samples with capacity labels for model training. SVGMR-A further incorporates incomplete or unlabeled charging-curve samples through variational inference. SVGMR-O introduces an online updating mechanism, enabling the model to be sequentially adjusted when new samples are available. The main differences among SVGMR-C, SVGMR-A, and SVGMR-O are summarized in table 1.

3. Methodology

To improve the SOH estimation accuracy of LIBs under incomplete charging conditions, this study extends the SVGMR framework by incorporating a historical capacity degradation trend prior and develops a Bayesian fusion-based online correction scheme.

The overall process of the proposed method is shown in figure 1, which mainly includes three parts. First, the SVGMR model is used to estimate the distribution of capacity values conditional on the features extracted from the incomplete charging curve of the current cycle. Second, the degradation trend prior distribution is constructed according to the observed historical capacity sequence of the target battery. Finally, the uncertainties of the two information sources are weighted through Bayesian fusion to obtain the final SOH estimation result.

Compared with the original SVGMR method, the proposed method not only utilizes the current cyclic charging characteristics, but also further considers the temporal degradation trend of the target battery capacity over cycles. Therefore, this method can improve the prediction accuracy of SOH and enhance the stability of prediction results under the condition of incomplete charging data. Figure 1 illustrates the overall framework of the proposed method.

3.1. Overview of the methodology

The method proposed in this paper is composed of three parts: SVGMR observation prediction branch, historical capacity degradation trend prior branch and Bayesian-fusion online correction module.

For the mth cycle, the available input information consists of the current-cycle incomplete charging-curve feature vector and the historical capacity sequence observed before the current prediction, which can be represented as

$$\{\boldsymbol{x}_m, c_1, c_2, \ldots, c_{m-1}\}, \tag{2}$$

where $\boldsymbol{x}_m$ denotes the feature vector extracted from the incomplete charging curve of the current cycle, and $\{c_1, c_2, \ldots, c_{m-1}\}$ denotes the historical real capacity sequence obtained before the prediction of the mth cycle. Specifically, $\boldsymbol{x}_m$ is constructed from the charging voltage-time curve and contains several health-related features that describe the voltage level, charging duration, voltage variation, and curve-shape evolution. The detailed feature extraction procedure is described in section 4.2.

The current-cycle feature vector $\boldsymbol{x}_m$ is used as the first type of information and is processed by the SVGMR observation prediction branch to infer the current-cycle capacity distribution. The historical capacity sequence $\{c_1, c_2, \ldots, c_{m-1}\}$ is used as the second type of information and is processed by the historical degradation trend prior branch to describe the recent capacity degradation trend of the target battery. Finally, the Bayesian fusion module combines the SVGMR observation prediction with the historical degradation prior to obtain the posterior SOH estimation.

The module calculates the recent capacity decline trend according to the historical capacity sequence, and constructs the prior distribution of the current cycle capacity. Finally, the Bayesian fusion module fuses the SVGMR observation prediction distribution with the historical trend prior distribution to obtain the posterior distribution, and takes its mean value as the final SOH estimation result. Therefore, the method used in this study can be summarized as follows:

$$\boldsymbol{x}_m \rightarrow c_m^{\text{obs}}, \tag{3}$$

$$c_1, c_2, \ldots, c_{m-1} \rightarrow c_m^{\text{prior}}, \tag{4}$$

$$c_m^{\text{obs}} + c_m^{\text{prior}} \rightarrow c_m^{\text{post}}, \tag{5}$$

where c_m^{obs} represents the observation prediction results obtained by SVGMR, c_m^{prior} represents the degradation trend

Table 1. Comparison of three variants of SVGMR method.

Method	Service data	Feature
SVGMR-C	Complete charging curve and capacity label	basic model
SVGMR-A	Complete samples + incomplete/unlabeled samples	Using incomplete sample information
SVGMR-O	Complete samples + new samples	Support online update

