A Combined Bi-LSTM and Self-Attention Approach for Li-Ion Battery SoC Estimation Under Varying Temperatures

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***Abstract*—Accurate State of Charge (SoC) estimation is essential for the efficient management of Li-ion batteries, especially under varying operating conditions. Traditional filtering approaches rely on predefined battery models, requiring prior knowledge of internal dynamics, which may introduce inaccuracies in real-world applications. In this study, we propose a data-driven SoC estimation method based on a Bidirectional Long Short-Term Memory (Bi-LSTM) network enhanced with a self-attention mechanism, designed to identify and prioritize key time steps in the battery's charge-discharge cycle. The model takes voltage, current, and temperature as inputs and has been validated across multiple battery profiles under diverse temperature conditions. Experimental results demonstrate that the proposed approach achieves an estimation accuracy of approximately 98%, with a Root Mean Squared Error (RMSE) below 1.7, significantly improving the reliability of SoC predictions. By using both past and future states, along with attention-driven feature weighting, the proposed model enhances SoC estimation robustness across different operating scenarios.**

***Index Terms*—Li-ion Battery, SoC Estimation, Time Series, Bi-LSTM, Attention Mechanism.**

I. Introduction

Estimating the State of Charge (SoC) of batteries remains a critical challenge for autonomous systems such as electric vehicles (EVs) and robots, as it directly impacts their autonomy and operational efficiency. Embedding a reliable SoC estimation system is therefore essential for any battery-powered embedded system. Numerous methods have been developed to tackle this issue, primarily categorized into direct measurement techniques, model-based approaches, and data-driven methods.

Direct methods, such as Coulomb counting [1], offer a straightforward solution but suffer from cumulative errors due to sensor drift over time. In contrast, model-based approaches rely on equivalent circuit models (ECMs) or electrochemical models, which require the implementation of state observers, such as the Extended Kalman Filter (EKF) [2] [3] or Luenberger observer [4], to estimate the SoC. While these techniques can provide high accuracy under controlled conditions, their performance heavily depends on the precision of the battery model, necessitating extensive characterization efforts. Moreover, their implementation is often complex and iterative due to the nonlinear and dynamic nature of battery behavior.

On the other hand, data-driven methods do not explicitly model the internal physical and electrochemical behavior of the battery but instead uses sensor data, such as voltage, current, and temperature, to estimate SoC. However, with the growing availability of large datasets generated from extensive battery characterization tests, there is a clear opportunity to use Artificial Intelligence (AI) techniques for SoC estimation [5].

AI-based approaches can capitalize on this wealth of data, offering a more flexible, data-driven alternative to model-based methods, and enabling more accurate, real-time SoC predictions under diverse operational conditions [6] [7].
In fact AI has emerged as a powerful tool in this domain, with various machine learning techniques [8] [7], including Support Vector Machines (SVM), decision trees, and deep learning architectures such as Multi-Layer Perceptrons (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNNs).

Recent advancements in AI-driven SoC estimation include the application of generative models, such as Generative Adversarial Networks (GANs) [9] and diffusion models, which introduce controlled Gaussian noise to data and reconstruct the original signal through denoising techniques. Additionally, transformer-based architectures and attention mechanisms have been explored to enhance feature extraction from voltage and current curves, particularly under varying C-rates and temperature conditions [10].

RNNs, particularly Long Short-Term Memory (LSTM) [11] and Bidirectional LSTM (Bi-LSTM) [12], have shown strong performance in SoC estimation due to their ability to capture time-dependent battery behavior. As voltage and current vary over time, these models are well-suited to handle the sequential nature of battery data [13]. LSTMs can retain long-term dependencies, making them ideal for modeling the extended timeframes typical of battery testing.

Bi-LSTM networks further enhance performance by processing data in both forward and backward directions, capturing dependencies during charging and discharging. However, they may struggle with abrupt changes, such as mode shifts, rapid current pulses, or temperature fluctuations.

To address this, we incorporate an attention mechanism inspired by generative AI, allowing the model to focus on critical time steps. This improves both accuracy and interpretability, enhancing robustness under varying real-world conditions.

