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A HYBRID CNN-BAYESIAN LSTM MODEL WITH AKIMA-EMD FOR RUL PREDICTION OF LITHIUM-ION BATTERIES

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Abstract

A hybrid framework for accurate remaining useful life (RUL) prediction of lithium-ion batteries is developed by integrating Akima-based empirical mode decomposition (Akima-EMD) with a CNN-Bayesian LSTM model. Existing approaches, such as EMD-LSTM and EMD-CNN-LSTM, have improved prediction accuracy but remain constrained by limitations of traditional EMD, including overshoot, envelope distortion, and sensitivity to irregular degradation patterns. To address these issues, Akima-EMD is employed as a preprocessing method to decompose and denoise capacity signals while preserving meaningful degradation trends. A one-dimensional convolutional neural network (1D-CNN) is used for feature extraction, and a bidirectional LSTM is adopted to capture temporal dependencies. In addition, Bayesian optimization is applied to automatically tune key hyperparameters, improving model robustness under noisy and limited data conditions. The proposed framework is validated using NASA Ames Prognostics Centre of Excellence datasets (B0005 and B0006) under varying training conditions. Experimental results demonstrate that the proposed model consistently outperforms conventional LSTM and CNN-LSTM models, achieving the lowest end-of-life prediction error when combined with Akima-EMD preprocessing. These findings indicate that the proposed framework effectively handles nonlinear and irregular degradation patterns, providing a robust and reliable solution for battery RUL prediction and contributing to predictive maintenance in energy storage and electric vehicle systems.

Keywords: Akima-EMD, CNN-Bayesian LSTM, Lithium-Ion battery, Remaining useful life (RUL) prediction.

1. Introduction

Lithium-ion batteries (LIBs) have been widely used as one of the most prominent rechargeable battery technologies due to their energy density, large capacity, reliability, and safety. In particular, they serve as primary power sources in various applications such as electric vehicles (EVs), energy storage systems (ESS), and intelligent manufacturing systems, including computational engineering, logistics, and aerospace industries.

However, LIBs gradually degrade over repeated charge and discharge cycles, leading to a reduction in capacity. This degradation can result in unexpected performance drops and failures in the systems powered by the batteries, potentially causing critical accidents or safety issues. Therefore, accurately predicting the remaining useful life (RUL) of a battery is essential to optimize replacement schedules, reduce maintenance costs, and improve overall system reliability and safety. RUL prediction is particularly crucial in intelligent manufacturing environments, where battery performance degradation can significantly affect operational efficiency and maintenance planning.

Conventional studies on LIB RUL prediction have primarily relied on model-driven methods, which analyse the physical and chemical properties of batteries and express them using mathematical or physical models. Typical approaches include Physics-of-Failure modelling, Kalman Filtering, and Particle Filtering (PF), which attempt to approximate the degradation trajectory of a battery and predict its future behaviour. However, the complexity of the internal electrochemical characteristics of LIBs makes it difficult to tune model parameters accurately and update them in real time under varying operational conditions.

Additionally, batteries are highly sensitive to external factors such as temperature and humidity, making it challenging to construct universally accurate mathematical models. Moreover, model-driven approaches often suffer from issues like particle degeneracy in PF, which severely limits their prediction accuracy.

To overcome these limitations, data-driven approaches have emerged as promising alternatives. These methods do not require physical modelling of the battery; instead, they utilize historical degradation data stored in battery management systems for prediction. Among them, Long Short-Term Memory (LSTM) networks have gained attention for their ability to learn dynamic time-series patterns in battery behaviour. However, in practical applications, noisy signals and intermittent capacity regeneration - an irregular increase in capacity caused by residual reaction product loss - can degrade LSTM performance. Hence, additional techniques are necessary to prevent learning performance deterioration in LSTM-based RUL prediction algorithms.

1.1. Related works

An LSTM-based recurrent neural network was proposed to predict the RUL of lithium-ion batteries by effectively learning long-term dependencies from degradation sequences. Although the model achieved higher prediction accuracy than support vector machines and particle filters under various conditions, it lacked a built-in mechanism to quantify prediction uncertainty. Instead, Monte

Carlo simulation was externally employed to approximate uncertainty, which may not align well with real-time or probabilistic modelling needs. This highlights the necessity for architectures that can estimate uncertainty internally, such as Bayesian deep learning frameworks [1].

A CNN-LSTM fusion model was proposed for predicting RUL of lithium-ion batteries, where the CNN was used for extracting spatial features and the LSTM for modelling temporal dependencies. Additionally, grey relational analysis was employed to enhance input feature selection. The model demonstrated improved accuracy over standalone deep learning architectures. However, it remained a deterministic framework without mechanisms for uncertainty quantification and did not explicitly address the effects of irregular capacity behaviour or signal noise. These limitations highlight the need for more robust probabilistic models that can both quantify prediction confidence and adapt to real-world capacity anomalies [2].

A hybrid model-based prognostics framework was developed for estimating the RUL of rolling bearings. The study showed that the CNN-Bayesian LSTM model outperformed the standard LSTM and CNN-LSTM models in terms of prediction accuracy and uncertainty estimation. In particular, the proposed model achieved the highest accuracy (R^2 = 0.9949) and the lowest RMSE (0.0182), demonstrating stable prediction capability even under noisy and variable conditions.

Although this framework was validated only on mechanical systems, its ability to handle noise and generate probabilistic outputs suggests strong potential for adaptation to lithium-ion battery prognostics. Considering the complex and irregular degradation patterns of batteries, such an architecture represents a promising direction for improving the reliability of RUL prediction under uncertain conditions [3].

A hybrid EMD-CNN-LSTM model was developed to predict the RUL of lithium-ion batteries. Empirical Mode Decomposition (EMD) was applied to decompose raw capacity data into intrinsic mode functions (IMFs), which were then processed using a CNN-LSTM architecture to capture both spatial and temporal features. This structure was designed to enhance learning from complex degradation patterns. However, the model's prediction accuracy was noticeably limited when trained on a small number of cycles, indicating that the architecture may require a relatively large amount of training data to achieve stable performance [4].

EMD was applied as a signal filtering technique aimed at processing nonlinear and non-stationary data. The study demonstrated that EMD could adaptively decompose signals into IMFs, allowing effective separation of noise and relevant signal components without requiring prior knowledge of the signal structure. This made EMD attractive for real-time signal processing and feature extraction in dynamic environments. However, cubic spline interpolation in envelope construction introduced issues such as mode mixing and boundary effects, which degraded the filtering quality and consistency of the decomposition process, especially when handling short or rapidly fluctuating signals [5].

Ensemble Empirical Mode Decomposition (EEMD) was proposed to address the mode mixing problem inherent in classical EMD. The method involves adding white noise to the original signal, applying EMD multiple times, and averaging the resulting IMFs across ensembles. This approach statistically stabilizes the decomposition process and improves the physical interpretability of IMFs in noisy environments. Despite these advantages, EEMD increases computational cost due to the need for multiple EMD runs and introduces residual noise into the reconstructed signal, which may affect the clarity and precision of downstream analyses [6].

The Complementary Ensemble Empirical Mode Decomposition (CEEMD) method was applied to denoise ground-penetrating radar (GPR) signals and enhance target extraction. CEEMD improves upon EEMD by adding pairs of positive and negative white noise to cancel out residual noise during ensemble averaging. This approach was shown to reduce mode mixing and enhance signal clarity without introducing significant artifacts.

