

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

LIBs tend to degrade over time, and their RUL decreases as the number of charge-discharge cycles increases. This has driven considerable research attention toward the estimation of battery SOH, aiming to ensure optimal performance and safe operation of battery systems. Many studies have proposed various methods for estimating SOH, including approaches based on deep learning, which have shown promising results in capturing complex patterns from time-series battery data. In addition, hybrid models that combine different machine learning techniques have also been developed to enhance estimation accuracy. Researchers have also focused on extracting useful features from battery measurement data collected during charge and discharge cycles. Among these, the ICA has been widely used as a feature extraction technique that helps to reveal internal battery degradation mechanisms and improve model performance.

2.2 Literature Overview

In recent years, the challenge of effectively estimating the SOH of LIBs has received growing attention. Numerous research approaches have been proposed to address this issue, differing in their use of experimental setups, model-based techniques including adaptive algorithms and data-driven methods, such as machine learning and deep learning. The variety of datasets used in different studies further contributes to the diversity in approaches and outcomes. This section provides a summary and overview of related research in a table format to highlight the current landscape and the remaining research gaps. The literature review has been divided

into three tables: Table 2.1 Battery Dataset. Table 2.2 Feature Extraction and Table 2.3 Model Development.

Table 2.1 The research considering battery dataset

Reference	Method	Objective	Description
(Xiong et al., 2023)	- GPR	- NASA	- Using random
	- LSTM	- Oxford	charging data and
		- Real-world	reconstructing missing health features with GPR-LSTM
(Liang Zhang et al., 2023)	- Ensemble	- NASA	- Uses an
		- Oxford	ensemble model based on improved LSTM neural network to estimate SOH
(Wu et al., 2023)	- GPR	- NASA	- HFs from
	- LSTM	- CALCE	multiple datasets
	- BP	- Oxford - UL-PUR	
(Lijun Zhang et al., 2023)	- LSTM	- NASA	- Using the LSTM
		- CALCE	model to predict the available capacity and RUL of LIBs.

Table 2.1 The research considering battery dataset (Continued)

Reference	Method	Objective	Description
(Dineva, 2024)	- ML and AI	- NASA - CALCE - Oxford	- A review of Li-ion battery SOH estimation techniques in EVs, focusing on advancements in ML and AI.
(Olabi et al., 2024)	- ANN - FNN - CNN	- FUDS - DST - Oxford - NASA	- Reviews the use of ANN in estimating Li-ion battery states, including SOC, SOH, RUL, thermal state, and other parameters.

From table 2.1 The research considering Battery Dataset, it is observed that most studies prefer to use open-source battery datasets. These datasets typically provide comprehensive recordings from the very beginning of battery usage, allowing for continuous monitoring of battery behavior and degradation over time.

Table 2.2 The research considering feature extraction

Reference	Method	Objective	Description
(B. Zou et al., 2023)	- Bi-LSTM model with AM	- NASA - Oxford	- A DL model is constructed using Bi-LSTM with AM to focus on important parts of the features.
(Sun et al., 2022)	- Bi-LSTM	- NASA	- Extraction of IC curve peaks and corresponding
(Bian et al., 2022)	- ANN	- NASA - CALCE	- Uses a fusion-based method combining OCV model and ICA with ANN to estimate SOH
(Z. Zou et al., 2023)	- BP - PCR	- Information gathered from past battery cells that the researchers	- Uses ICA and PCA combined with Multi-chaotic Sparrow Search Algorithm to estimate SOH
(Stephens et al., 2024)	- GPR	- NASA	- ICA-DTA outperforms using ICA and DTA individually

Table 2.2 The research considering feature extraction (Continued)

Reference	Method	Objective	Description
(Wei et al., 2025)	- MSHHO-DELM	- Oxford	- Uses the MSHHO-DELM framework improved from Harris Hawks Optimization and Deep Extreme Learning Machine to estimate SOH
(Rao et al., 2024)	- LSTM - DNN - GRU	- NASA	- Battery data is processed using Fourier Resampling to produce uniform and denoised signals, enhancing the accuracy of SOH prediction. - Incremental capacity-based input datasets have been considered as input to GRU

Table 2.2 The research considering feature extraction (Continued)

Reference	Method	Objective	Description
(Techanok et al., 2025)	- LSTM	- Oxford	- Compare the results of evaluating the role of OCV in estimating the SOH of batteries. - Use the variable AUC to effectively highlight differences between battery cycles.

The table 2.2 The research considering Feature Extraction summarizes studies focusing on the extraction of informative features from battery usage data for use as model inputs in SOH estimation. These studies highlight the critical role of proper feature selection in improving model accuracy. Various techniques have been applied, such as ICA, and in some cases, resampling of raw signals to enhance temporal resolution.

Table 2.3 The research considering model development

Reference	Method	Objective	Description
(Fan et al., 2020)	- GRU-CNN	- NASA - Oxford	- Using a hybrid GRU-CNN model, which can learn shared information and time dependencies of the charging curve with deep learning technology.
(Aliberti et al., 2022)	- LSTM - GRU - 1D-CNN - CNN-LSTM	- NASA	- Various neural network models - 1D-CNN best predicts SOH
(Audin et al., 2021)	- Autoencoders and LSTM	- SNL - MIT - NASA	- Using Autoencoders and LSTM Neural Networks applied to usage data (voltage, current, temperature)
(Nguyen Van & Quang, 2023)	- LSTM - FNN	- NASA	- LSTM has higher accuracy than FNN in estimating SOH and internal resistances

Table 2.3 The research considering model development (Continued)