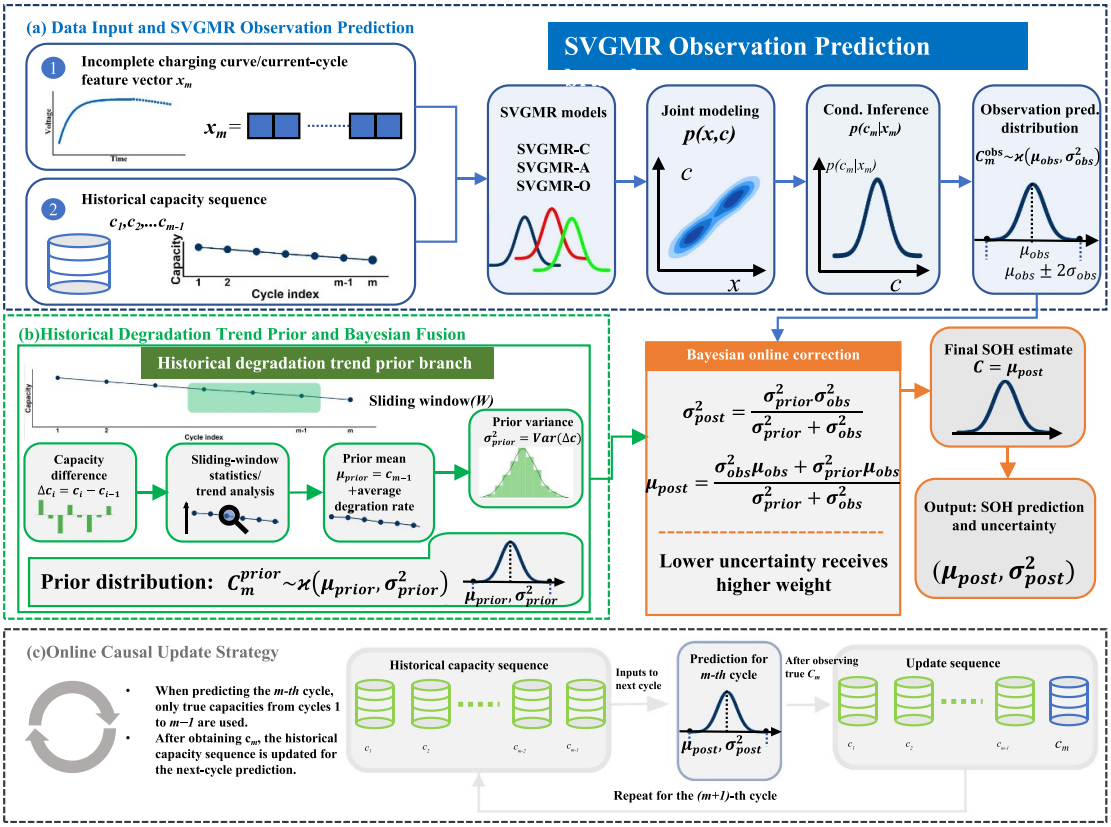


Figure 1. Overall framework of the proposed Bayesian-fusion online correction method based on historical capacity degradation trend prior. The framework consists of three modules: (a) data input and SOH estimation with SVGMR, where the incomplete charging curve feature vector x_m is used to infer the capacity distribution; (b) historical degradation trend prior and Bayesian fusion, where the historical capacity sequence $c_1, c_2, \ldots, c_{m-1}$ is used to construct the degradation prior and fused with the SOH estimation obtained by SVGMR through uncertainty-weighted Bayesian correction; and (c) online causal update strategy, where only true capacities before the mth cycle are used for prediction, and the historical sequence is updated after observing c_m.

prior obtained by the historical capacity sequence, and c_m^{post} represents the posterior estimation results after Bayesian fusion.

3.2. Observation predictive distribution of SVGMR

The SVGMR model uses the Gaussian mixture model to model the joint distribution between the charging curve characteristics and the battery capacity. For the incomplete charging curve feature x_m of the current cycle, SVGMR can perform conditional inference under the joint probability model to obtain the prediction result of the current cycle capacity.

In this method, the SVGMR output is not only regarded as a single-point prediction value, but is expressed as an observation estimation distribution with uncertainty:

$$c_m^{\text{obs}} \sim \mathcal{N}\left(\mu_{\text{obs}}, \sigma_{\text{obs}}^2\right), \tag{6}$$

where μ_{obs} represents the mean value of SVGMR's estimation of the capacity of the mth cycle, and σ_{obs}^2 represents the uncertainty of the prediction results.

Since the charging curve may be missing or truncated in practical applications, the advantage of SVGMR is that it can process incomplete input features under the framework of probability model. Specifically, the model does not need to complete the incomplete charging curve first, but can use the observed feature information to infer the condition and directly obtain the capacity estimation distribution.

As shown in the SOH estimation obtained by SVGMR branch in figure 1, the incomplete charging-curve feature $\boldsymbol{x}_m$ of the current cycle is first input to SVGMR-C, SVGMR-A, or SVGMR-O. Then, the joint distribution $p(\boldsymbol{x}, c)$ is modeled, and the conditional inference $p(c_m|\boldsymbol{x}_m)$ is performed to estimate the capacity distribution c_m^{obs}. This distribution provides observation information for subsequent Bayesian fusion.

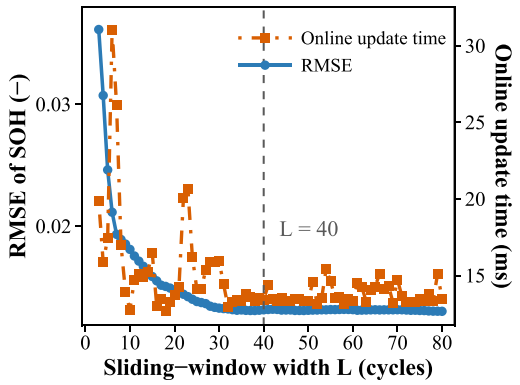


Figure 2. Sensitivity analysis of sliding-window width for balancing SOH prediction accuracy and online update efficiency.

3.3. Construction of historical capacity trend prior

Although SVGMR can estimate capacity from the current charging characteristics, LIB capacity degradation exhibits clear temporal continuity. Typically, the capacity of the mth cycle is not likely to deviate significantly from the degradation trend observed in previous cycles. Therefore, relying solely on the current cycle charging characteristics may not be able to make full use of the historical degradation law of the target battery itself. To this end, this paper introduces the historical capacity degradation trend prior. When predicting the mth cycle, the known historical capacity sequence is:

$$c_1, c_2, \ldots, c_{m-1}, \tag{7}$$

where c_{m-1} is the latest real capacity that can be obtained before the current prediction time. In order to characterize the capacity degradation trend, we first calculate the capacity difference between adjacent cycles:

$$\Delta c_i = c_i - c_{i-1}, \tag{8}$$

where Δc_i represents the capacity variation between the $i-1$ cycle and the i cycle, which can be understood as the local capacity degradation rate.

Considering that the capacity change of the earlier cycle may not accurately reflect the current degradation state, this paper uses the sliding window method to extract the capacity change trend of the latest L cycles.

To determine the window width, as shown in figure 2, a sliding-window sensitivity analysis was conducted by testing $L = 3 - 80$ cycles. The results show that the prediction error decreases rapidly as L increases from small values and then enters a stable region after approximately $L = 40$. Therefore, the window width is set to $L = 40$ in this study, which provides a balance between prediction accuracy and local trend-tracking ability. The sliding step length is set to one cycle because the proposed method performs SOH estimation cycle by cycle. After the true capacity of the current cycle is observed, the historical capacity sequence is updated, and the sliding window moves forward by one cycle for the next-cycle prediction.

Let the mean value of capacity difference in the nearest window be:

$$\overline{\Delta c} = \frac{1}{L} \sum_{i=m-L}^{m-1} \Delta c_i. \tag{9}$$

Then the prior mean of the mth cycle capacity can be expressed as:

$$\mu_{\text{prior}} = c_{m-1} + \overline{\Delta c}. \tag{10}$$

The formula shows that the capacity of the next cycle can be obtained by adding the capacity of the previous cycle to the recent average capacity change. At the same time, to describe the uncertainty of the historical degradation trend, this paper uses the variance of the capacity differences within the sliding window to construct the prior variance:

$$\sigma^2_{\text{prior}} = \text{Var}\left(\Delta c\right). \tag{11}$$

When the recent capacity change is relatively stable, σ^2_{prior} is smaller, indicating that the historical trend prior is more reliable. When the capacity change fluctuates greatly, σ^2_{prior} is larger, indicating that there is a strong uncertainty in the historical trend.