The remainder of this article is then structured as follows: First, we focus on related works, detailing how Bi-LSTM and the attention mechanism operate and presenting recent studies that have attempted to use the attention mechanism in the context of SoC estimation.Next, we introduce our proposed approach along with the dataset used. In the third section, we present the obtained results and performance evaluation.Finally, we conclude with a comprehensive discussion, highlighting new avenues for extending this work towards autonomous systems.

II. Related Works

In this section, we first outline the functionning the functioning of Bidirectional LSTM networks and the self-attention mechanism. We then provide an overview of existing works that integrates attention mechanisms with neural networks for SoC estimation.

A. Bi-LSTM Architecture

LSTM networks are a type of recurrent neural network designed to capture dependencies in sequential data through a gating mechanism. They consist of three key gates, each utilizing activation functions to regulate information flow: the forget gate, which uses a sigmoid (σ) activation to determine which past information to discard; the input gate, which applies both a sigmoid function to decide what information to update and a hyperbolic tangent (tanh) function to generate candidate values for the cell state; and the output gate, which employs a sigmoid activation to filter the cell state's output while a tanh activation scales the final output.

Bi-LSTM networks consist of two LSTM layers: one processes past input features in the forward direction, while the other handles future input features in the backward direction. The architecture is illustrated in Fig. 1 .

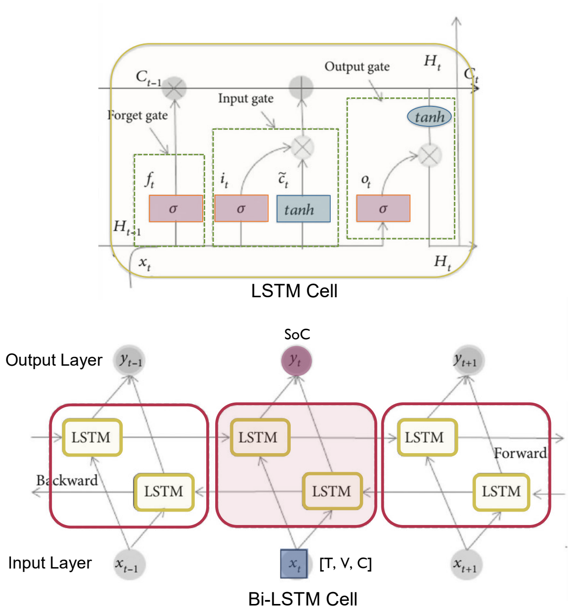

Fig. 1. Bi-LSTM Architecture

This bidirectional processing enhances prediction accuracy, especially for long sequential data like battery profiles, by capturing both historical dependencies and future trends.

In SoC estimation, where battery behavior is influenced by dynamic factors such as varying C-rates and temperatures, Bi-LSTMs provide a more robust and precise modeling approach.

B. Attention Mechanism

The attention mechanism has demonstrated its effectiveness in a wide range of deep learning tasks, including image processing, laguage translation, and time series forecasting. A particularly powerful variant is the self-attention mechanism, widely used in Transformer architectures. In self-attention, each element of an input sequence interacts with all other elements of the same sequence to compute a new representation. This is achieved by projecting the input into three distinct vectors: the query (Q), key (K), and value (V). The attention score between each pair of elements is computed by taking the dot product of Q and K, which is then scaled and passed through a softmax function to obtain normalized weights [14]. These weights are used to compute a weighted sum of the value vectors (V), resulting in a context-aware representation of each element as in Fig.2.

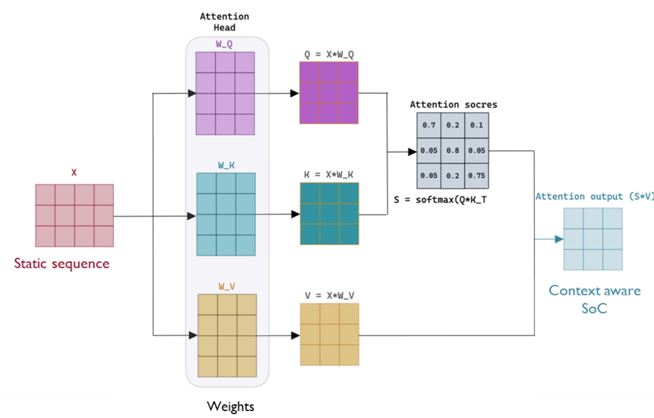

Fig. 2. Self-Attention Mechanism [15]

Since Q, K, and V are all derived from the same input sequence in self-attention, the model can dynamically capture complex dependencies and relationships across time steps, regardless of their distance in the sequence. This capability is especially valuable in SoC estimation for batteries, where the SoC at a given moment can be influenced by both recent and distant patterns in voltage, current, and temperature [16].