However, the method still involves multiple EMD iterations, leading to high computational cost, and its effectiveness is sensitive to the amplitude and number of noise pairs, requiring careful parameter tuning for different signal conditions [7].

A modified empirical mode decomposition method called Akima-EMD was proposed, which replaces the conventional cubic spline interpolation with Akima spline interpolation to improve the stability of signal decomposition. Through extensive experiments, the study compared Akima-EMD with classical EMD, EEMD, and CEEMD techniques, demonstrating that Akima-EMD consistently achieved superior performance in terms of decomposition clarity and denoising accuracy. These results suggest that Akima-EMD is a robust preprocessing approach and may be particularly effective when applied to lithium-ion battery capacity signals, which often include nonlinear degradation and capacity regeneration behaviour [8].

A hybrid model combining complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and long short-term memory (LSTM) networks was proposed for lithium-ion battery life prediction. CEEMDAN was used to decompose nonlinear capacity degradation signals into IMFs, which were individually processed by LSTM to capture temporal patterns. The hybrid structure aimed to improve prediction accuracy under complex degradation conditions. However, the approach remained sensitive to decomposition noise, and CEEMDAN required careful parameter tuning to avoid redundant or meaningless components. In addition, LSTM may overfit when trained on limited battery cycles, particularly in the early stages of degradation [9].

An RUL prediction model for lithium-ion batteries was developed by combining an improved variational mode decomposition (VMD) technique with traditional machine learning algorithms. The improved VMD was used to extract intrinsic signal components with reduced mode aliasing and better frequency localization, and the resulting features were used as inputs to regression models such as random forest and support vector regression. This approach aimed to improve prediction accuracy by enhancing signal quality before model training. However, the overall performance was still affected by the sensitivity of VMD to decomposition parameters and the dependence of learning accuracy on manual feature selection and model tuning [10].

Overall, prior studies employing EMD, CEEMDAN, VMD, and attention-based hybrid models have significantly advanced RUL prediction by improving feature representation and capturing nonlinear degradation dynamics. Nevertheless, several limitations remain, including instability in signal decomposition, sensitivity to parameter selection, insufficient mechanisms for uncertainty quantification, and restricted performance under data-scarce or irregular degradation conditions. To address these gaps, this study proposes a hybrid framework that integrates Akima-EMD with a CNN-Bayesian LSTM architecture, aiming to achieve more stable signal decomposition, robust spatio-temporal feature learning, and uncertainty-aware prediction.

To this end, the proposed model incorporates Akima-based Empirical Mode Decomposition (Akima-EMD) as a preprocessing technique to decompose noisy time-series signals using Akima interpolation, thereby reducing noise caused by capacity regeneration and enabling effective extraction of degradation patterns. A CNN-Bayesian LSTM architecture is then employed to learn both spatial and temporal features, with Bayesian Optimization dynamically tuning key hyperparameters to improve prediction accuracy and generalization compared to conventional CNN-LSTM models.

As shown in Fig. 1, the overall framework of the proposed approach utilizes the B0005 and B0006 datasets from the NASA PCoE, with training subsets consisting of 40, 50, and 60 cycles. These data are employed either in their raw form or after preprocessing with EMD and Akima-EMD, and subsequently used to train LSTM, CNN-LSTM, and CNN-Bayesian LSTM models. The framework culminates in RUL prediction based on a 70–80% capacity threshold, followed by performance evaluation.

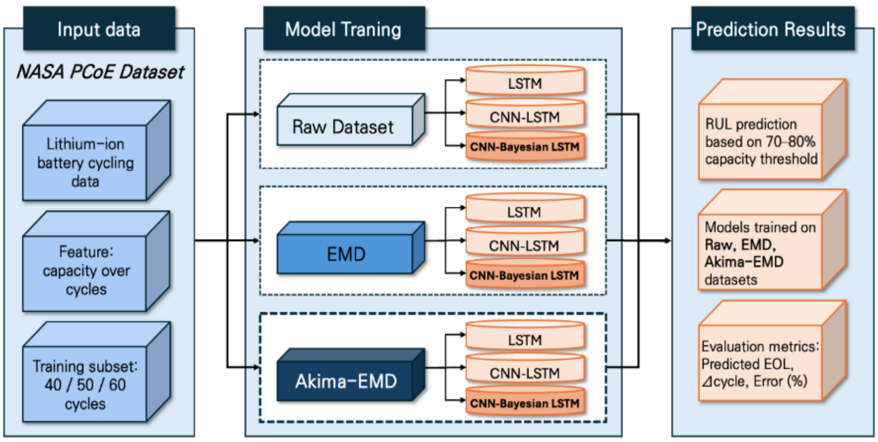

Fig. 1. Workflow of the proposed CNN-Bayesian LSTM with Akima-EMD.

The remainder of this paper is structured as follows: Section 2 introduces the NASA Ames PCoE dataset and describes the Akima-EMD preprocessing technique and outlines the architecture and functioning of the CNN-Bayesian LSTM model. Section 3 presents experimental results that validate the proposed approach by comparing the performance of LSTM, CNN-LSTM, and CNN-

Bayesian LSTM models across raw, EMD-pre-processed, and Akima-EMD-pre-processed datasets.

2. Proposed Methodology

2.1. NASA Ames PCoE battery life dataset

Lithium-ion battery degradation data provided by the NASA Ames Prognostics Centre of Excellence (PCoE) was utilized to predict the RUL of batteries in this research. The dataset contains measurements of capacity reduction obtained through repeated charge and discharge cycles of 18650 lithium-ion battery cells. Among the available data, B0005 and B0006 cells were selected for analysis.

As shown in Fig. 2, although both batteries were tested under similar experimental conditions, they exhibit different degradation rates and fluctuation patterns, allowing the model to learn diverse capacity degradation trends. In particular, the red-circled regions indicate the occurrence of capacity regeneration phenomena, highlighting that the dataset contains high volatility. Both batteries nevertheless demonstrate a gradual decline in capacity as the number of charge-discharge cycles increases over time.

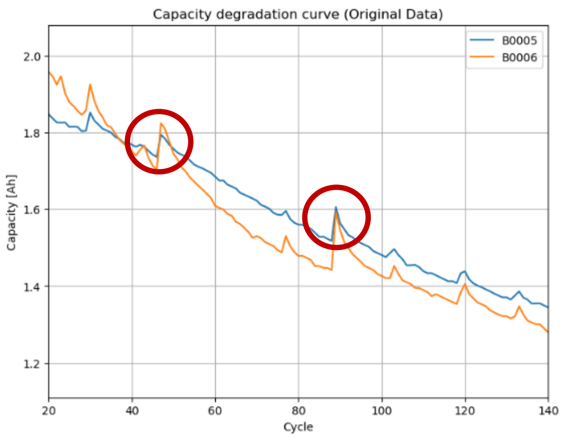

Fig. 2. Capacity degradation curve of the NASA PCoE lithium-ion battery.