Therefore, the prior of historical capacity degradation trend can be expressed as:

$$c_m^{\text{prior}} \sim \mathcal{N}\left(\mu_{\text{prior}}, \sigma^2_{\text{prior}}\right). \tag{12}$$

From the prior branch of the historical degradation trend of figure 1, it can be seen that the module first inputs the historical capacity sequence $(c_1, c_2, \ldots, c_{m-1})$, and then obtains the prior mean and prior variance through capacity difference, sliding window statistics and trend analysis. Finally, the prior distribution of the current cycle capacity is constructed.

3.4. Bayesian fusion

After obtaining the SVGMR-based SOH estimation and the historical degradation trend prior, Bayesian fusion is used to integrate these two sources of information in an uncertainty-aware manner. Unlike simple averaging, Bayesian fusion assigns adaptive weights according to the uncertainties of different information sources. This is consistent with recent studies on probabilistic machine learning, data fusion, and filtering-based battery state estimation, where explicit uncertainty quantification has been shown to improve the robustness and reliability of prognostic models [20, 26, 27].

For the capacity corresponding to the mth cycle, the SVGMR-based estimation and the historical degradation trend prior are both represented as Gaussian distributions:

$$c_m^{\text{obs}} \sim \mathcal{N}\left(\mu_{\text{obs}}, \sigma^2_{\text{obs}}\right), \tag{13}$$

$$c_m^{\text{prior}} \sim \mathcal{N}\left(\mu_{\text{prior}}, \sigma^2_{\text{prior}}\right). \tag{14}$$

Under the Gaussian assumption, the fused posterior distribution can be written as

$$c_m^{\text{post}} \sim \mathcal{N}\left(\mu_{\text{post}}, \sigma^2_{\text{post}}\right), \tag{15}$$

where the posterior variance and posterior mean are calculated as:

$$\sigma^2_{\text{post}} = \frac{\sigma^2_{\text{prior}}\sigma^2_{\text{obs}}}{\sigma^2_{\text{prior}} + \sigma^2_{\text{obs}}}, \tag{16}$$

$$\mu_{\text{post}} = \frac{\sigma^2_{\text{obs}}\mu_{\text{prior}} + \sigma^2_{\text{prior}}\mu_{\text{obs}}}{\sigma^2_{\text{prior}} + \sigma^2_{\text{obs}}}. \tag{17}$$

It should be noted that the term 'uncertainty-weighted' means that the fusion weight is adaptively determined by the predictive uncertainty of each information source. According to equation (17), the contribution of the SVGMR-based estimation and the historical degradation prior is controlled by their variances, i.e. σ^2_{obs} and σ^2_{prior}. The information source with a smaller variance is assigned a larger contribution to the posterior estimate.

The posterior mean is then used as the final capacity estimate of the mth cycle:

$$\hat{c}_m = \mu_{\text{post}}. \tag{18}$$

These equations indicate that the fused result is automatically biased toward the information source with lower uncertainty. When the recent degradation trend is stable, σ^2_{prior} becomes smaller, and the posterior estimate tends to be closer to the historical trend prior. Conversely, when the SVGMR observation prediction is more reliable, σ^2_{obs} becomes smaller, and the posterior estimate is more strongly influenced by the current-cycle charging-curve information. Therefore, the proposed Bayesian fusion mechanism adaptively balances the current-cycle observation and the historical degradation trend, thereby improving the stability and accuracy of online SOH estimation.

4. Experimental design and evaluation metrics

In order to verify the effectiveness of the Bayesian fusion online correction method based on the historical capacity degradation trend prior proposed in this paper in the SOH estimation of LIBs, this chapter shows the dataset, data preprocessing method, experimental setting and evaluation metric used in the experiment. The experiment consist of two parts: the prognostic performance validation on the NASA LIBs aging datasets, and the cross-dataset generalization verification on the CALCE LIBs aging datasets from the University of Maryland.

4.1. Datasets

In this paper, two public LIB data sets are used for experimental verification, which are NASA LIB data set and University of Maryland CALCE data set. Both data sets contain information such as voltage, current, time and capacity of the battery during cycle charging and discharging.

B0005, B0006, and B0007 from the NASA dataset are selected as the research object. These three batteries are 18 650 LIBs with a rated capacity of about 2 Ah. During the experiment, the battery was first charged in constant current mode, and then switched to constant voltage mode. The discharge stage is carried out under constant current conditions until the battery terminal voltage drops to the set cut-off voltage [2, 20, 21]. The dataset records the charging, discharging and capacity changes of the battery under different cycles. As the number of cycles increases, the overall battery capacity shows a downward trend, which can reflect the aging process of LIBs. This paper mainly uses the characteristics of the charging curve and the corresponding capacity label for estimation.

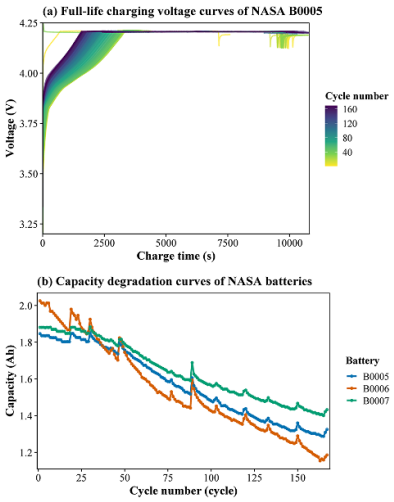


Figure 3. Charging voltage curves of B0005 and capacity degradation trajectories of NASA batteries.

Figure 3 presents the charging voltage curves of the NASA B0005 battery over its full life cycle and the capacity degradation trajectories of B0005, B0006, and B0007 batteries. As shown in figure 3(a), the charging voltage curves exhibit a clear evolution with increasing cycle number. Although the overall charging voltage profile remains similar, the curve shape gradually shifts during aging, indicating that the charging process contains degradation-related information. In particular, changes in the voltage rise stage and the constant-voltage region reflect the variation of battery internal characteristics caused by aging. Therefore, charging voltage curves can be used as effective health-related features for SOH estimation.

Figure 3(b) shows the capacity degradation curves of three NASA batteries. The capacity of B0005, B0006, and B0007 all decrease with cycling, but their degradation rates and fluctuation patterns are different. This indicates that battery aging is not completely consistent even under similar experimental conditions, and there are obvious cell-to-cell differences. Such differences increase the difficulty of SOH prediction and require the prediction model to have good generalization ability. Overall, this figure demonstrates the relationship between charging curve evolution and capacity fade, providing the data basis for subsequent SOH estimation based on incomplete charging curves.