C. Attention based Approach for SoC estimation

Bi-LSTM is a widely used model in the context of State of Charge (SOC) estimation because it handles time series data in both directions, which aligns well with the bidirectional nature of battery behavior during charging and discharging. This behavior is also influenced by ambient temperature, as demonstrated in many studies in the literature.

However, this method remains insufficient when the battery's behavior is not smooth over time and is subject to sudden variations, such as transitions between charging and discharging, temperature spikes or drops, or abrupt current impulses as explained in the Fig.3

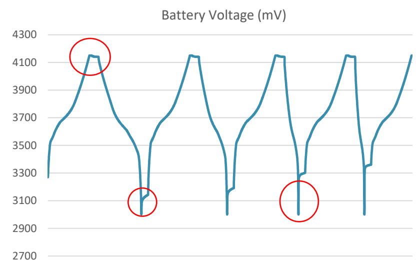

Fig. 3. Li-ion battery voltage : focus on behaviour variations

These challenges can be addressed through the use of the self-attention mechanism, which allows the model to compute attention scores on the important events affecting battery behavior and thereby refine the estimated SOC. The attention mechanism has been introduced in the literature for battery SoC estimation to enhance model performance by effectively capturing long-term dependencies and improving feature representation. Several studies have explored its integration with various AI algorithms. For instance, Li et al. proposed a self-attention-based CNN-Bi-LSTM model that accurately estimates SoC across varying temperature conditions by capturing both spatial and temporal dependencies [17].
Similarly, Wang et al. developed a SoC estimation method based on a multi-head attention mechanism combined with a Gated Recurrent Unit (GRU), effectively mitigating long-term dependency and gradient vanishing issues.
Additionally, Zhao et al. introduced a hybrid approach using an LSTM network with an attention mechanism and a Kalman filter, demonstrating RMSE and MAE across different driving cycles [19].
Furthermore, Ding et al. proposed a CALSE-LSTM model incorporating self-attention and a squeeze-and-excitation mechanism, optimized using the Pelican Algorithm, which significantly reduced estimation errors compared to conventional deep learning models [20].

These studies highlight the potential of attention mechanisms to improve the accuracy of the SoC estimation by enhancing temporal feature extraction and mitigating common challenges in deep learning-based battery modeling.

III. Proposed Methtod: Attention Based Bi-LSTM SoC estimation

In this section, we first present the dataset used in this study, along with the key characteristics of the battery under investigation. We then describe the adopted methodology and detail the proposed architecture implemented for SoC estimation.

A. Battery Dataset

The dataset used in our experiments was initially collected for battery characterization conducted in Mobi Battery Center [21], which motivated its application in AI models due to its abundance and relevance. The data were obtained from multiple batteries of the same type, ensuring diverse testing conditions and robustness in the results. The battery details are detailed in table I.
The test bench consisted of battery tester connected to a battery placed inside a climate chamber, where the temperature was varied for each set of experiments as explained in [22]. The dataset includes two main types of tests:

- Capacity Test: This test involved successive charge and discharge cycles under different C-rates at various controlled temperatures, providing insights into battery aging and performance.

- Dynamic Discharge Pulse Test (DDPT): A more realistic evaluation, where the battery was subjected to current pulse patterns simulating real driving conditions, such as acceleration and deceleration phases.

TABLE II
Tested Li-ion Battery Characteritics

Battery Type	Pouch battery (NMC)
Nominal capacity	20000 mAh
Tests	Capacity test, DDP test
Temperatures	15, 25, 35, 40

All test data were recorded as time series CSV files, sampled at one-second intervals, with some tests extending over several hours. In this study, data from four battery cells were used: three were dedicated to training and testing (using a 80%-20% split), while the fourth battery was reserved exclusively for validation. This independent validation ensured that the generalizability of the model was assessed on previously unseen data.