To predict RUL, only the capacity variable was used in this study. Capacity is the primary indicator of battery performance degradation and decreases steadily with cycling, making it a reliable metric for predictive modelling. Signal processing techniques including Empirical Mode Decomposition (EMD) and Akima-based EMD (Akima-EMD) were applied to eliminate noise and extract essential signal features. After applying both preprocessing methods, the signals were used as inputs to evaluate the prediction performance of the CNN-Bayesian LSTM model.

EMD decomposes the battery capacity degradation curve into multiple frequency components (IMFs), providing insight into the signal's underlying patterns. However, the EMD method is prone to the mode mixing problem, which can obscure the meaningful structure of the signal. To address this limitation, Akima-EMD was employed. This approach utilizes Akima spline interpolation instead of cubic splines, enabling smoother and more stable signal decomposition. By more accurately extracting meaningful patterns in the data, Akima-EMD improves the reliability of prediction inputs and enhances the interpretability of battery degradation trends. Developing a precise and trustworthy model for RUL prediction by effectively analysing battery degradation patterns through this preprocessing is a central objective of this research.

2.2. Akima-EMD (Empirical Mode Decomposition)

Empirical Mode Decomposition (EMD) is a signal processing technique developed to analyse nonlinear and non-stationary signals. It decomposes the original signal into a series of Intrinsic Mode Functions (IMFs) by identifying local extrema, generating upper and lower envelopes using cubic spline interpolation, and computing the mean of these envelopes to isolate oscillatory components. The remaining signal is iteratively decomposed until a monotonic residue is obtained.

Akima-EMD (Akima-Empirical Mode Decomposition) was proposed to overcome limitations of conventional EMD. The cubic spline interpolation used in EMD can cause overshoot and undershoot, distorting the signal and resulting in less accurate IMFs. In contrast, Akima-EMD uses Akima spline interpolation, which mitigates these issues and produces more stable signal decompositions.

Akima-EMD begins by isolating the initial oscillatory components from the signal, constructs upper and lower envelopes using local extrema, and calculates their mean using Akima interpolation. This mean is then subtracted from the original signal to extract the first IMF. This process is repeated until a predefined stopping criterion is met. In this study, the decomposition was terminated when one of the following conditions was satisfied: (i) the standard deviation of the residual signal fell below 5% of the original signal's standard deviation, (ii) fewer than two local maxima or minima remained, preventing further envelope construction, or (iii) the maximum number of IMFs, set to 10, was reached. If residual oscillations remained after these conditions, further decomposition could be performed using a revised EMD version.

Unlike cubic spline interpolation used in traditional EMD, that can suffer from overshoot and undershoot due to its global nature, Akima spline interpolation relies on local gradients, thereby ensuring higher stability in constructing envelopes. This stability leads to more accurate IMFs, providing theoretical support for the superior prediction performance observed with Akima-EMD.

Algorithm 1 Akima-EMD algorithm [8].

1. By using the Akima spline interpolation approach, isolate the initial oscillatory component $k^*(t)$ from the noisy signal $y(t)$.
2. Determine the upper $\{U(t)\}$, and lower $\{L(t)\}$ envelopes of the signal $y_i\ (t)$ respectively.
3. To obtain the mean of the upper and lower envelopes, or $M(t)$, join all the minima and maxima using the Akima spline interpolation approach, i.e.

$$Mean(t) = \frac{U(t)+L(t)}{2} \tag{1}$$

4. The mean envelope calculated in step 3 will be subtracted from the actual signal to obtain the first component, i.e.

$$k_1(t) = y(t) - Mean(t) \tag{2}$$

5. Repeat steps 1-4 for the component $k(t)$ until a stopping criterion is satisfied and take the resulting $k(t)$ as $k^*(t)$.

If the remaining signal i.e., $r(t) = y(t) - k^*(t)$ has still some oscillation components then it can be further decomposed with the help of a new version of EMD. until the signal becomes constant across more than two consecutive nodes.

By employing Akima-EMD, noise in battery capacity data is effectively removed, and dominant patterns in the signal are accurately identified. This preprocessing improves the data quality for the CNN-Bayesian LSTM model and ultimately maximizes the accuracy and reliability of RUL prediction.

2.3. CNN-Bayesian LSTM architecture

The CNN-Bayesian LSTM model integrates three core components—Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Bayesian Optimization—to enhance the robustness and accuracy of RUL prediction for lithium-ion batteries. CNN layers are employed to extract salient features, the LSTM component captures temporal dependencies, and Bayesian Optimization dynamically tunes key hyperparameters. The following subsections provide detailed descriptions of each component.

LSTM is a type of recurrent neural network (RNN) architecture designed to learn time-series data while addressing the limitations of standard RNNs, particularly the vanishing gradient problem. To overcome this, LSTM introduces a cell state and gating mechanisms that control the flow of information through the network, enabling the retention or forgetting of long-term dependencies.

The LSTM architecture includes three gates: the forget gate, input gate, and output gate. These gates interact with the cell state (C_t), which is updated through a combination of the previous state and candidate information. The internal computations of LSTM are given by the following equations:

$$f\_t = \sigma(W\_f\,[h\_\{t-1\}, x\_t] + b\_f) \tag{3}$$

$$i\_t = \sigma(W\_i\,[h\_\{t-1\}, x\_t] + b\_i) \tag{4}$$

$$o\_t = \sigma(W\_o\,[h\_\{t-1\}, x\_t] + b\_o) \tag{5}$$

$$\bar{C}\_t = tanh(W\_c\,[h\_\{t-1\}, x\_t] + b\_c) \tag{6}$$

$$C\_t = f\_t \odot C\_\{t-1\} + i\_t \odot \bar{C}\_t \tag{7}$$

$$h\_t = o\_t \odot tanh(C\_t) \tag{8}$$

To predict the remaining useful life (RUL) of a battery, the LSTM receives a sequence of time-series data ($x\_1, x\_2, \ldots, x\_n$) and outputs a predicted value ($\hat{y}$). In a many-to-one framework, the final output at the end of the sequence represents the estimated EOL point. The predicted output ($\hat{x}_{n+1}$) can be used recursively as the next input, continuing the prediction process autoregressively.

By learning from past cycle data, the LSTM effectively captures degradation trends and temporal dependencies in battery capacity signals, forming the foundation for RUL prediction in sequential models.

As described in Section 2.3.1, LSTM excels at learning temporal dependencies in time-series data. However, when the degradation data contains irregular fluctuations or regeneration effects such as capacity recovery, LSTM may struggle to accurately learn the underlying trend using only internal parameters. This limitation can lead to inaccurate RUL predictions, especially under noisy conditions.

To address this, a hybrid model that combines a Convolutional Neural Network (CNN) with LSTM is employed. CNN is capable of extracting spatial features from sequential signals by applying one-dimensional convolution operations to reduce noise and emphasize meaningful patterns. The convolution process is defined as follows:

$$s(t) = (x * w)(t) = \sum_{\tau} x(\tau) w(t - \tau) \tag{8}$$

In this context, $x(\tau)$ is the input signal, $w(t - \tau)$ is the convolution kernel, and $s(t)$ represents the resulting feature map. CNN transforms the original signal into a lower-dimensional representation that highlights key degradation trends.

The feature maps extracted by the 1D-CNN are passed to the LSTM, which learns long-term dependencies from the transformed input sequences. CNN effectively filters out noise and emphasizes key degradation patterns, while LSTM captures the temporal relationships within the signal. This hybrid architecture improves the robustness of the model against irregular or fluctuating degradation data, enhancing the reliability and accuracy of RUL prediction.