Reference	Method	Objective	Description
(Oyewole et al., 2022)	- CDTL	- Information gathered from past battery cells that the researchers	- Construction of a CDTL model consisting of two LSTM networks: source LSTM and target LSTM
(Wang et al., 2022)	- GPR	- Oxford	- Uses Pearson correlation coefficient to select health features and GPR to estimate the SOH
(Li et al., 2023)	- GPR	- NASA -Oxford	- Estimation of SOH and RUL of batteries using a hybrid Temporal Convolutional Network-Long Short-Term Memory (TCN-LSTM) model.
(Gong et al., 2021)	- CNN - ULSAM - GRU	- NASA - Oxford	- Uses a hybrid CNN-ULSAM-GRU model to estimate SOC of LIBs

Table 2.3 The research considering model development (Continued)

Reference	Method	Objective	Description
(Hossain Lipu et al., 2022)	- DL	- Data from various studies related to the estimation of SOC, SOH, and RUL of EV batteries	- Reviews the use of DL in estimating SOC, SOH, and RUL of EV batteries, including methods, implementations, strengths, weaknesses, accuracy, and future recommendations
(Jarraya et al., 2025)	- SOH-KLSTM	- NASA	- Integrating KAN with LSTM to estimate SOH of LIBs networks: source LSTM and target LSTM
(Li et al., 2025)	- MC-CNN-TimesNet.	- NASA - CALCE - MIT	- Estimation of Li-ion battery SOH and RUL using the MC-CNN-TimesNet model.

Table 2.3 The research considering model development (Continued)

Reference	Method	Objective	Description
(Ma et al., 2024)	- Bagged-GPR	- LMBs dataset	- Uses a data-driven health estimation framework and Bagged-GPR to estimate SOH of lithium metal batteries, validated with data from test cells.
(Safavi et al., 2024)	- CNN - LSTM	- NASA	- 2D voltage data and use the sliding window technique to create a new dataset, automatically extracting health features. - The sampling rate was increased to have one voltage measurement every 20 s

Based on table 2.3 research considering Model Development, it is evident that many studies have focused on the development of hybrid models by combining the strengths of various approaches. These hybrid strategies have shown significant improvements in SOH estimation accuracy. The literature reviewed in this table highlights a clear trend in recent research toward multi-method integration, aiming to enhance model performance in response to the complex characteristics of battery data.

2.3 Model Development and Hybridization Approaches

Estimating a battery's SOH is essential for precisely forecasting its performance and lifespan, allowing for preventive maintenance, and boosting the dependability of ESS. To increase the accuracy of SOH estimate models, a lot of research has been done. Hybrid modeling techniques have drawn a lot of interest among these initiatives. To improve prediction performance, these strategies integrate the advantages of several methodologies, such as combining several learning models or combining machine learning with model-based techniques. In order to improve robustness and capture the intricate, nonlinear behavior seen in battery degrading processes, hybrid models are intended to address the shortcomings of individual models.

The three main components of the hybrid neural network model suggested by (Qingrui Gong et al. 2021) are a GRU module, an ULSAM module, and a convolutional module. The GRU module processes the feature sequences to estimate the SOC over time after the convolutional and ULSAM modules collaborate to extract features from sequences of sampled voltage, current, and temperature data. Both temporal relationships and deep feature representations in the data are successfully captured by this approach. (Yaxiang Fan et al. 2020) proposed a hybrid modeling approach for battery SOH estimation by combining GRU and CNN. The GRU is utilized to capture temporal dependencies, while the CNN extracts key features from the charging curves under CC-CV mode. This hybrid structure enables the model to effectively learn relevant patterns associated with battery health. (Aliberti et al. 2022) developed and compared various neural network architectures for estimating the SOH of LIBs using a

data-driven approach at the single-cell level. The models evaluated include LSTM, GRU, 1D-CNN, and CNN-LSTM, combining sequential learning and feature extraction techniques to identify the most suitable structure for battery condition analysis. (Li et al. 2023) proposed a novel hybrid model combining TCN and LSTM for SOH and RUL estimations of batteries. This architecture leverages both temporal sequence modeling and deep feature extraction capabilities. Additionally, Bayesian optimization is applied to fine-tune the hyperparameters of each layer in the model. (Chaoran Li et al. 2023) proposed a model centered on creating a hybrid model for estimating batteries' SOH and RUL. TCN and LSTM are combined in its suggested TCN-LSTM architecture to take advantage of sequential learning and temporal feature extraction. We use Bayesian optimization to optimize the model's hyperparameters.

The objective of these projects is to create sophisticated models that use real-world usage data, such as voltage, current, and temperature, to forecast the SOH of LIBs. LSTM networks, which are well-known for their ability to effectively simulate time-series data, are at the heart of both strategies. In order to improve the input representation prior to SOH prediction, (Paul AUDIN et al. 2021) combine LSTM with an autoencoder, which serves as a feature extractor. In order to better represent intricate, nonlinear degradation processes, (Imen Jarraya et al. 2025). suggest a more advanced hybrid model that combines LSTM with KAN. Even if the model architectures differ, both approaches aim to improve prediction accuracy and robustness under realistic and variable operating conditions.

2.4 Feature Extraction and Input Variable Selection

Input feature extraction and selection play a vital role in the accuracy of battery SOH estimation models. Typically, input variables are derived from recorded voltage, current, and temperature data during battery charge and discharge cycles. One widely used technique for feature extraction is ICA, which reveals subtle degradation patterns in the battery. This section provides a summary of prior research focusing on the methods and strategies for selecting and extracting input features, highlighting the diversity of approaches proposed in the literature.