In order to further verify the generalization ability of the proposed method, this paper introduces the University of

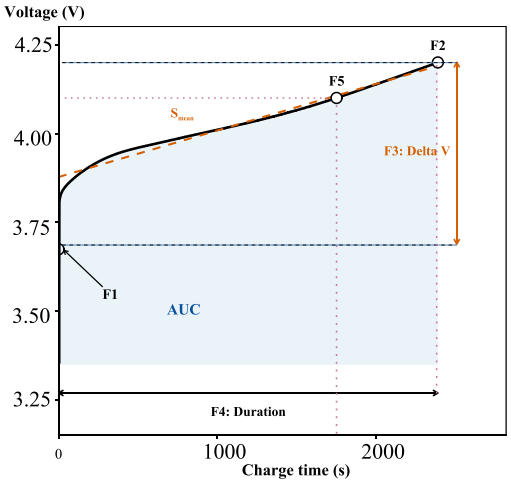


Figure 4. Feature extraction from a NASA B0005 charging voltage curve.

Maryland CALCE dataset as the additional validation dataset. The related research usually uses CS2-35, CS2-36, CS2-37 and CS2-38 as the same group of experimental batteries, with a nominal capacity of about 1.1 Ah, and uses constant current-constant voltage charging and constant current discharge methods for cycle testing. Similar to the NASA data set, the CALCE data set also contains charging voltage curves and capacity degradation information under different cycles, which can be used to test the applicability of the model on different data sources and different battery samples.

4.2. Data preprocessing and feature extraction

Before the model training, it is necessary to preprocess the original battery cycle data and extract the characteristics that can reflect the aging state of the battery from the charging curve [28, 29]. This paper focuses on the voltage, current and time information during the charging process, because the shape of the charging curve will change with battery aging, such as voltage platform offset, charging time change and curve slope change. These changes can reflect the decline of battery capacity to a certain extent.

Figure 4 illustrates the extraction of representative charging-voltage features from one NASA B0005 charging cycle. F1 and F2 denote the initial and final voltages, respectively. F3 represents the voltage change during charging, while F4 denotes the charging duration.

F5 denotes the time required for the voltage to reach 4.10 V. The threshold of 4.10 V was selected because it is located in the high-voltage charging region of the NASA batteries but remains below the upper cut-off voltage of about 4.20 V. Therefore, this feature can reflect the evolution of the voltage-rise process before the strong saturation behavior near the end of charging. As battery aging progresses, the internal resistance, polarization behavior, and available capacity change, which affects the time required to reach this voltage threshold. Thus, the time to 4.10 V can serve as a representative health-related feature for SOH estimation. It should be noted that this threshold is selected according to the charging protocol and voltage range of the NASA dataset, and it can be adjusted when the method is applied to other battery chemistries or charging protocols. In addition, the shaded region represents the voltage-time integral area, and the dashed line indicates the mean voltage-rise slope obtained by linear fitting. These features characterize the global shape, rising behavior, and temporal evolution of the charging curve, and are therefore used as health indicators for SOH estimation.

For the mth charging cycle, the feature vector $\boldsymbol{x}_m$ is obtained from the corresponding charging voltage–time curve. In this study, representative features are extracted to characterize the charging behavior and degradation-related curve evolution, including the initial charging voltage, final charging voltage, voltage change during charging, charging duration, time required to reach a specified voltage threshold, area under the voltage–time curve, and mean voltage-rise slope. These features are denoted as F1–F5, area under the voltage–time curve (AUC), and mean voltage-rise slope obtained by linear fitting (S_{mean}) in figure 4. Therefore, the feature vector can be written as

$$\boldsymbol{x}_m = [V_{\text{start}}, V_{\text{end}}, \Delta V, T_{\text{ch}}, T_{4.10\text{V}}, \text{AUC}, S_{\text{mean}}], \tag{19}$$

where V_{start} and V_{end} are the initial and final voltages of the selected charging segment, ΔV is the voltage change, T_{ch} is the charging duration, $T_{4.10\text{V}}$ is the time required to reach 4.10 V, AUC, and S_{mean}.

For each cycle, the voltage, current and time series of the charging stage are first extracted, and the outliers and missing values are removed. Then, the feature vector is constructed according to the charging curve to represent the battery state of the cycle. Let the charging curve feature vector of the mth cycle be :

$$\boldsymbol{x}_m = [x_{m,1}, x_{m,2}, \ldots, x_{m,d}], \tag{20}$$

where d denotes the feature dimension. The corresponding measured capacity is recorded as c_m. Therefore, the entire battery data can be expressed as:

$$\mathbf{D} = \{(\boldsymbol{x}_m, c_m)\}_{m=1}^{N}, \tag{21}$$

where N is the number of battery cycle samples.

In order to facilitate the comparison between different batteries, the capacity can also be further converted to SOH :

$$\text{SOH}_m = \frac{C_m}{C_0}, \tag{22}$$

where C_0 represents the initial capacity of the battery, and C_m represents the capacity of the mth cycle. If the model directly predicts the capacity, the subsequent evaluation index is calculated based on the estimation error. If the model predicts SOH, the evaluation index is calculated based on the SOH error. This paper maintains the consistency of training labels and evaluation indicators in the experiment.

Because the charging process in practical battery operation may be affected by user behavior, charging interruption, and inconsistent initial and final SOC, the complete charging curve is often difficult to obtain. In order to simulate the incomplete

charging data in practical applications, this paper randomly sets some charging features as missing values in the training samples, and records the missing positions through the missing indication matrix. For missing features, NA is used for labeling; at the same time, some capacity labels are set to unknown or censored states to simulate unlabeled or semi-supervised learning scenarios.

In the SVGMR framework, incomplete samples are not simply deleted, but participate in model training by missing indicator matrix and censoring boundary. Specifically, SVGMR-C mainly uses complete samples for modeling; SVGMR-A uses both complete and incomplete samples. SVGMR-O further introduces an online update mechanism based on SVGMR-A. On this basis, this paper introduces the historical capacity degradation trend prior and Bayesian fusion correction to further improve the SOH prediction accuracy.

In addition, in order to eliminate the influence of different feature dimension differences on model training, this paper standardizes input features and capacity labels. The standardization process only uses the mean and standard deviation of the training set, and the test set uses the same training set statistics for transformation to avoid the leakage of test information. The standardized formula is as follows:

$$x^* = \frac{x - \mu_{\text{train}}}{\sigma_{\text{train}}}, \tag{23}$$

where μ_{train} and σ_{train} denote the mean and standard deviation of the training set, respectively, and x^* denotes the normalized eigenvalue.