However, the performance of the CNN-LSTM model remains highly sensitive to the choice of hyperparameters, such as the number of filters, sequence length, and LSTM units. Manually tuning these parameters can be time-consuming and may result in suboptimal generalization performance. Additionally, conventional LSTM does not explicitly account for uncertainty during the learning process, limiting its capacity to handle noisy or ambiguous data. To overcome these limitations, this study proposes a CNN-Bayesian LSTM model that incorporates Bayesian Optimization for dynamic hyperparameter tuning and enhances predictive reliability by modelling uncertainty within the LSTM framework.

To implement the CNN-Bayesian LSTM model, we extended a standard CNN-LSTM structure by incorporating Monte Carlo dropout to estimate predictive uncertainty. The architecture consists of three 1D convolutional layers for local feature extraction, followed by an LSTM network with multiple layers and dropout regularization. The dropout layer is intentionally activated during both training and inference to simulate Bayesian posterior sampling.

Instead of performing explicit Bayesian inference, we adopt Monte Carlo dropout, a commonly employed variational Bayesian approximation technique, to approximate the predictive distribution. Specifically, we enable dropout layers during test time and perform multiple stochastic forward passes through the model. The mean of these outputs is taken as the final prediction, and the standard deviation is interpreted as the model's predictive uncertainty.

Let $f(x;\ \theta)$ be the output of the CNN-Bayesian LSTM for input x and let $\widehat{y_i}$ denote the prediction from the i-th forward pass with dropout activated. The final prediction μ and uncertainty σ are computed as:

$$f\mu = \frac{1}{N}\sum_{i=1}^{N}\breve{y_i} \tag{10}$$

$$\sigma = \sqrt{\frac{1}{N}\sum i = (\widehat{y_i} - \mu)^2} \tag{11}$$

Here, N is the number of Monte Carlo samples. This approach allows the model to quantify uncertainty and improve the reliability of RUL predictions, particularly in noisy or ambiguous battery degradation scenarios.

In addition, we define a customized EOL evaluation metric. The predicted EOL is determined by identifying the first-time step at which the predicted capacity drops below a defined threshold. The error is quantified as the difference between the predicted EOL and the actual EOL and is expressed both as an absolute cycle difference and as a percentage of the actual EOL value.

The CNN-Bayesian LSTM model combines the local feature extraction capabilities of one-dimensional convolutional neural networks (1D-CNN) with the temporal sequence modelling power of bidirectional LSTM, while employing Bayesian Optimization to dynamically adjust key hyperparameters.

In this architecture, time-series capacity degradation signals are first processed through a 1D-CNN layer to extract relevant features across local temporal windows. The 1D convolution operation applied to an input sequence x is defined as:

$$s(t) = (x * w)(t) = \sum_{\tau} x(\tau)w(t-\tau) \tag{12}$$

where $x(\tau)$ is the input signal, $w(t-\tau)$ is the convolutional kernel, and $s(t)$ represents the extracted feature at time t. This process helps suppress noise while emphasizing the key degradation patterns in the signal.

The output feature vectors from the 1D-CNN are passed sequentially into a bidirectional LSTM, which captures both past and future dependencies. The forward and backward hidden states at each time step are computed as follows:

$$\underset{h_t}{\rightarrow} = \underset{LSTM}{\longrightarrow}(h_{t-1}, x_t) \tag{13}$$

$$\underset{h_t}{\rightarrow} = \underset{LSTM}{\longrightarrow}(h_{t+1}, x_t) \tag{14}$$

$$h_t = [\underset{h_t}{\rightarrow}, \underset{h_t}{\leftarrow}] \tag{15}$$

The concatenated hidden state $\underset{h_t}{\rightarrow}$ is then passed through a fully connected layer or attention mechanism to produce the final prediction of RUL. The model is trained using backpropagation to minimize the prediction error.

To improve the learning efficiency and prediction performance, Bayesian Optimization is applied to automatically tune hyperparameters such as learning rate, number of LSTM units, and convolutional filter size. This method allows the model to explore optimal configurations without exhaustive manual tuning, thereby enhancing generalization and robustness in predicting battery degradation trends.

For model training, we set the learning rate to 0.001 with the Adam optimizer, a batch size of 64, and trained for 200 epochs. The CNN component consisted of three one-dimensional convolutional layers with filter sizes 32, 64, 128, and a kernel size of 3. The LSTM layer contained 128 units, followed by a dropout layer with a rate of 0.2. During Bayesian inference, Monte Carlo dropout was applied with 50 stochastic forward passes to estimate predictive uncertainty.

In addition to Bayesian Optimization, the LSTM component in this model incorporates uncertainty estimation through Monte Carlo dropout. By keeping dropout layers active during both training and inference, the model simulates Bayesian posterior sampling. Monte Carlo dropout can be interpreted as a variational Bayesian approximation, where applying dropout during inference is equivalent to sampling from an approximate posterior distribution of the network weights. Each stochastic forward pass corresponds to drawing a different thinned network, and aggregating these outputs approximates the predictive posterior distribution. As the number of Monte Carlo samples increases, the empirical mean converges to the predictive mean, while the variance estimates predictive uncertainty. This property offers a Bayesian interpretation of the LSTM framework, clarifying why Monte Carlo dropout can be regarded as a practical and computationally efficient approximation to Bayesian inference [11].

3. Experimental Setup and Results

3.1. Data preprocessing

To enhance the prediction performance of the proposed model and improve the interpretability of battery aging patterns, the lithium-ion battery degradation dataset provided by NASA PCoE (B0005 and B0006) was used. The analysis was conducted using data from cycles 20 to 140, a range that better captures the progressive capacity decline while eliminating outliers during early stabilization and extreme degradation phases.

Data preprocessing was conducted using both EMD and Akima-EMD. While EMD effectively decomposed the signal into multiple IMFs, issues such as overshoot and undershoot due to cubic spline interpolation distorted the envelope curves, impairing the accuracy of IMF extraction.

To address these limitations, Akima interpolation was applied in place of cubic splines, resulting in the Akima-EMD. Akima-EMD yielded smoother and more stable envelope curves and demonstrated better preservation of original signal variability. Comparative analysis showed that while EMD decomposed the signal into four IMFs, Akima-EMD required only three IMFs to sufficiently represent the same signal. This suggests that Akima-EMD achieves more efficient decomposition.

Figure 3 shows that the red-circled regions in the capacity degradation curves illustrate how Akima-EMD captures the overall degradation trend more clearly than conventional EMD, which still retains irregularities from the raw signal. In the 40–60 cycle range of the B0005 dataset, the red curve demonstrates that Akima-EMD preserves the intrinsic characteristics of the data more effectively. These results indicate that Akima-EMD provides a more accurate representation of the underlying degradation trajectory of lithium-ion batteries.