(Daniel Stephens et al. 2024) provide a unique method to enhance the efficiency of Li-ion battery SOH estimate by combining ICA with DTA. When combined, ICA and DTA's complimentary qualities can help overcome the drawbacks of each technique alone, as the work demonstrates. SOH estimation's stability and accuracy are improved by this methodical integration. The results emphasize how crucial ICA is as a tool for obtaining features linked to deterioration, especially when paired with other analytical techniques. (Zhanxin Zou et al. 2023) work uses ICA, a crucial method for gleaning health-related characteristics from LIBs constant current charging phase. PCA is used to reduce the dimensionality of the four HFs that were extracted via ICA. This results in a single principal component that is then utilized for linear regression. To optimize the regression model, a learning mechanism-based Multi-Chaotic Sparrow Search Algorithm is used. This method demonstrates how ICA-derived features may successfully enable correct modeling even in low-resource contexts, highlighting the relevance of ICA in providing lightweight and computationally efficient SOH estimate.

Both studies share a common approach in leveraging ICA to extract features that better reflect battery degradation (Hanlei Sun et al. 2020). utilize ICA to extract peak points and corresponding voltages as additional inputs to a Bi-LSTM model. (Bosong Zou et al. 2023). combine ICA with other features like equal voltage interval discharge time and thermal analysis before feeding them into a Bi-LSTM model with an attention mechanism. Although the implementation differs, both studies agree on the crucial role of ICA in enhancing the accuracy and robustness of SOH estimation. (K. Dhananjay Rao et al. 2024) investigates SOH estimation utilizing a variety of machine learning algorithms, including LSTM, DNN, and GRU, with a focus on optimal hyperparameter optimization. The integration of ICA-based input datasets into the GRU model is a significant study feature. By reflecting realistic internal degradation parameters like battery chemistry and operating conditions, these ICA-derived inputs help the GRU model more closely resemble real-world aging behavior. Both studies share a common approach in leveraging ICA to extract features that better reflect battery degradation (Hanlei Sun et al. 2020). utilize ICA to extract peak points and corresponding voltages as additional inputs to a Bi-LSTM model. (Bosong Zou et al. 2023). combine ICA with other features like equal voltage interval discharge time and

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(S. Techanok, N. Junhuathon, and K. Chayakulkheeree 2025) investigates the impact of incorporating OCV as an input feature for SOH estimation using an LSTM model trained on battery degradation data from Oxford University. The model uses inputs such as charge/discharge current, voltage, time, and temperature, and the inclusion of OCV is shown to significantly improve estimation accuracy. Additionally, the AUC is used to highlight the differences between battery cycles, providing insights into voltage behavior changes due to degradation. This research underscores the importance of OCV and AUC as critical variables in enhancing SOH prediction performance.

2.5 Battery Dataset

To estimate the SOH of a battery, it is essential to use data collected during the battery's charge and discharge cycles, including voltage, current, and temperature measurements. Many reviewed studies use a variety of datasets some are publicly available open-source datasets, while others are obtained through laboratory experiments conducted by the researchers themselves. These datasets differ in terms of quality, structure, and experimental conditions, which can significantly affect model training and estimation performance. This section provides an overview of the datasets used in related research.

(Jiang Wu et al. 2023) utilized datasets from multiple sources including NASA, CALCE, Oxford, and UL-PUR for the selection of Li-ion battery HFs prior to SOH estimation. The work by (Adrienn Dineva 2024) presents a review of SOH estimation

techniques for LIBs in EVs, pointing out that a number of papers use NASA, CALCE, and Oxford databases as important assessment references. (Vahid Safavi et al. 2024) utilizes datasets from NASA, Oxford, and real-world sources to develop a GPR-LSTM model aimed at improving the efficiency of SOH estimation across various data sources. Many studies that review SOH estimation techniques for LIBs commonly utilize open-source datasets from NASA and Oxford.

From the literature review, it is evident that most research has focused on developing hybrid models in order to minimize the estimation error of battery SOH. While this approach enhances model accuracy, improving the practical usability of such models such as reducing training time, simplifying input data, and lowering computational complexity is equally important and often underexplored.

Therefore, this study proposes the use of a resampling technique to adjust data resolution to a more manageable level, along with the selection of the ICA feature, which is widely recognized in the literature for its effectiveness in reflecting battery degradation behavior. The datasets used in this research are the Oxford Battery Dataset and the NASA Battery Dataset

Table 2.4 Presents a comparison of previous research

Reference	Dataset		ICA	Resampling	Method
	Oxford	NASA			
Yaxiang Fan et al. (2020)	✓	✓		✓	GRU-CNN
Alessandro Aliberti et al. (2022)		✓			LSTM, GRU, 1D-CNN, CNN-LSTM
Paul AUDIN et al. (2021)		✓			Autoencoders and LSTM
Chi Nguyen Van et al. (2023)		✓			LSTM, FNN
Isaiah Oyewole et al. (2022)					CDTL
Zuolu Wang et al. (2022)	✓				GPR
Chaoran Li et al. (2023)	✓	✓			TCN-LSTM
Qingrui Gong et al. (2021)	✓	✓		✓	CNN-ULSAM-GRU
M.S. Hossain Lipu et al. (2022)	✓	✓			Deep Learning
Imen Jarraya et al. (2025)	✓				SOH-KLSTM

Table 2.4 Presents a comparison of previous research (Continued)

Reference	Dataset		ICA	Resampling	Method
	Oxford	NASA			
Yanming Li et al. (2025)		✓			MC-CNN-TimesNet.
Wenting Ma et al. (2025)			✓		Bagged-GPR
Vahid Safavi et al. (2024)		✓		✓	CNN, LSTM
Daniel Stephens et al. (2024)		✓	✓		GPR
Zhiyuan Wei et al. (2025)	✓		✓		MSHHO-DELM
K. Dhananjay Rao et al. (2024)		✓	✓		LSTM, DNN, GRU
Bosong Zou et al. (2023)	✓	✓	✓		Bi-LSTM with AM
Hanlei Sun et al. (2020)		✓	✓		Bi-LSTM
Xiaolei Bian et al. (2022)		✓	✓		ANN
Zhanxin Zou et al. (2023)			✓		BP, PCR
Xin Xiong et al. (2023)	✓	✓	✓	✓	GPR, LSTM