4.3. Evaluation metrics

In order to quantitatively evaluate the SOH prediction performance of different methods, this paper uses RMSE and MAE as the main evaluation indicators.

RMSE is defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N_r}\sum_{i=1}^{N_r}(\hat{c}_i - c_i)^2}, \tag{24}$$

where c_i represents the true capacity or true SOH of the ith sample, $\hat{c}_i$ represents the predicted value of the model, and N_r represents the number of test samples. RMSE is more sensitive to larger prediction errors and can reflect the overall prediction bias of the model.

$$\text{MAE} = \frac{1}{N_r}\sum_{i=1}^{N_r}|\hat{c}_i - c_i|. \tag{25}$$

MAE represents the average absolute deviation between the predicted value and the true value, which can more intuitively reflect the average prediction error of the model.

In summary, this chapter describes the experimentaI scheme from three aspects: dataset sources, datapreprocessing procedures, and evaluation indices. In the next chapter, based on the above experimental design, the prediction results of the proposed method on NASA dataset and CALCE dataset are analyzed in detail.

5. Results

Based on the experimental design described in Chapter 4, this chapter verifies and analyzes the proposed Bayesian fusion online correction method based on historical capacity degradation trend prior.

5.1. Prediction performance on the NASA dataset

In order to verify the improvement of the prediction performance of the original SVGMR model by the Bayesian fusion online correction method, this paper first analyzes the three models of SVGMR-C, SVGMR-A and SVGMR-O on the NASA dataset, and compares the original prediction results with prediction results after Bayesian fusion. Figure 5 shows the SOH estimation curve, RMSE comparison, absolute error trend and uncertainty analysis results of three SVGMR variants on the NASA dataset.

As shown in figure 5(a), the original SVGMR predictions generally follow the overall declining trend of battery SOH. However, noticeable deviations remain in certain cycle intervals, particularly during the later stages of degradation and in regions with significant local fluctuations. The difference between the original prediction curve and the real SOH curve is more obvious. As shown in figure 5(b), after adding Bayesian fusion, RMSE of the three SVGMR models is significantly reduced, indicating that the historical capacity degradation trend prior can effectively improve SOH prediction accuracy. The incorporation of Bayesian fusion further improves the prediction accuracy of all three SVGMR variants. This improvement indicates that the proposed fusion strategy serves as a general online correction mechanism that is not limited to any specific SVGMR variant. In figure 5(c), after introducing historical capacity degradation trend prior and Bayesian fusion, the overall estimated SOH curve is closer to the actual one. Figure 5(d) presents the uncertainty analysis of the Bayesian-fused SVMR-O model, showing that its estimated SOH mean closely follows the true degradationtrajectory, with confidence intervals that properly characterize the prediction uncertainty across the full battery cycle range.

In summary, results show that the Bayesian fusion method can make full use of historical capacity degradation trends of the target battery and dynamically correct the estimates of SVGMR, so that the estimated curve is closer to the real SOH degradation trajectory.

5.2. Ablation study

In order to verify the contribution of each module in the proposed method, an ablation experiment was further designed. The final Bayesian fusion method was compared with SVGMR-O original prediction, historical prior only, and fixed-window fusion [15, 27]. Figure 6 presents the SOH prediction curve, RMSE comparison, absolute error trend, and uncertainty analysis results of different ablation models.

As shown in figure 6(a), SVGMR-O can roughly follow the overall decreasing trend of SOH, but obvious deviations still exist in some cycle intervals. The historical prior only

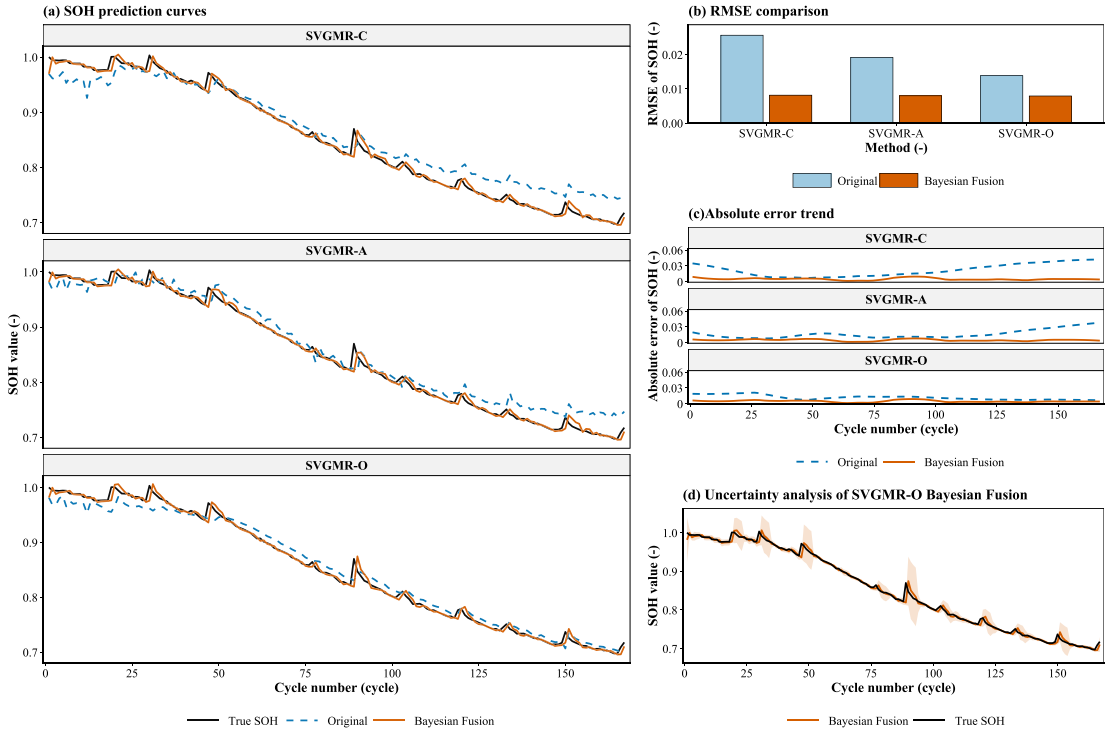


Figure 5. SOH prediction performance of SVGMR variants with Bayesian fusion on the NASA dataset.