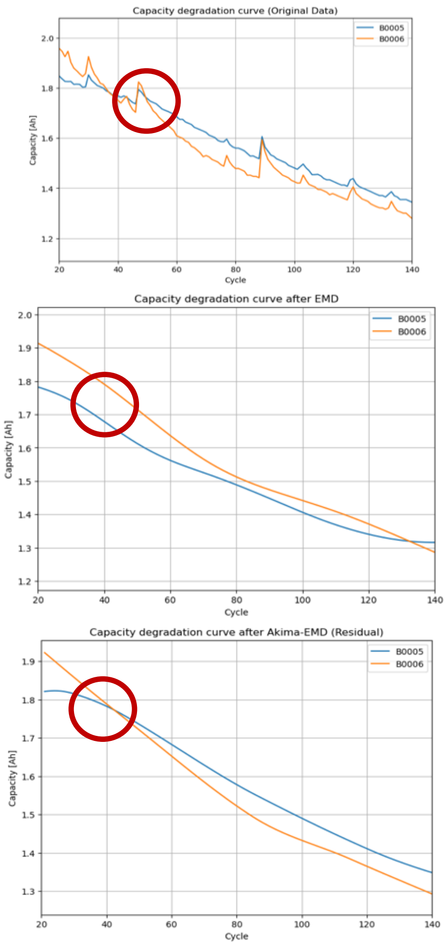

Fig. 3. NASA PCoE Ames lithium-ion battery degradation dataset processed with EMD and Akima-EMD.

3.2. Threshold definition

In RUL prediction tasks, defining an appropriate threshold is crucial for determining the EOL point where battery replacement becomes necessary. Battery degradation progresses nonlinearly, and once the capacity falls below a certain level, continued usage may lead to inefficiency or safety concerns.

In studies using EMD-CNN-LSTM models, thresholds for end-of-life prediction were typically set between 70% and 80% of the battery's initial capacity, based on the NASA PCoE dataset. These studies adopted this range to reflect the practical usable life of lithium-ion batteries while minimizing the effects of capacity regeneration and signal noise on prediction accuracy. For instance, EMD-CNN-LSTM approaches have demonstrated improved performance when using a 75% threshold, as it provides a clear and consistent cutoff point for model training and evaluation [4]. The use of this threshold range has become a standard practice in RUL prediction studies involving signal decomposition and deep learning architectures.

To ensure consistency with prior work, the present study adopted a threshold range of 70%-80% of the initial battery capacity. This range reflects the practical usable life of the battery while minimizing the impact of capacity fluctuations on prediction error. The chosen threshold thus improves prediction reliability and facilitates comparative analysis with existing RUL estimation studies.

3.3. Prediction modeling

Three models were implemented to compare RUL prediction performance: LSTM, CNN-LSTM, and CNN-Bayesian LSTM. Experiments were conducted using B0005 and B0006 datasets. To assess the effect of training data size, training cycles were set to 40, 50, and 60. In addition, the effect of data preprocessing was evaluated by comparing model performance across raw datasets, EMD-pre-processed datasets, and Akima-EMD-pre-processed datasets.

3.3.1. Modeling on raw dataset (B0005)

Table 1 and Figure 4 present the prediction performance of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the raw dataset. At a training cycle of 40, both LSTM and CNN-LSTM failed to provide an EOL prediction, while CNN-Bayesian LSTM estimated the EOL at 103 cycles (error of 19 cycles, 22.67%). When the training cycle increased to 50, all models produced EOL predictions: LSTM at 96 cycles (error of 12 cycles, 14.29%), CNN-LSTM at 95 cycles (11-cycle error, 13.1%), and CNN-Bayesian LSTM at 88 cycles (error of 4 cycles, 4.76%). With 60 training cycles, LSTM predicted the EOL at 91 cycles (error of 7 cycles, 8.33%), CNN-LSTM at 111 cycles (error of 27 cycles, 32.14%), and CNN-Bayesian LSTM at 81 cycles (error of 3 cycles, 3.57%). CNN-Bayesian LSTM recorded the lowest error even when applied to the raw dataset without Akima-EMD preprocessing.

Table 1. Prediction performance of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the raw dataset.

Training Cycle	Model	EOL Error	Predicted EOL	ΔCycle	Error (%)
40	LSTM	x	x	x	x
	CNN-LSTM	x	x	x	x
	CNN-Bayesian LSTM	**19**	**103**	**19**	**22.67**
50	LSTM	12	96	12	14.29
	CNN-LSTM	11	95	11	13.1
	CNN-Bayesian LSTM	**4**	**88**	**4**	**4.76**
60	LSTM	7	91	7	8.33
	CNN-LSTM	27	111	27	32.14
	CNN-Bayesian LSTM	**-3**	**81**	**3**	**3.57**

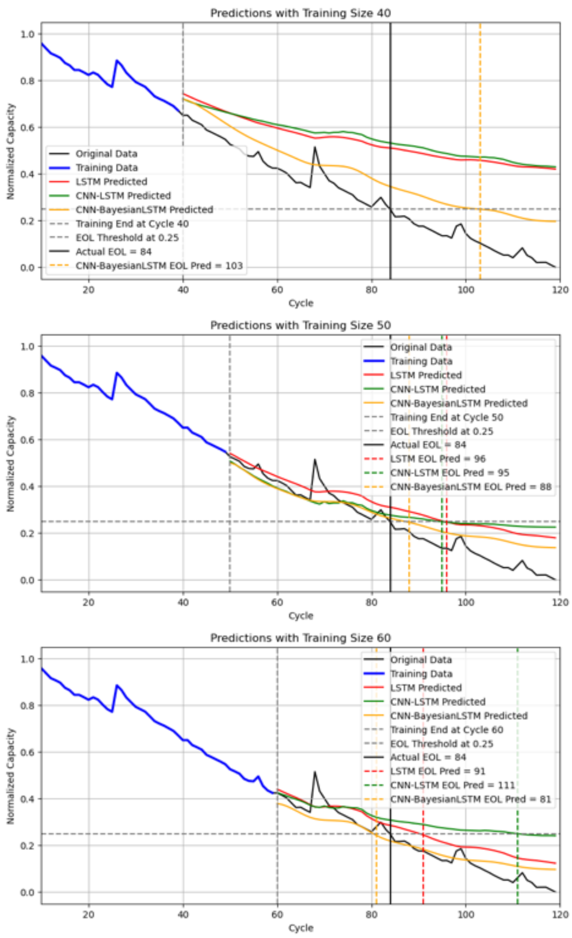

Fig. 4. Prediction results of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the raw dataset.

These results indicate that CNN-Bayesian LSTM consistently achieved the lowest error across training conditions, demonstrating robustness and adaptability to raw data with high volatility. In contrast, CNN-LSTM showed instability, particularly at larger training sizes, leading to significant overestimation of EOL. The findings underscore the necessity of incorporating preprocessing techniques to mitigate noise and irregularities in the degradation signal, thereby enhancing the reliability and stability of RUL predictions.

3.3.2. Modeling on EMD dataset (B0005)

Figure 5 and Table 2 illustrate the prediction results of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the EMD-pre-processed B0005 dataset. At a training cycle of 40, LSTM failed to provide an EOL prediction, while CNN-LSTM estimated the EOL at 111 cycles with a large error of 27 cycles (32.14%). In contrast, CNN-Bayesian LSTM predicted the EOL at 101 cycles, reducing the error of 17 cycles (20.24%). This result demonstrates the relative robustness of CNN-Bayesian LSTM compared with the other models under minimal training conditions.