Table 2.4 Presents a comparison of previous research (Continued)

Reference	Dataset		ICA	Resampling	Method
	Oxford	NASA			
Liang Zhang et al. (2023)	✓	✓			Ensemble
Jiang Wu et al. (2023)	✓	✓			GPR, LSTM, BP
Lijun Zhang (2023)		✓			LSTM
Adrienn Dineva (2024)	✓	✓			ML and AI
A.G. Olabi et al. (2024)	✓	✓			ANN, FNN, CNN
S. Techanok, N. Junhuathon and K. Chayakulkheeree (2025)	✓				LSTM
Proposed Framework	✓	✓	✓	✓	LSTM, Bi-LSTM, AM-LSTM, GRU, GPR

Based on Table 2.4, which presents a comparative review of previous research related to battery SOH estimation including aspects such as model selection, data preparation techniques, and dataset usage a set of summary charts has been created to clearly illustrate the prevailing research trends. Figure 2.1 shows the proportion of studies using datasets such as Oxford and NASA. Figure 2.2 summarizes the application of feature extraction techniques, notably ICA and resampling, while Fig. 2.3 compares the frequency of use for various model types, including LSTM, Bi-LSTM, AM-LSTM, GRU,

and GPR. Together, these figures provide a comprehensive overview of common practices in SOH estimation.

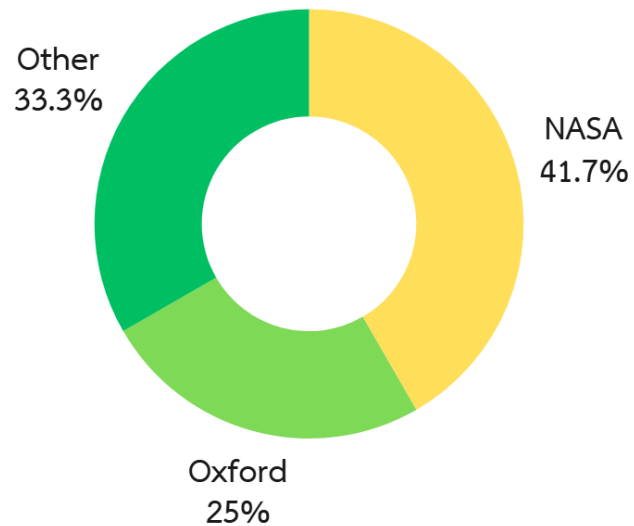


Figure 2.1 The comparison of battery datasets

Figure 2.1 shows the distribution of battery datasets used in the reviewed research. The NASA dataset is the most frequently used, appearing in 41.7% of the studies, followed by the Oxford dataset at 25%. Other datasets account for 33.3%.

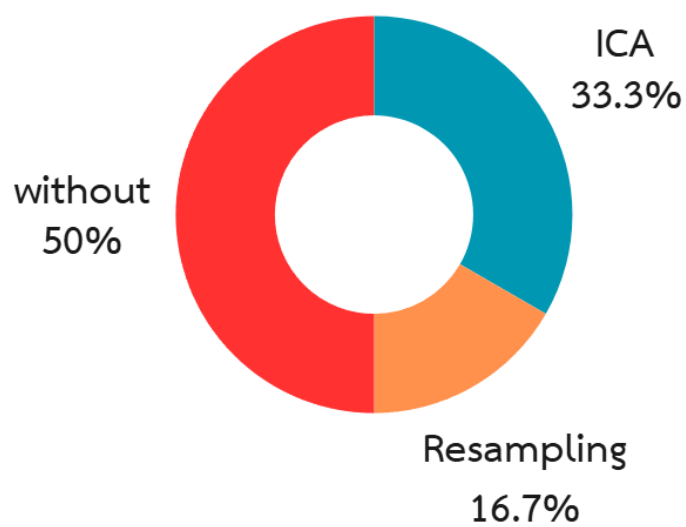


Figure 2.2 The comparison of feature engineering techniques

Figure 2.2 illustrates the use of data preprocessing techniques in the reviewed studies. Among all studies, 33.3% applied ICA for feature extraction, while only 16% employed resampling techniques. Notably, 50% of the studies did not apply either ICA or resampling, indicating that such preprocessing methods are not yet widely adopted compared to the focus on model development.

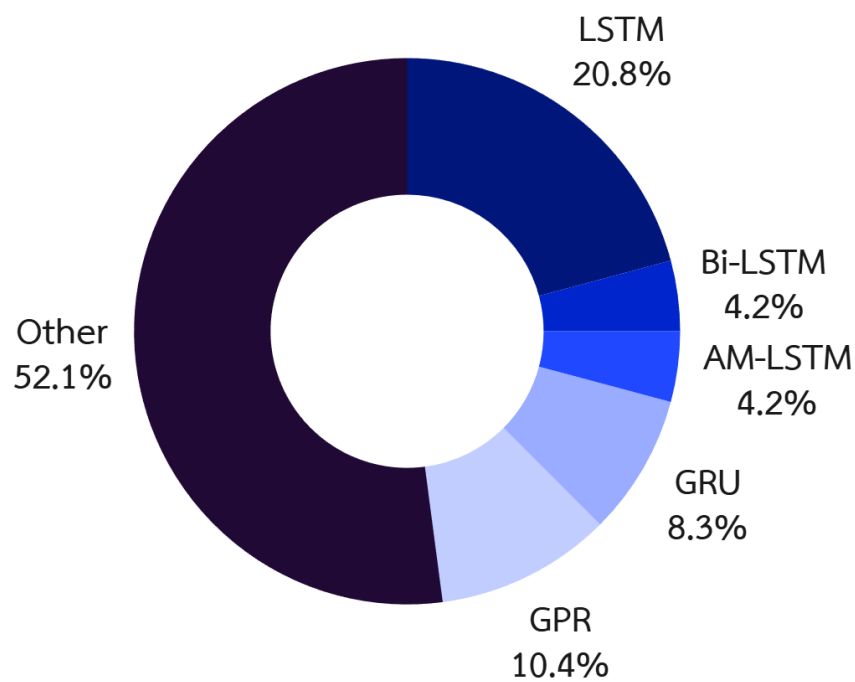


Figure 2.3 The comparison of model usage rates

Figure 2.3 illustrates the distribution of model types used for SOH estimation. Among them, LSTM is the most frequently adopted, accounting for 20.8% of the studies, followed by Bi-LSTM and AM-LSTM at 4.2%, GRU at 8.3% and GPR at 10.4%. Other models not included in the main categories make up 52.1% of the total.