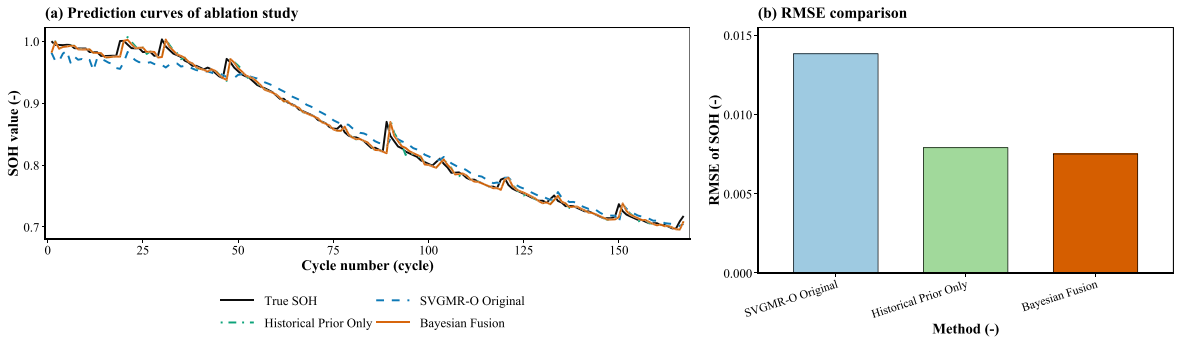


Figure 6. Ablation study of historical degradation prior and Bayesian fusion strategy.

method relies on the historical capacity degradation trend for prediction, and can describe the general direction of capacity fade. However, since it does not fully use the state information contained in the current-cycle charging curve, its ability to characterize local fluctuations and abrupt changes is limited. Compared with these two single-source methods, Bayesian fusion combines the SVGMR observation prediction and the historical degradation prior, leading to a prediction curve that is closer to the true SOH trajectory. This indicates that the charging-curve-based observation information and historical degradation trend information are complementary for SOH estimation.

Figure 6(b) further compares the RMSE values of different ablation models. The Bayesian fusion method achieves a lower RMSE than SVGMR-O original prediction and historical prior only, demonstrating that the fusion of current observation prediction and historical trend prior can effectively reduce the overall prediction error.

Therefore, the ablation experiment verifies the rationality of the proposed method design. The historical capacity degradation trend provides effective prior information for SOH prediction, while the Bayesian fusion mechanism integrates this prior with the SVGMR observation prediction. The performance improvement is not caused by a single module, but by the joint effect of historical degradation prior modeling and Bayesian uncertainty fusion, which improves the accuracy and stability of SOH estimation.

5.3. Leave-one-battery-out cross-validation results

In order to verify the generalization ability of the model among different batteries, this study adopts a leave-one-battery-out

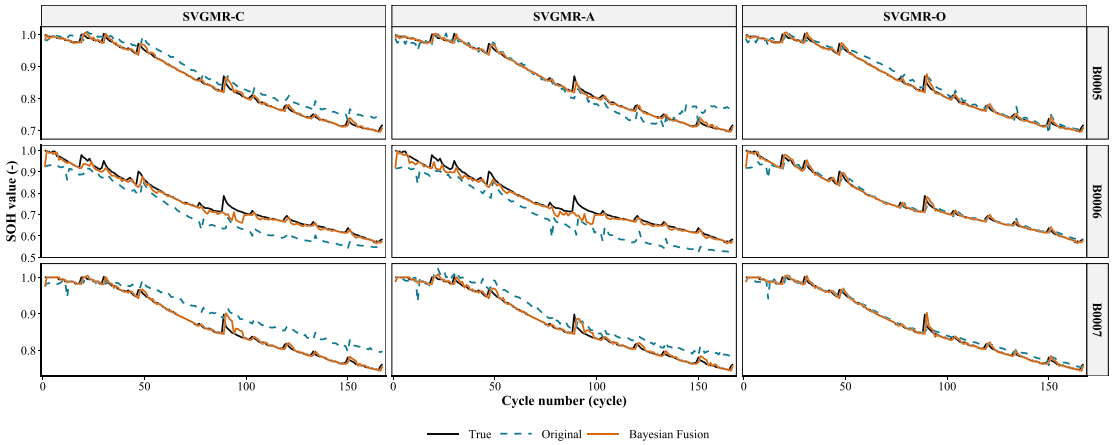


Figure 7. Leave-one-battery-out cross-validation results of SVGMR variants with Bayesian fusion.

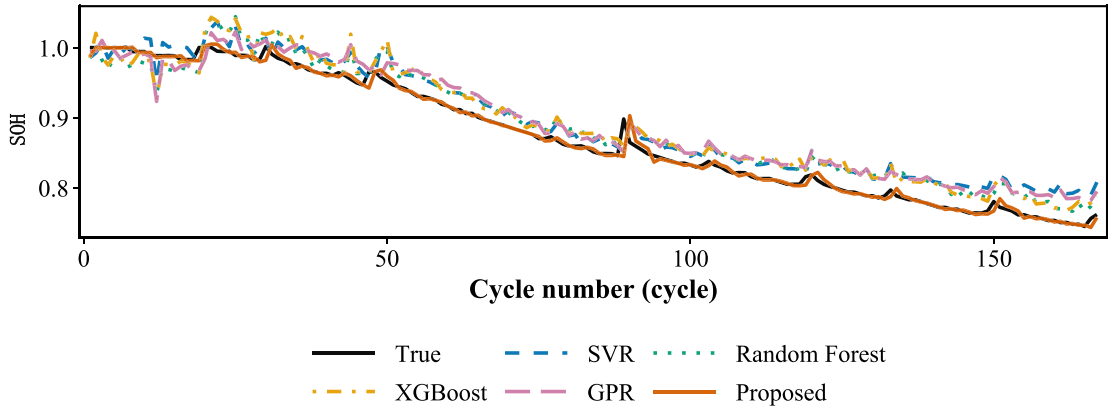


Figure 8. Comparison of SOH prediction performance with traditional machine learning baselines.

cross-validation strategy to conduct experiments. Specifically, a leave-one-battery-out strategy is adopted, where one of B0005, B0006, and B0007 is heldout as the test set while the other two serve as the training set, and this process is repeated for each battery.

As shown in figure 7, Bayesian fusion results for test batteries B0005, B0006, and B0007 track the real SOH degradation trend more closely, indicating that the proposed method generalizes well to unseen batteries. The leave-one-battery-out validation results therefore confirm that the proposed method not only improves estimation accuracy on a single battery but also maintains stable prediction performance across different batteries.