When the training cycle increased to 50, all models successfully produced EOL predictions. CNN-Bayesian LSTM achieved the best performance, predicting the EOL at cycle 87 with an error of only 3 cycles (3.57%). LSTM and CNN-LSTM followed with errors of 19 cycles (22.62%) and 6 cycles (7.14%), respectively. Notably, CNN-Bayesian LSTM showed superior adaptability to the additional training data, yielding the most accurate results.

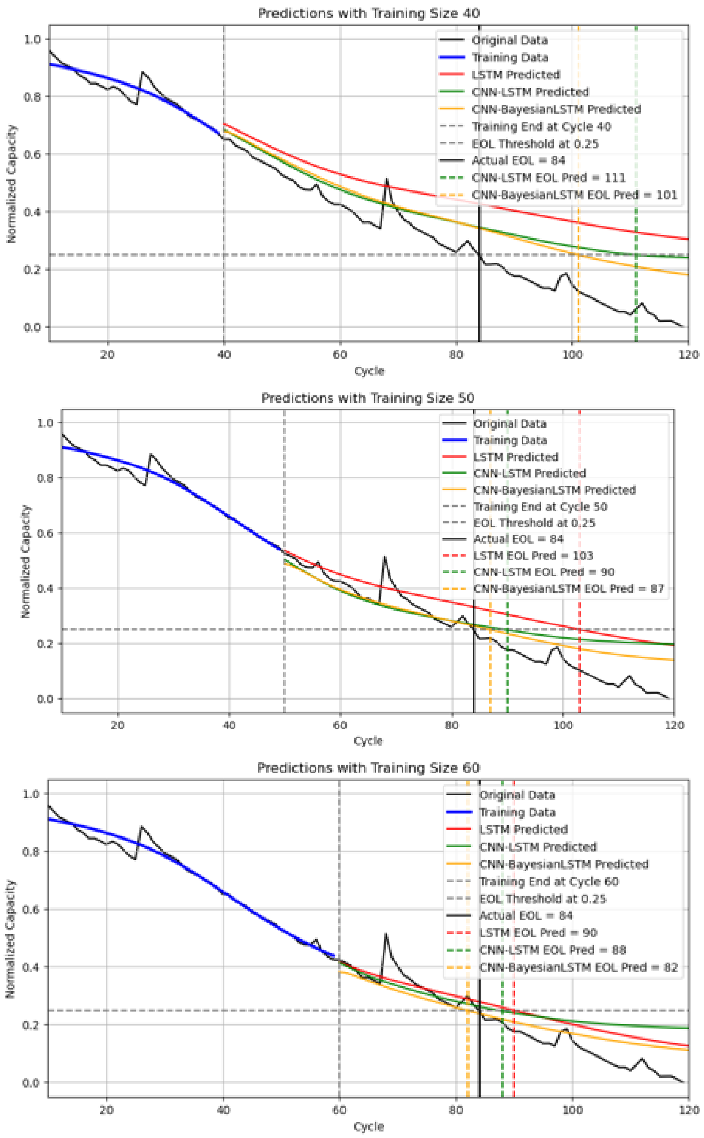

Fig. 5. Prediction results of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the EMD dataset.

Table 2. Performance analysis of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the EMD dataset.

Training Cycle	Model	EOL Error	Predicted EOL	ΔCycle	Error (%)
40	LSTM	x	x	x	x
	CNN-LSTM	27	111	27	32.14
	CNN-Bayesian LSTM	**17**	**101**	**17**	**20.24**
50	LSTM	19	103	19	22.62
	CNN-LSTM	6	90	6	7.14
	CNN-Bayesian LSTM	**3**	**87**	**3**	**3.57**
60	LSTM	6	90	6	7.14
	CNN-LSTM	4	88	4	4.76
	CNN-Bayesian LSTM	**-2**	**82**	**2**	**2.38**

At a training cycle of 60, all three models further improved their predictions. CNN-Bayesian LSTM again outperformed the others, estimating the EOL at 82 cycles with an error of only 2 cycles (2.38%). By comparison, LSTM predicted 90 cycles (error of 6, 7.14%), and CNN-LSTM predicted 88 cycles (error of 4, 4.76%).

Overall, the application of EMD preprocessing enhanced the prediction accuracy and stability of all models by mitigating signal irregularities. Among them, CNN-Bayesian LSTM consistently achieved the lowest error rates across different training cycles, confirming its robustness and reliability under both limited and sufficient training conditions.

3.3.3. Modeling on Akima-EMD dataset (B0005)

Figure 6 and Table 3 show the prediction results on the Akima-EMD pre-processed B0005 dataset, highlighting substantial improvements across all models in terms of reducing EOL errors and enhancing prediction stability. Compared with standard EMD preprocessing, Akima-EMD provided more reliable intrinsic mode functions (IMFs) by alleviating mode mixing and spline-induced distortions, thereby creating more favourable conditions for deep learning models.

At a training cycle of 40, all models successfully predicted the EOL. LSTM and CNN-LSTM produced errors of 13 cycles (15.48%) and 11 cycles (13.1%), respectively. In contrast, CNN-Bayesian LSTM achieved the best performance with an error of only 2 cycles (2.38%), demonstrating strong robustness under limited training data.

When the training cycle increased to 50, CNN-Bayesian LSTM again provided the most accurate result, predicting the EOL exactly at 84 cycles with zero error. CNN-LSTM also performed well, with an error of 2 cycles (2.38%), while LSTM lagged with an error of 27 cycles (32.14%).