2.6 Battery Degradation

The degradation of LIBs is an inevitable process that occurs progressively with repeated charge–discharge cycles. It arises from both electrochemical and structural changes within the cell, which gradually deteriorate its performance over time. During normal operation, lithium ions shuttle between the cathode and anode through the electrolyte. Over many cycles, several irreversible phenomena occur, including:

- 1) Formation of the SEI: This layer forms on the anode surface as a result of side reactions between the electrolyte and electrode materials. Although the SEI layer initially helps stabilize the interface, it continues to grow with cycling, increasing internal resistance and hindering Li-ion transport.
- 2) Loss of Active Lithium Ions: Some lithium ions become trapped within the SEI layer or participate in unwanted side reactions, reducing the number of active ions available for charge transfer. This directly contributes to the gradual loss of battery capacity.
- 3) Electrode Structural Deformation: The repetitive expansion and contraction of electrode materials during lithiation and delithiation can lead to particle cracking or detachment, decreasing the effective reaction surface area.

Lithium Plating: Under conditions such as fast charging or low temperature, metallic lithium may deposit on the anode surface instead of intercalating into the carbon structure. This not only accelerates capacity fading but also poses safety risks due to potential short circuits.

The degradation of LIBs, as described earlier, directly affects their performance, particularly in terms of capacity and internal resistance. These two parameters have long been the main indicators used to evaluate the SOH of a battery before modern estimation techniques were introduced. In the early stages of battery research, SOH assessment relied heavily on experimental and electrochemical analysis methods. Researchers often measured the loss of capacity after each full charge–discharge cycle or observed the increase in internal resistance using techniques such as Electrochemical Impedance Spectroscopy (EIS) or DC resistance measurement. Some studies also analyzed open-circuit voltage (OCV) curves to identify chemical or

structural changes inside the cell. Although these traditional approaches provided accurate insights into degradation behavior, they required time-consuming experiments and specialized laboratory equipment. Moreover, they were not suitable for real-time monitoring, as the battery had to be taken out of operation for each test. (Berecibar et al. (2016))

To overcome these limitations, researchers later developed model-based estimation methods, such as the Equivalent Circuit Model (ECM) and Electrochemical Model (EM), which aimed to represent battery behavior through mathematical and physical equations. However, these models often required complex parameter identification and detailed information about internal cell characteristics, which are difficult to obtain in practice.

With the advancement of computing power and data availability, the focus gradually shifted toward data-driven approaches, which estimate SOH by analyzing measurable parameters such as voltage, current, temperature, and time during battery operation. Instead of relying on physical modeling, these methods allow the system to learn degradation patterns directly from operational data, leading to more flexible and efficient SOH estimation.

2.7 Definition and Calculation of SOH

SOH is a measure of the overall condition of a battery compared to its ideal or new state. It reflects the battery's ability to store and deliver energy effectively. SOH is expressed as a percentage, where 100% represents a battery in perfect condition, and lower percentages indicate varying degrees of degradation. SOH is influenced by various factors such as the number of charge-discharge cycles, temperature, and usage patterns. It helps in assessing the battery's performance and predicting its RUL. SOH can be calculated using the following formula in Equation (2.1).

$$\%SOH = \frac{C_{remain}}{C_{initial}} \quad (2.1)$$

Where: C_{remain} is the maximum charge, the battery can hold at its current state. $C_{initial}$ is the rated capacity of the battery when it was new. As the battery ages, C_{remain} decreases with increased usage.

2.8 Model Definition

Deep learning models come in various forms, and choosing the appropriate one depends on the nature of the data and the objectives of the analysis. In the context of battery charge/discharge processes, it is essential to employ models that can learn sequential patterns and temporal dependencies. This ability allows the model to detect subtle variations that reflect battery degradation more accurately. Therefore, this section introduces the selected model used for assessing battery performance based on the extracted features.

2.8.1 LSTM Model Architecture

The LSTM neural network is a type of RNN developed to address the vanishing gradient problem, which commonly occurs in traditional RNNs when dealing with long or complex time sequences. LSTM is designed to efficiently remember and selectively retain important information across time sequences.

The structure illustrated in the figure represents the internal architecture of a LSTM cell, which is composed of three main gates: the Forget Gate,

Input Gate, and Output Gate. These gates collectively regulate the flow of information through time, enabling the network to retain long-term dependencies while discarding irrelevant information effectively. The overall architecture of the LSTM model used in this study is shown in Fig. 2.4.

1) Forget Gate (f_t) This gate determines which information from the previous cell state (C_{t-1}) should be retained or discarded. A sigmoid activation function (σ) is applied to the combination of the current input (x_t) and the previous hidden state (h_{t-1}), producing a value between 0 and 1. A value closer to 0 indicates that the information in C_{t-1} is largely forgotten, while a value near 1 means it is mostly preserved.

2) Input Gate (i_t, g_t) The input gate controls how much new information from the current input x_t and the previous hidden state h_{t-1} should be added to the cell state. The sigmoid function (σ) computes the input weight (i_t), while the tanh activation generates a candidate input (g_t). These two components are then multiplied together and integrated into the cell state, allowing selective updating of memory with relevant information.