5.4. Comparison with baseline data-driven models

To further verify advantages of the proposed method over common data-driven models, this paper selects SVR, random forest, XGBoost and GPR as traditional machine learning baseline models [30, 31]. Figure 8 shows SOH prediction curves on NASA dataset.

As shown in figure 8, traditional machine learning models can track the overall degradation trends of SOH to a certain extent, but exhibit varying degrees of deviation in the late degradation and local fluctuationregions. In contrast, the prediction curve of our proposed method closely follows the real SOH, indicating that it more accurately captures the battery capacity degradation process. Furthermore, the proposed method achieves the lowest prediction error across all three test batteries.

Figure 9 further compares the average RMSE values of different models across the test batteries. The proposed method achieves the lowest average RMSE among all compared methods. Specifically, the RMSE values of the proposed method on B0005, B0006, and B0007 are approximately 0.0080, 0.0141, and 0.0072, respectively, which are consistently lower than those of benchmark models. The average RMSE of the proposed method is about 0.0098, whereas the average RMSE values of SVR, RF, XGBoost, and GPR are approximately 0.0461, 0.0400, 0.0390, and 0.0582, respectively. These results demonstrate that the proposed method has better overall prediction accuracy and stronger degradation-trend tracking ability than the selected baseline data-driven models.

5.5. Generalization verification of CALCE datasets

This experiment is designed to validate the generalization performance of the proposed model on unseen batteries excluded from the training set. Given inherent variations in

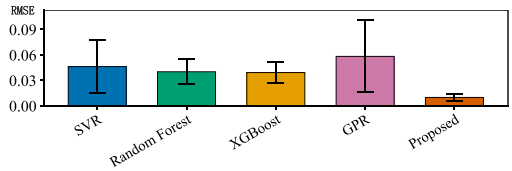


Figure 9. Average RMSE comparison between the proposed method and baseline data-driven models on the NASA dataset.

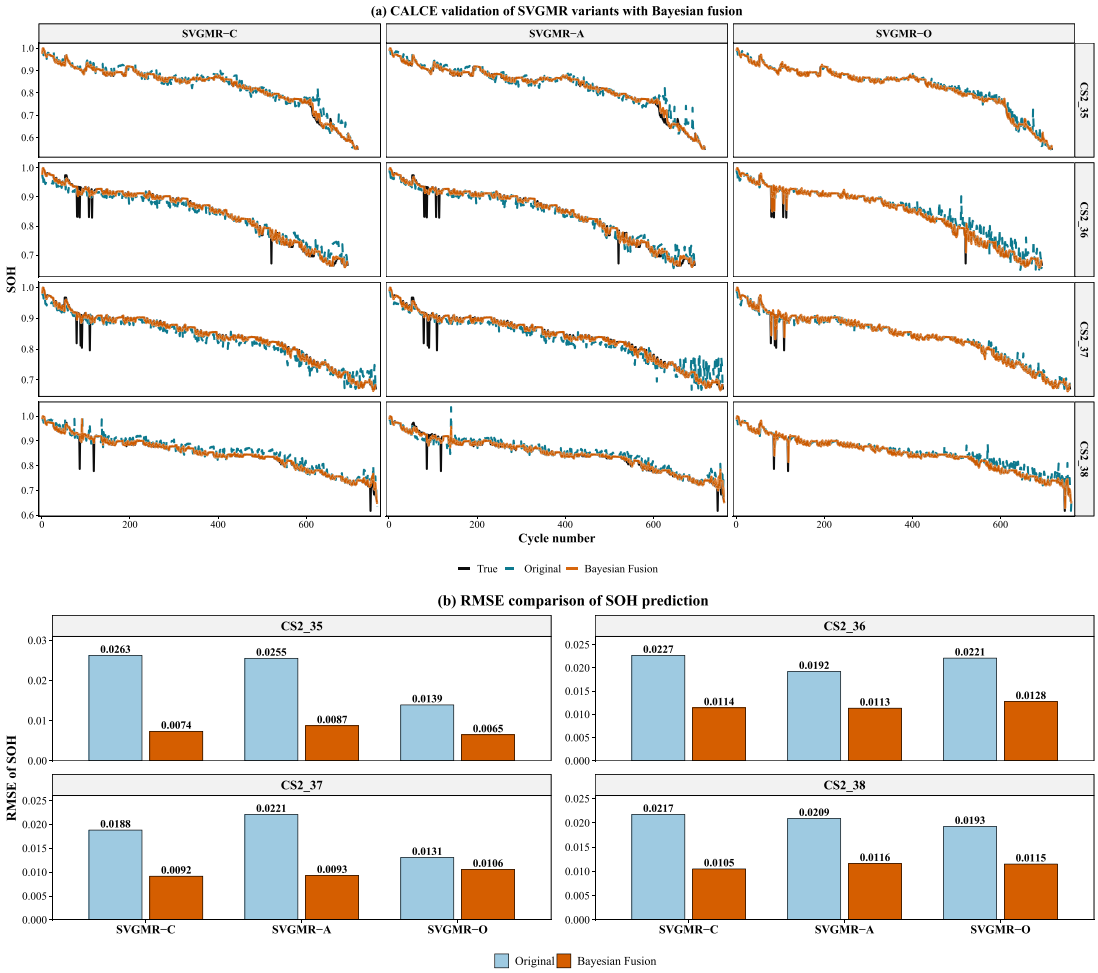


Figure 10. Generalization validation of Bayesian fusion method on the CALCE dataset.

material properties, manufacturing inconsistencies and degradation trajectories across individual batteries, cross-battery generalization capability has emerged as a critical evaluation dimension in SOH estimation research over the past decade [9, 32, 33]. To further verify the applicability of the Bayesian fusion online correction method proposed in this paper to different data sources, we conduct external generalization verification using the University of Maryland CALCE dataset. Compared with the NASA dataset the CALCE dataset originates from a different experimental platform and exhibits distinct battery specifications, cycle lengths, and degradation characteristics, making it suitable for testing the cross-dataset generalization ability of the proposed method.