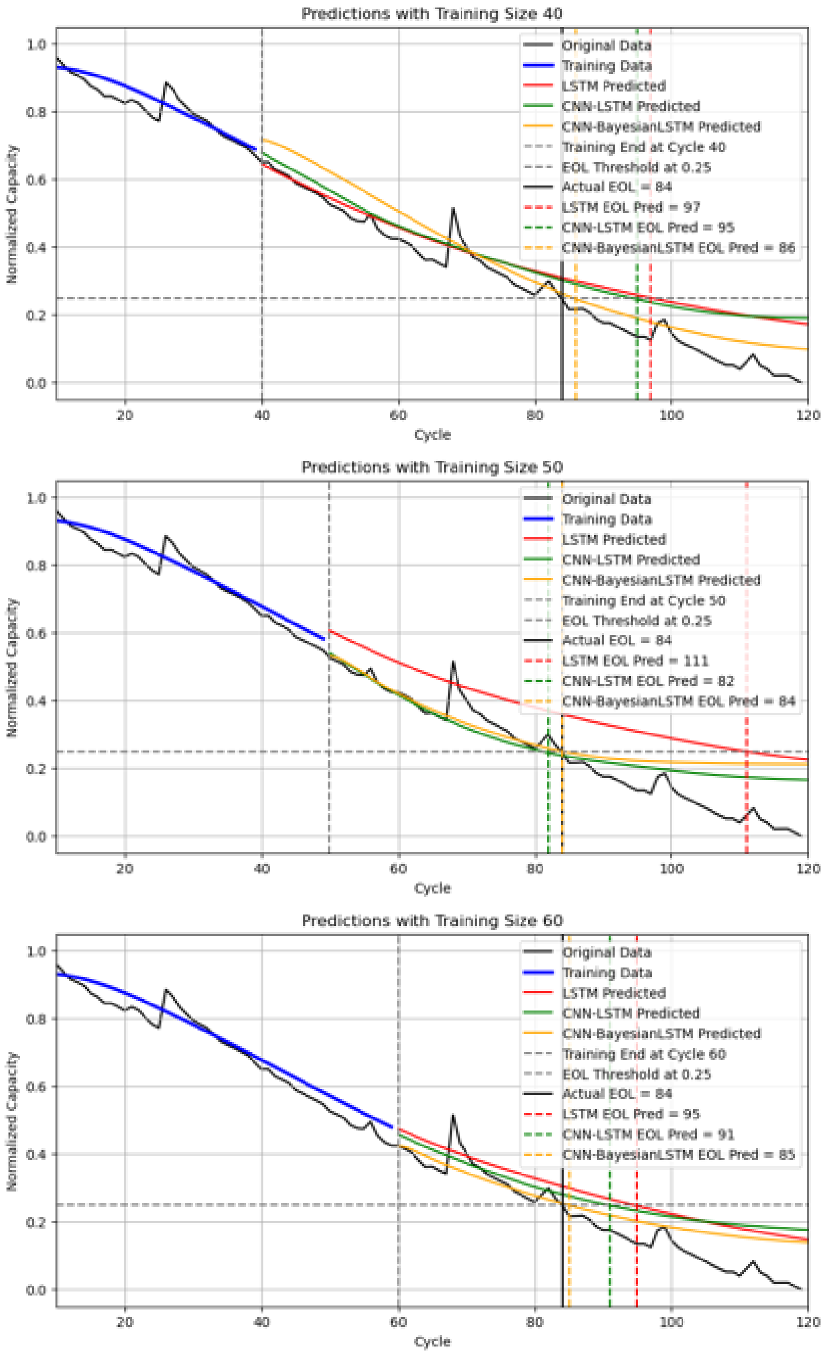

Fig. 6. Prediction results of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the Akima-EMD dataset.

Table 3. Performance analysis of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the Akima-EMD dataset.

Training Cycle	Model	EOL Error	Predicted EOL	ΔCycle	Error (%)
40	LSTM	13	97	13	15.48
	CNN-LSTM	11	95	11	13.1
	CNN-Bayesian LSTM	**2**	**86**	**2**	**2.38**
50	LSTM	27	111	27	32.14
	CNN-LSTM	-2	82	2	2.38
	CNN-Bayesian LSTM	**0**	**84**	**0**	**0**
60	LSTM	11	95	11	13.1
	CNN-LSTM	7	91	7	8.33
	CNN-Bayesian LSTM	**1**	**85**	**1**	**1.19**

At a training cycle of 60, all models exhibited improved accuracy. LSTM and CNN-LSTM recorded errors of 11 cycles (13.1%) and 7 cycles (8.33%), respectively. CNN-Bayesian LSTM once more outperformed the others, achieving an error of only 1 cycle (1.19%).

Overall, the integration of Akima-EMD preprocessing significantly improved predictive performance compared to the raw and EMD datasets. CNN-Bayesian LSTM consistently achieved the lowest error rates across training sizes, confirming its robustness and adaptability. These findings demonstrate that the combination of Akima-EMD and CNN-Bayesian LSTM establishes an effective and reliable framework for battery RUL prediction.

3.3.4. Modeling on Akima-EMD Dataset (B0006)

Figure 7 and Table 4 present the prediction 5 results obtained using the B0006 dataset with Akima-EMD preprocessing, comparing the performance of LSTM, CNN-LSTM, and CNN-Bayesian LSTM. At a training cycle of 40, LSTM and CNN-LSTM produced substantial errors of 44 cycles (51.16%) and 21 cycles (24.42%), respectively. In contrast, CNN-Bayesian LSTM achieved an almost exact prediction with an error of only 1 cycle (1.16%), confirming its robustness and reliability under highly constrained data conditions.

When the training cycle increased to 50, CNN-Bayesian LSTM again showed superior accuracy by predicting the EOL at 84 cycles with an error of 2 cycles (2.33%). LSTM followed with an error of 20 cycles (23.26%), while CNN-LSTM was unable to produce a reliable EOL prediction under this condition.

At 60 training cycles, CNN-Bayesian LSTM maintained its advantage, achieving an error of only 1 cycle (1.16%). LSTM predicted the EOL at 89 cycles with an error of 3 cycles (3.49%), whereas CNN-LSTM was unable to generate an estimate.

These results clearly demonstrate that Akima-EMD preprocessing significantly improved the predictive stability of all models, but its benefits were most pronounced when combined with CNN-Bayesian LSTM. This model consistently outperformed LSTM and CNN-LSTM, particularly at low training sizes, highlighting its strong adaptability and the effectiveness of Akima-EMD in mitigating signal irregularities for accurate battery RUL prediction.

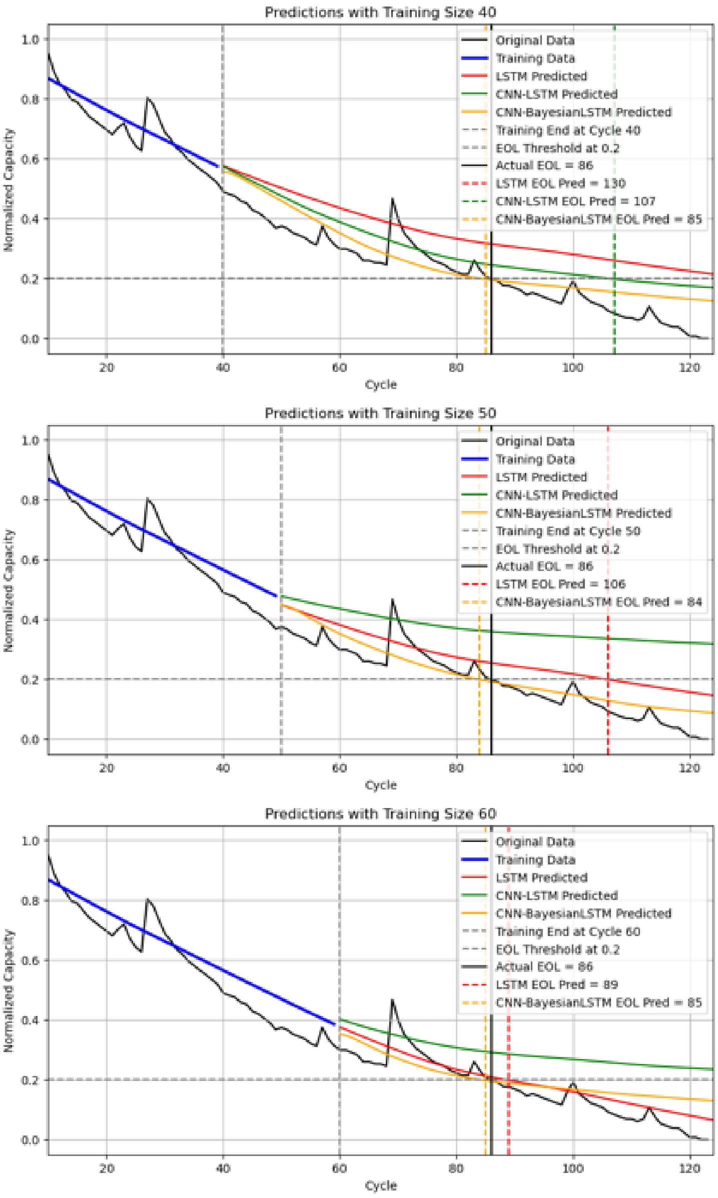

Fig. 7. Prediction results of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the Akima-EMD dataset.