3) Output Gate (o_t) The output gate decides which part of the cell state will be passed to the hidden state h_t . A sigmoid activation generates the output weight (o_t), while the updated cell state C_t passes through a tanh activation to produce the final hidden state $h_t = o_t \times \tanh(C_t)$, which serves as the LSTM's output at time step t .

4) Cell State Update (C_t) The updated cell state C_t is obtained by combining two components:

- The retained portion of the previous state ($f_t \times C_{t-1}$)
- The newly added information from the input gate ($i_t \times g_t$)

This mechanism enables the LSTM to preserve essential long-term information across multiple time steps.

5) Fully Connected Layer and SOH Estimation The resulting hidden state h_t is then fed into a fully connected layer, which captures both linear and nonlinear relationships among features before producing the final output representing the estimated SOH of the battery.

These mechanisms enable LSTM to effectively learn temporal relationships without losing important information from previous sequences, while also discarding irrelevant data. This makes it highly suitable for processing time-series data, such as voltage, current, and temperature measurements of batteries, which vary continuously over charge and discharge cycles. For further details, see (Nguyen Van & Quang, 2023)

Therefore, LSTM is an appropriate model for estimating the SOH of batteries, as it can capture gradual degradation patterns occurring across multiple charge–discharge cycles.

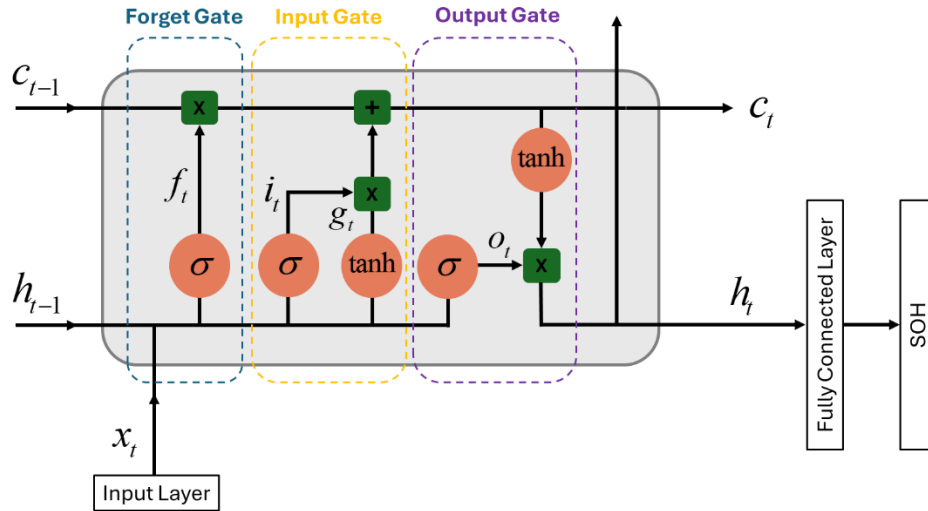


Figure 2.4 An example of the LSTM cell

2.8.2 Bi-LSTM Model Architecture

The Bi-LSTM network is an advanced extension of the conventional LSTM architecture designed to enhance the model's ability to learn temporal dependencies from both past and future contexts. In a Bi-LSTM layer, two parallel LSTM units operate simultaneously: one processes the input sequence in the forward direction (from past to future), while the other processes it in the reverse direction (from future to past). The outputs from both directions are then concatenated to form a unified representation that captures bidirectional temporal information within the sequence.

The architecture of the Bi-LSTM model, as illustrated in the Fig. 2.5, demonstrates the bidirectional processing of sequential data using two parallel LSTM layers: the Forward Layer and the Backward Layer. This structure allows the model to capture temporal dependencies in both directions, enhancing its ability to understand complex time-series relationships.

In the Forward Layer, data are processed sequentially from left to right, where each input at time step x_t is propagated to the next time step $t + 1$, allowing the model to learn temporal patterns in the normal direction. Meanwhile, the Backward Layer processes the same sequence in the opposite direction from right to left enabling the model to retain contextual information from both past and future time steps simultaneously.

At each time step, the outputs from both directions are concatenated and passed through an activation layer to form a comprehensive feature representation that integrates information from the entire sequence. This bidirectional mechanism enables the Bi-LSTM to better capture dependencies that a unidirectional LSTM might miss, leading to smoother and more context-aware predictions.

For the SOH estimation task, the combined output from the forward and backward layers is passed through a fully connected layer to produce the final estimation. This structure enhances the model's capability to learn the complex, nonlinear degradation behavior of batteries over time, resulting in improved accuracy and robustness in prediction performance. For further details, see (B. Zou et al., 2023)

Although incorporating the backward direction increases the model's structural complexity and requires more training time, the benefit lies in its enhanced ability to capture temporal patterns with greater smoothness and precision than the standard LSTM. This makes it particularly suitable for estimation tasks that rely heavily on the continuity and consistency of time-series data.