Figure 10(a) presents the SOH prediction curves of different SVGMR variants on the CALCE dataset. It can be seen that the SOH of four batteries showed different degrees of decline with the increase in the number of cycles. Among them, CS2-35 and CS2-38 decreased more obviously in the later degradation stage, while CS2-36 and CS2-37 showed some local fluctuations. The original SVGMR prediction results can roughly track the overall degradation trend of SOH, but there are still fluctuations and deviations in some cycle intervals. After introduction of Bayesian fusion, the prediction curve is closer to the real SOH curve as a whole, especially in the later stage of degradation and the area with obvious local fluctuation, the fusion result shows better stability. Figure 10(b) gives RMSE comparison results on the CALCE dataset. It can be seen that on the four batteries, the RMSE of the three SVGMR variants decreased to varying degrees after Bayesian fusion. Taking CS2-35 as an example, the RMSE of SVGMR-C

decreased from 0.0263 to 0.0074, SVGMR-A decreased from 0.0255 to 0.0087, and SVGMR-O decreased from 0.0139 to 0.0065. It shows that the proposed method can still maintain a low prediction error on the CALCE dataset.

Consistent with experimental results of NASA dataset, the validation of CALCE dataset further shows that the historical capacity degradation trend prior can provide an effective supplement to the current observation prediction of SVGMR. When the original prediction curve is affected by local fluctuations or model generalization errors, Bayesian fusion can use historical degradation trends to constrain and correct the prediction results, thereby improving the stability of SOH estimation. Due to the difference in data sources and degradation characteristics between CALCE dataset and NASA dataset, the experimental result show that the proposed method has certain cross-dataset generalization ability.

In summary, external verification results on CALCE dataset further prove the effectiveness of the proposed Bayesian fusion online correction method. This method can not only improve the prediction accuracy from SVGMR on the NASA dataset, but also maintain good prediction performance on the CALCE dataset of the University of Maryland, indicating that the fusion mechanism of historical capacity degradation trend prior and Bayesian uncertainty has good versatility and robustness.

6. Conclusion

This study proposed a Bayesian-fusion SVGMR framework for LIB SOH estimation under incomplete charging-curve conditions. The proposed method integrated the SVGMR observation prediction with a historical capacity degradation trend prior, so that both current-cycle charging-curve information and historical degradation behavior could be used for online SOH estimation.

Main findings of this study were summarized as follows. First, the historical degradation trend prior provided effective supplementary information to the current-cycle SVGMR prediction, especially when incomplete charging features or local prediction fluctuations reduce the reliability of the observation prediction. Second, the uncertainty-weighted Bayesian fusion mechanism adaptively balanced the SVGMR observation prediction and the historical prior according to their uncertainties, thereby improving prediction accuracy and stability. Third, experimental results on the NASA dataset showed that Bayesian fusion consistently improves the prediction performance of SVGMR-C, SVGMR-A, and SVGMR-O. The ablation study further confirmed that the improvement is achieved through the joint effect of historical trend modeling and Bayesian fusion. Finally, the leave-one-battery-out validation and CALCE dataset verification demonstrated that the proposed framework has good robustness and generalization ability under incomplete charging conditions.

Overall, the proposed BF-SVGMR framework provided an effective and interpretable solution for online battery SOH estimation when complete charging curves are difficult to obtain. The results indicated that incorporating historical degradation behavior into probabilistic regression is beneficial for improving the reliability of SOH estimation in practical battery management applications. Nevertheless, the present study was mainly validated on public datasets under relatively controlled experimental conditions. Future work will focus on extending the proposed framework to more complex operating scenarios, including variable temperature, different charging protocols, dynamic current profiles, and real-world electric vehicle data. In addition, the integration of the proposed Bayesian fusion strategy with physics-informed battery models will be further investigated to improve interpretability and generalization ability.

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ORCID iD

Xingchen Liu 0000-0001-6576-2434

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Hongjie Lv received a BE degree in Automation from Taiyuan University of Technology, Taiyuan, China, in 2025. He is currently pursuing an MS degree in Instrument Science and Technology at Hebei University of Technology, Tianjin, China. His research interests include health prognostics of batteries.



Xingchen Liu received a BE degree in Measurement and Control Technology and Instruments from Hunan University, Changsha, China, in 2014, an MS degree in Instrument Science and Technology from the University of Science and Technology of China, Hefei, China, in 2017, and a PhD degree in Industrial Systems Engineering and Management from the National University of Singapore, Singapore, in 2021. He is currently a Research Assistant Professor at the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China. His research interests include machine learning, process monitoring, reliability engineering, and prognostics and health management.



Dong Wang received his PhD degree from the City University of Hong Kong, Hong Kong, in 2015. He then held positions as a Senior Research Assistant, a Postdoctoral Fellow, and a Research Fellow at the same university from 2015 to 2018. He is currently a Tenured Associate Professor in the Department of Industrial Engineering and Management School of Mechanical Engineering, at Shanghai Jiao Tong University, Shanghai, China, where he is also affiliated with the State Key Laboratory of Mechanical System and Vibration. His research interests include sparsity and complexity measures, signal processing, statistical learning, probability models, optimization, and their applications to condition monitoring, fault diagnosis, prognostics and health management, and nondestructive testing.



Bingchang Hou received his PhD degree in Mechanical Engineering, Industrial Engineering, from Shanghai Jiao Tong University, Shanghai, China, in 2024. During his PhD study, he was a visiting student at the City University of Hong Kong for one year. He is currently with the State Key Laboratory of Mechanical Transmission for Advanced Equipment, Chongqing University, Chongqing, China. His research interests include machine fault diagnosis and prognostics, intelligent autonomous systems, and robotics. Dr Hou has received five Outstanding Reviewer Awards from *IEEE Transactions on Instrumentation and Measurement* and *Mechanical Systems and Signal Processing*.



Dong Zhen received BS and MS degrees from Shandong University of Science and Technology, Qingdao, China, in 2006 and 2009, respectively, and a PhD degree from the University of Huddersfield, Huddersfield, UK, in 2012, all in Mechanical Engineering. He is currently a Professor of the School of Mechanical Engineering, Hebei University of Technology, Tianjin, China. His main research interests include machinery fault diagnostics, signal processing, and intelligent algorithms development.



Jinzhen Kong received a BS degree from Harbin Engineering University, Harbin, China, in 2017, and a PhD degree from Shanghai Jiao Tong University, Shanghai, China, in 2023. She is currently an Associate Professor in School of Mechanical Engineering, Hebei University of Technology, Tianjin, China. Her research interests are prognostics and health management, degradation modeling, and health prognostics of batteries.