B. Methodology

The process followed in this work begins with data loading and pre-processing, where multiple CSV files containing battery measurements (voltage, current, temperature, and SoC) are loaded, concatenated, and normalized to get values between 0 and 1.
Next, in time series data preparation, sequences of 10-time steps are created to structure the data for LSTM processing, and the dataset is split into training and testing.
The model architecture consists of two stacked Bi-LSTM layers that capture temporal dependencies, followed by an attention mechanism that enhances the model's focus on the most relevant time steps. In model training, the network is trained using the Adam optimizer with Mean Squared Error (MSE) loss for 10 epochs to optimize SoC predictions.
Finally, in testing and validation, the trained model is evaluated on the test set using performance metrics Mean absolute error (MAE), Root mean square error (RMSE), and R^2-score that measure how well a model fits data, to assess its accuracy in estimating SoC.

TABLE I
OVERVIEW OF SOC ESTIMATION METHODS USING ATTENTION MECHANISMS

Reference	Approach	Battery Type	Tests Conducted	RMSE
[Li2024] [17]	CNN-Bi-LSTM with Self-Attention	Madison dataset (Panasonic 18650 PF)	US06, HWFET, UDDS	RMSE: 0.92%
[Wang2024] [18]	GRU with Multi-Head Self-Attention	NASA ,CALCE Datasets (18650 Li-ion LCO)	Capacity tests	RMSE: 2.10%
[Zhao2024] [19]	LSTM with Attention and Kalman Filter	18650-20R Li-ion Batteries	DST, FUDS, US06	RMSE: 1.895%
[Ding2024] [20]	LSTM with Self-Attention optimized by Pelican Algorithm	Lithium-ion batteries	UDDS conditions	RMSE: 1.73%

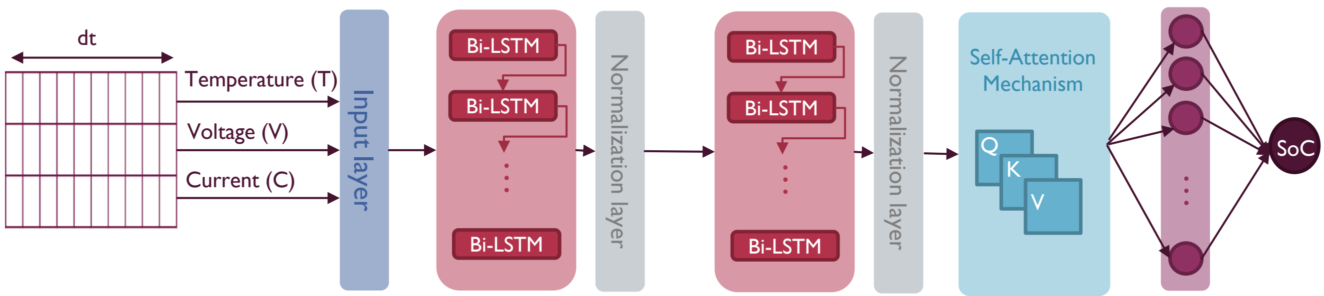

Fig. 4. Architecture of the proposed approach of SoC estimation using Bi-LSTM and Self-Attention.

C. Proposed Architecture

The proposed model is based on Bi-LSTM layers to capture temporal dependencies in both directions and incorporates an attention mechanism to focus on the most relevant time steps.

The final prediction is made using a fully connected dense output layer. We detail the architecture in Fig.4.

- **Input Layer**
  The input layer receives sequences of sensor measurements over multiple time steps. Each sequence has a fixed length and includes voltage, current, and temperature. In fact, it accepts sequences of shape (10,3), 10 time steps(dt), 3 features (T,V,C).This ensures compatibility with sequential processing, allowing the model to analyze time-dependent patterns in the data.
- **First Bi-LSTM Layer**
  The first bidirectional LSTM layer captures past and future dependencies by processing the sequence in both directions. It retains the full sequence structure for deeper analysis, which helps in understanding long-term dependencies in the SoC estimation problem. The stack of Bi-LSTM consists of 64 unit cell.
- **Normalization Layer**
  Layer normalization is applied after the first Bi-LSTM to stabilize activations. It prevents issues such as vanishing or exploding gradients, ensuring smooth learning and improving convergence speed.
- **Second Bi-LSTM Layer**
  The second bidirectional LSTM layer further refines the temporal patterns extracted by the first Bi-LSTM. It captures higher-level sequence relationships, enhancing the accuracy of SoC estimation while preserving time-step-wise dependencies.
- **Second Normalization Layer**
  The second layer normalization ensures stable learning across layers, preventing degradation of learned data.
- **Attention Mechanism**
  The attention mechanism assigns importance scores to each time step by using query (Q), key (K), and value (V) representations to compute attention scores. A softmax function is then applied to determine the most relevant time steps. It creates a context vector, emphasizing the most useful information.
- **Dense Output Layer**
  This layer is a fully connected layer with a multiple neuron. It uses a linear activation function for the continuous prediction of the SoC and receives the processed context vector as input to generate the final prediction.