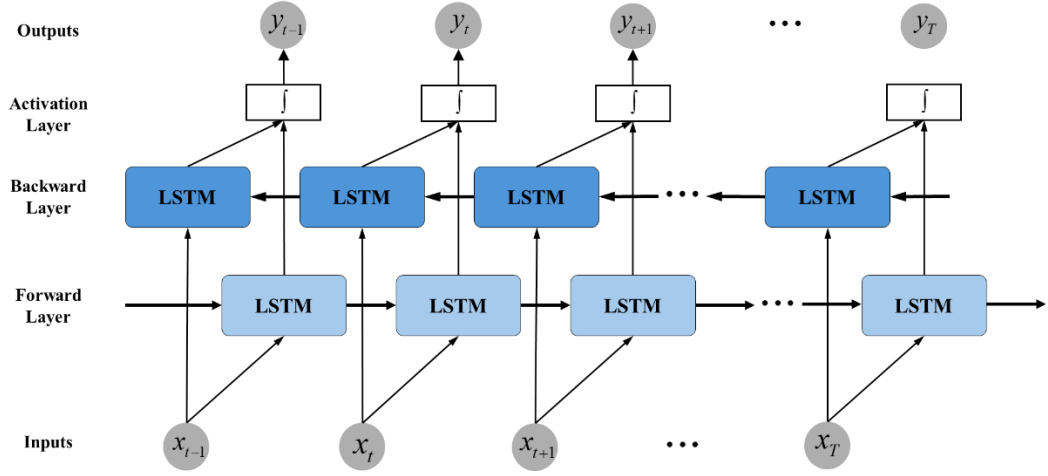


Figure 2.5 The Bi-LSTM network architecture

2.8.3 AM-LSTM Model Architecture

The AM-LSTM network is an enhanced architecture designed to improve the model's ability to focus on the most relevant parts of a temporal sequence. The attention mechanism acts as a dynamic weighting process that evaluates the importance of each time step with respect to the prediction target. Instead of treating all input information equally, the model assigns higher weights to time steps that contribute more significantly to the output while reducing the influence of less relevant data.

The structure of the Attention-based LSTM model, as illustrated in the Fig. 2.6, By integrating an Attention Layer, the model can “focus” on the most relevant time steps that significantly influence the prediction, instead of treating all input sequences with equal importance as in a standard LSTM.

Within the LSTM Layer, the model processes the sequential inputs $x_t, x_{t+1}, \dots, x_T$ to generate a series of hidden states $(h_t, h_{t+1}, \dots, h_T)$, each capturing contextual information at a specific time step. These hidden states are then fed into the Attention Mechanism, which computes the importance weights (attention scores) corresponding to each temporal step. In the Attention Layer, the tanh activation function is used to transform each hidden state into a relevance vector that reflects its contribution to the output. Then, the Softmax function normalizes these values into a probability distribution, ensuring that the attention weights sum to one. This allows the model to determine the relative importance of each time step. The final

context vector (Z) is obtained by computing the weighted sum of all hidden states according to their respective attention weights.

Subsequently, the output from the Attention Layer is passed to a Fully Connected Layer, which performs the final regression to estimate the SOH. The incorporation of the Attention mechanism enables the model to effectively capture critical patterns in specific time intervals that reflect battery degradation behavior, thereby improving the accuracy and robustness of SOH estimation compared to the conventional LSTM model. For further details, see (B. Zou et al., 2023)

In the context of battery SOH estimation, the attention mechanism allows the model to concentrate on critical moments such as abrupt voltage or current variations that indicate degradation behaviors. This selective focus leads to more accurate and robust SOH predictions, as the model can better capture the underlying dynamics of battery aging over multiple charge-discharge cycles.

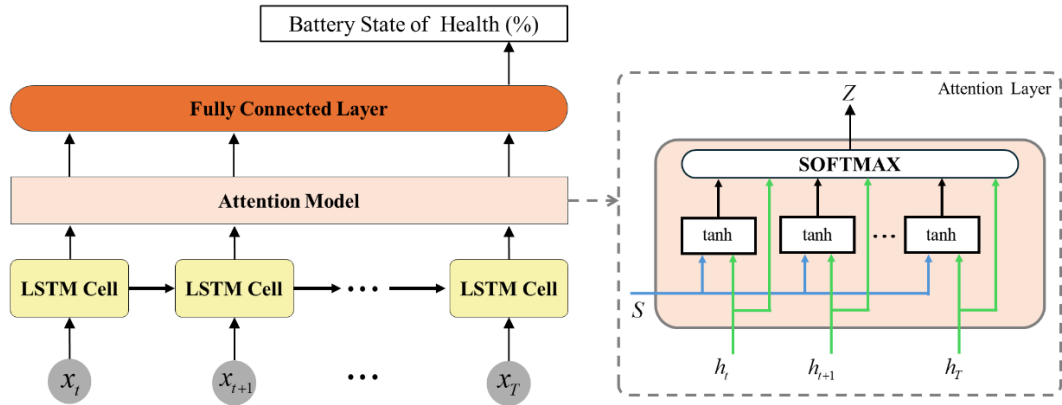


Figure 2.6 The ATT-LSTM network architecture

2.8.4 GRU Model Architecture

The GRU is an advanced RNN architecture designed to address the vanishing gradient problem commonly encountered in traditional RNNs. Similar in concept to the LSTM network, GRU introduces a simplified yet efficient structure that reduces computational complexity and the number of trainable parameters, while still maintaining the ability to capture long-term dependencies within sequential data. Structurally, GRU employs two main gating mechanisms: the update gate and the reset gate.

1) Reset Gate (r_t), This gate acts like a filter for past information. It takes the current input (x_t) and the previous hidden state (h_{t-1}) to decide how much of the old memory (h_{t-1}) is irrelevant to the current input. Essentially, it determines what to "forget" or "reset" from the past before the cell calculates its new candidate information ($\tilde{h}_t$).

2) Update Gate (z_t), This gate is key for blending the data. The update gate (z_t) learns (from x_t and h_{t-1}) to decide the "proportion" of new information to add. Its value (between 0 and 1) determines how much of the old memory (h_{t-1}) to keep (the $1 - z_t$ part) and how much of the new candidate information ($\tilde{h}_t$) to accept (the z_t part)

3) New Hidden State (h_t), This is the final output for this time step. It's the "merged" result of the old and new information, based on the proportions set by the update gate (z_t) in the equation $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$. This h_t becomes the new "updated memory," which is then passed on to the next time step ($t - 1$) to continue analyzing the battery's SOH trend.