Table 4. Performance analysis of LSTM, CNN-LSTM, and CNN-Bayesian LSTM on the Akima-EMD dataset.

Training Cycle	Model	EOL Error	Predicted EOL	Δcycle	Error (%)
40	LSTM	44	130	44	51.16
	CNN-LSTM	21	107	21	24.42
	CNN-Bayesian LSTM	**-1**	**85**	**1**	**1.16**
50	LSTM	20	106	20	23.26
	CNN-LSTM	x	x	x	x
	CNN-Bayesian LSTM	**-2**	**84**	**2**	**2.33**
60	LSTM	3	89	3	3.49
	CNN-LSTM	x	x	x	x
	CNN-Bayesian LSTM	**-1**	**85**	**1**	**1.16**

4. Results and Discussion

4.1. Result analysis

The prediction results on the Akima-EMD pre-processed dataset show that CNN-Bayesian LSTM achieved the lowest errors across all training cycle settings. At a training cycle of 40, CNN-Bayesian LSTM predicted the end-of-life (EOL) with an error of 2 cycles (2.38%), while LSTM and CNN-LSTM recorded larger errors of 13 cycles (15.48%) and 11 cycles (13.1%). When the training cycle was increased to 50, CNN-Bayesian LSTM reached an error of 0, compared to 2 cycles (2.38%) for CNN-LSTM and 27 cycles (32.14%) for LSTM. At a training cycle of 60, CNN-Bayesian LSTM maintained an error of only 1 cycle (1.19%), whereas LSTM and CNN-LSTM had errors of 11 cycles (13.1%) and 7 cycles (8.33%).

To better understand these results, the weaker performance of CNN-LSTM may be related to structural mismatches in its components. First, while CNN layers are generally effective at extracting local patterns, their advantage can be reduced when Akima-EMD preprocessing smooths out local fluctuations, thereby limiting the benefit of convolutional feature extraction. Second, the use of Conv1D layers with small kernels and stride, combined with pooling operations, may lead to resolution loss and disrupt long-term temporal dependencies. Third, the gradual degradation trajectory near the end of life (EOL) can be fragmented into disjoint feature maps, which may cause the subsequent LSTM layers to reconstruct partially distorted trends rather than fully capturing the overall trajectory.

Taken together, these findings indicate that the combination of Akima-EMD and CNN-Bayesian LSTM provides more accurate RUL prediction than LSTM and CNN-LSTM under all tested conditions, and that the proposed model achieves high prediction accuracy even under very limited training data of only 40 cycles.

4.2. Model-wise performance discussion

Among the three models, CNN-Bayesian LSTM consistently delivered the most accurate and reliable predictions across all training cycles, regardless of data quantity. Even under limited data conditions, its performance remained stable, whereas LSTM and CNN-LSTM exhibited higher variance and sensitivity to training size.

At a training cycle of 50, CNN-Bayesian LSTM achieved perfect prediction with zero error, clearly outperforming CNN-LSTM (2 cycles, 2.35%) and LSTM (33 cycles, 38.82%). At 60 cycles, CNN-Bayesian LSTM again recorded zero prediction error, while LSTM showed an error of 13 cycles (15.29%).

These results provide strong evidence that CNN-Bayesian LSTM, especially when integrated with Akima-EMD preprocessing, constitutes a highly robust, generalizable, and precise framework for predicting the remaining useful life of lithium-ion batteries. Moreover, the use of Bayesian optimization to dynamically tune key hyperparameters such as the learning rate, number of hidden units, and dropout probability significantly contributes to the model's ability to maintain prediction stability and minimize error across varying data scenarios.

The superior performance of the CNN-Bayesian LSTM with Akima-EMD can be attributed to the complementary strengths of its components. Akima-EMD reduces overshoot and undershoot effects common in traditional EMD, thereby preserving stable degradation patterns for model training. The CNN layers filter out residual noise and emphasize salient local features, while the LSTM component captures long-term temporal dependencies in the degradation signal. Furthermore, Bayesian dropout provides a probabilistic mechanism to quantify predictive uncertainty, preventing overfitting under limited-data conditions and improving generalization. Together, these mechanisms explain why the proposed framework consistently outperforms baseline models across different training scenarios.

In addition, practical applicability should be validated through case studies or real-world deployment scenarios, such as electric vehicle battery monitoring, which would further demonstrate the robustness of the proposed framework.

5. Conclusions

To improve the prediction accuracy of RUL of lithium-ion batteries, a CNN-Bayesian LSTM model was employed, and three types of data preprocessing raw dataset, EMD, and Akima-EMD were compared. Experimental results showed that CNN-Bayesian LSTM outperformed conventional LSTM and CNN-LSTM models across all training cycle settings, achieving the lowest EOL error. Furthermore, the application of Bayesian Optimization enabled dynamic tuning of model hyperparameters, which improved the generalization performance of the model.

Among the preprocessing techniques, the dataset processed with Akima-EMD achieved the lowest prediction errors. This is attributed to Akima-EMD's ability to alleviate the overshoot and undershoot problems inherent in conventional EMD while effectively preserving the signal's variability. Notably, even in scenarios with limited training data, models trained on Akima-EMD pre-processed datasets demonstrated stable and reliable prediction results, suggesting its suitability for small-sample learning environments.

Overall, the combination of CNN-Bayesian LSTM and Akima-EMD was confirmed to be the most reliable approach for battery RUL prediction. This combination holds strong potential for application in future battery health monitoring and prognostics systems. While Bayesian Optimization was employed to optimize CNN-Bayesian LSTM, further improvements in prediction accuracy may be possible by incorporating more diverse hyperparameter search strategies.

Additionally, future research should include experimental conditions that reflect various operational environments and temperature fluctuations of batteries. Such efforts would contribute to the development of more practical and robust battery life prediction models. Moreover, future work should explore Transformer-based architectures to better capture long-range dependencies in degradation signals, leverage additional datasets to enhance model generalization, and integrate electrochemical degradation mechanisms with data-driven models to establish a stronger physical foundation for RUL prediction.

Furthermore, it is necessary to quantitatively evaluate the computational costs of Akima-EMD preprocessing and Bayesian LSTM training, and to contrast these with those of other baseline models to better understand the trade-off between accuracy and efficiency. In addition, statistical significance tests should be applied alongside error-based metrics to rigorously validate the consistency and reliability of the reported improvements. Finally, explainability analyses, such as evaluating the relative importance of each IMF and visualizing CNN feature importance maps, should be conducted to provide deeper insights into how the model learns degradation patterns and to enhance the interpretability of RUL prediction.

The proposed CNN-Bayesian LSTM combined with Akima-EMD preprocessing significantly enhances the reliability of lithium-ion battery life prediction. Beyond achieving higher accuracy, the model provides confidence intervals around RUL estimates, which can directly support practical decision-making for maintenance scheduling and safety assurance in critical applications. This approach is therefore well-suited for deployment in real-world scenarios such as electric vehicles and energy storage systems (ESS), offering both methodological advances and practical value.

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