IV. EXPERIMENTS AND RESULTS

In this section, we present a thorough evaluation of the proposed stacked BiLSTM architecture integrated with a self-attention mechanism, and compare its performance against a basic Bi-LSTM model without attention.
The experiments were carried out using the hyperparameters presented in table III. The assessment is done using two evaluation metrics: RMSE and MAE, across a range of ambient temperatures. The testing is performed on a test set comprising

TABLE III
MODEL PARAMETERS

Parameter	Value
Number of epochs	10
Batch size	32
Optimizer	Adam
Learning rate	0.001
Number of Bi-LSTM layers	2
Units per LSTM layer	10 (in each direction)

20% of the dataset, selected randomly. The proposed BiLSTM with self-attention achieves a 98% of accuracy and a lower RMSE of 1.85%, compared to 2.56% recorded by the Bi-LSTM model without attention.
Fig.5 illustrates the SoC estimation using the proposed model, highlighting a strong correlation with the actual values.

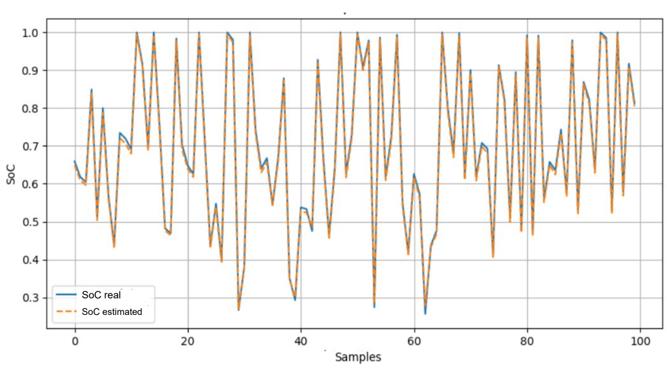

Fig. 5. Result of SoC estimated using the proposed approach on the test dataset (focus on the first 100 samples)

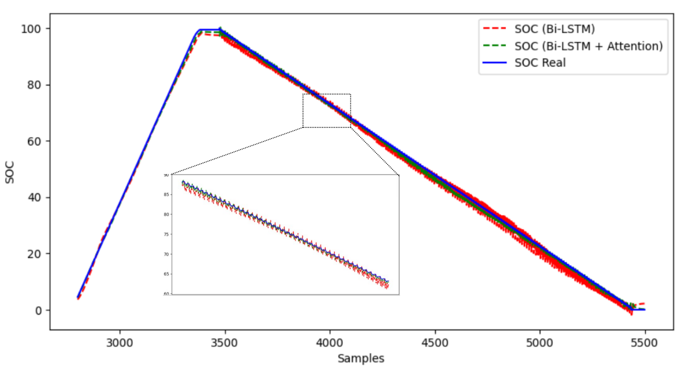

Fig. 6. SoC estimation using Bi-LSTM and Bi-LSTM combined with the attention mechanism for DDPT profile at 25°C

To further validate the robustness of the proposed model, inference was conducted using data from a completely unseen battery—specifically, voltage, current, and temperature measurements that were not included in either the training or testing datasets. The model achieved an impressive accuracy of 98%, along with RMSE and MAE values that were significantly lower than those recorded by the BiLSTM model without attention mechanism. These results underscore the effectiveness and strong generalization capability of the proposed Bi-LSTM with self-attention architecture.

The fig.6 shows that the proposed approach performs better than Bi-LSTM only for soc estimation at the ambiant temperature 25°C and this is well reported with metrics in Table.IV.

Table.IV presents the results at different ambient temperatures, illustrating the effect of adding the attention mechanism on the evaluation metrics. It is clear that there is an improvement, with both RMSE and MAE significantly decreasing, especially at 15°C.