The architecture of the GRU is presented in Fig. 2.7. Unlike LSTM, GRU eliminates the separate memory cell state and relies solely on the hidden state to store and update information. For further details, see (Fan et al., 2020). This design simplification allows for faster training and reduced computational cost, while still achieving comparable accuracy in learning long-term temporal relationships. Due to its efficiency and compact architecture, GRU often provides faster convergence when handling large or repetitive datasets, such as charging–discharging sequences in battery systems.

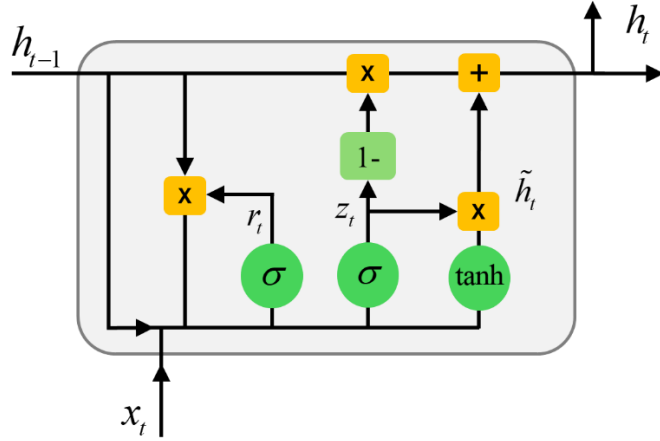


Figure 2.7 The GRU network architecture

2.8.5 GPR Model Architecture

GPR is a statistical technique based on the concept of the Gaussian distribution, which is used to model the relationship between input and output variables without requiring an explicit predefined functional form. GPR can be viewed as an extension of linear regression to a more flexible, non-parametric approach by defining a Gaussian process over possible functions rather than focusing solely on specific model parameters. The core principle of GPR lies in the covariance function, also known as the kernel function, which determines how similar or related different data points are to one another. This kernel-based formulation allows GPR to capture complex and nonlinear relationships in the data effectively. By computing the correlations between all input samples, GPR constructs a probabilistic model that provides smooth and consistent predictions even when the data distribution is irregular or noisy. One of the main advantages of GPR is its ability to provide both predicted values and uncertainty estimates simultaneously. This characteristic is particularly beneficial in battery SOH estimation, where understanding the model's confidence level in each prediction is as important as the prediction itself. The uncertainty quantification enhances the interpretability and reliability of the estimation results. For further details, see (Wang et al., 2022)

However, GPR has a major limitation in terms of computational cost when dealing with large datasets, since it must compute correlations between all pairs

of data points. As the dataset size increases, the amount of required computation grows significantly, resulting in longer training times and higher memory consumption. Therefore, GPR is generally more suitable for problems with smaller datasets or for use as a benchmark model to compare against deep learning-based approaches in terms of accuracy and interpretability.

Based on the reviewed literature, various models have been employed for estimating the SOH of batteries, ranging from statistical to deep learning approaches. Each model possesses distinct principles and structural designs to handle the complexity and time-dependent characteristics of battery data. Deep learning models such as LSTM, Bi-LSTM, GRU, and Attention-based LSTM have demonstrated strong capabilities in capturing temporal dependencies and degradation behaviors effectively, while the statistical model GPR offers advantages in interpretability and in providing uncertainty estimates for predictions. Comparing these models highlights their respective strengths and limitations, providing a clearer understanding of different methodological perspectives in battery health estimation.

2.9 Evaluation Metrics

To evaluate the performance of the models used for estimating the battery SOH, which is expressed as a percentage (%SOH), several evaluation metrics are employed to assess both accuracy and consistency. In this study, four commonly used metrics are selected: MSE, RMSE, MAE, and MAPE. Each of these metrics provides a different perspective on the model's estimation capability.

2.9.1 Root Mean Squared Error

RMSE, defined in Equation (2.2), is the square root of MSE and provides an interpretable measure of error in the same unit as the output variable (%SOH). It offers an intuitive understanding of the model's estimation precision and is sensitive to large errors. RMSE is especially useful in this study for evaluating how well the model can maintain consistent estimation accuracy across different degradation stages.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (SOH(i) - SOH_e(i))^2} \quad (2.2)$$

Where n is a number of cycles SOH , is actual capacity, SOH_e is estimated capacity.

2.9.2 Mean Squared Error

MSE measures the average of the squared differences between the estimated and actual SOH values, as shown in Equation (2.3). This metric emphasizes larger deviations by squaring the error terms, making it particularly useful for identifying models that minimize large prediction discrepancies. A lower MSE value indicates that the model's estimations are closer to the actual SOH across the dataset.

$$MSE = \frac{1}{n} \sum_{i=1}^n (SOH(i) - SOH_e(i))^2 \quad (2.3)$$

2.9.3 Mean Absolute Error

MAE represents the average magnitude of the absolute differences between estimated and actual SOH values, as expressed in Equation (2.4). Unlike MSE or RMSE, MAE does not square the differences, making it less sensitive to outliers. This metric highlights the model's general estimation capability and provides an interpretable measure of average error that directly corresponds to the deviation percentage of SOH.

$$MAE = \frac{1}{n} \sum_{i=1}^n |SOH(i) - SOH_e(i)| \quad (2.4)$$

2.9.4 Mean Absolute Percentage Error

MAPE, formulated in Equation (2.5), expresses the average estimation error as a percentage of the actual SOH values. This allows for straightforward comparison between datasets with different scales. Since the SOH output in this study is represented in percentage form (%SOH), MAPE provides an intuitive metric for understanding how far, on average, the estimated battery health deviates from its true value.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{SOH(i) - SOH_e(i)}{SOH(i)} \right| \times 100\% \quad (2.5)$$

Using all four metrics provides a comprehensive evaluation of model accuracy, covering aspects such as absolute error, squared error, and relative error in percentage terms.