TABLE IV
RMSE AND MAE VALUES OF IMPLEMENTED BI-LSTM AND BI-LSTM +ATTENTION AT 15°C, 25°C, 35°C, AND 40°C.

			Bi-LSTM	Bi-LSTM + Self attention
Test (Random Temperatures)		RMSE	2.56%	1.85%
		MAE	1.90%	1.24%
Validation	25°C	RMSE	2.33%	**1.77%**
		MAE	1.73%	**1.08%**
	35°C	RMSE	1.58%	1.51%
		MAE	1.22%	1.20%
	40°C	RMSE	1.6%	1.4%
		MAE	1.25%	1.21%
	15°C	RMSE	4.18%	**2.1%**
		MAE	3.55%	**1.27%**

This improvement is well-justified by the fig.7, where a spike can be observed when the charge-discharge transition occurs. The BiLSTM model without attention is unable to follow this change as seen in the red curve, while the attention mechanism does as shown in the green curve. The RMSE value then decreases by 2%, which is a significant improvement, especially in the context of autonomous systems.

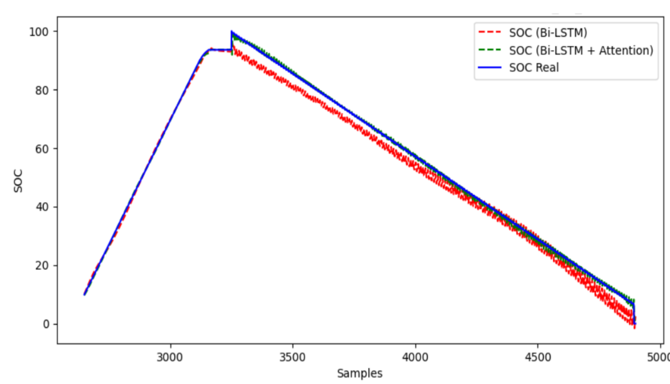

Fig. 7. SoC estimation using Bi-LSTM and Bi-LSTM combined with attention mechanism for DDPT profile at 15°C

Fig.8 presents a summary of the minimum results obtained for RMSE and MAE across various deep learning approaches combined with attention mechanisms used SoC estimation under different temperatures, as explored in the following works: [18] [19] [20] [16]. Our proposed approach demonstrated strong performance, achieving competitive results.

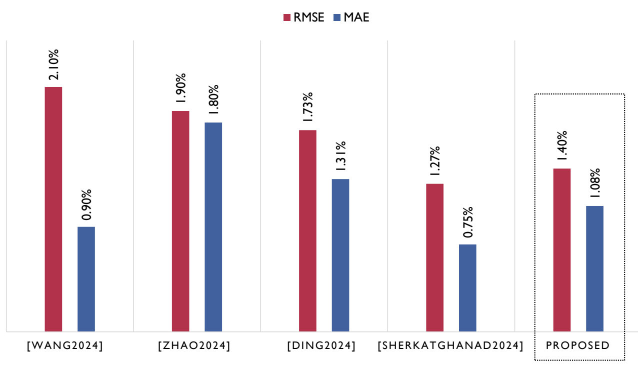

Fig. 8. Performance comparaison of deeplearning approches using attention mechanism for SOC estimation

V. Conclusion

In this study, we present a robust and data-driven approach for estimating the SoC of lithium-ion batteries using a Bi-LSTM network enhanced with a self-attention mechanism. Unlike traditional model-based estimators that rely on physical parameters and prior knowledge of battery dynamics, our approach learns from raw sensor data: voltage, current, and temperature, capturing complex temporal dependencies and highlighting the critical time steps through attention weighting.

Experimental results demonstrated the effectiveness of the proposed model across various temperatures and operating conditions, achieving a SoC estimation accuracy of approximately 98% with an RMSE not exeeding 2% in wost case. Furthermore, the model generalized well to previously unseen battery data, confirming its robustness and suitability to be implemented in an autonomous system.

As a future works, we aim to extend our approach by incorporating a wider range of driving profiles, such as Worldwide Harmonized Light Vehicles Test Cycle (WLTC). Additionally, integrating a Physically-Informed Neural Network (PINN) could offer the combined benefits of data-driven learning and battery modeling, for accurate and reliable SoC estimation.

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