Physically-Informed BiLSTM for Lithium-Ion Battery SoC Estimation

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***Abstract*—Accurate estimation of battery State of Charge (SoC) is essential for reliable battery management systems. Traditional methods such as Coulomb counting may accumulate errors over time, while purely data-driven models often lack physical consistency. In this paper, a physics-informed Bidirectional Long Short-Term Memory (BiLSTM) model is proposed for SoC estimation. The approach combines a Coulomb counting model with a neural network that learns the residual error between the physical estimate and the measured SoC. Experimental results show that the proposed model improves estimation accuracy and robustness, achieving an average RMSE of around 1.5% during the testing phase and outperforming the purely data-driven BiLSTM model.**

***Index Terms*—Li-ion Battery, SoC Estimation, BiLSTM , Physically informed, Coulomb-counting**

I. Introduction

The rapid adoption of electric vehicles (EVs) has increased the importance of efficient battery management systems (BMS). Among the key variables monitored in a BMS, the State of Charge (SoC) plays a crucial role in ensuring safe operation, optimal energy utilization, and prolonged battery lifetime. However, SoC cannot be measured directly and must be estimated using measurable signals such as voltage, current, and temperature. Traditional SoC estimation methods are typically based on electrochemical or equivalent circuit models combined with state observers such as the Extended Kalman Filter or Unscented Kalman Filter [1], [2]. Although these techniques can achieve accurate estimation under certain conditions, they require precise parameter identification and may suffer from performance degradation under varying operating environments.

With the increasing availability of battery operation data and computational resources, artificial intelligence (AI) and machine learning techniques have emerged as promising alternatives for SoC estimation. Data-driven methods are capable of learning complex nonlinear relationships between battery measurements and SoC without relying on detailed electrochemical modeling [3]. Various machine learning approaches have been investigated, including artificial neural networks, support vector machines, convolutional neural networks, and recurrent neural networks [4]. In particular, Long Short-Term Memory (LSTM) networks have shown strong potential due to their ability to capture temporal dependencies within sequential battery data.

More recently, Bidirectional Long Short-Term Memory (Bi-LSTM) architectures have attracted attention in SoC estimation tasks because they process information in both forward and backward temporal directions. This allows the network to exploit a richer representation of battery dynamics, improving prediction accuracy under dynamic driving conditions [5]. Deep recurrent models such as LSTM, GRU, and Bi-LSTM have demonstrated superior performance compared to conventional estimation techniques when trained on voltage, current, and temperature measurements collected under various charge-discharge profiles [6].

Despite their strong predictive capabilities, purely data-driven approaches present several limitations. In particular, they often lack physical interpretability and may generate predictions that violate the fundamental electrochemical behavior of lithium-ion batteries when exposed to unseen operating conditions. This issue becomes critical in practical applications where batteries operate under different temperatures, load profiles, and aging states. To address these limitations, recent research has explored the integration of physical knowledge into machine learning frameworks, leading to the development of physics-informed machine learning models [**?**]. These approaches incorporate domain knowledge directly into the learning process through constraints, hybrid architectures, or physics-based loss functions.

In this work, we propose a physically-informed deep learning framework for lithium-ion battery SoC estimation that combines the advantages of data-driven learning and physical modeling. The proposed method leverages the temporal modeling capability of a Bi-LSTM architecture while embedding physical constraints derived from battery dynamics into the training process. By integrating physical behavior within the learning framework, the proposed approach aims to improve estimation accuracy, robustness, and generalization capability for online battery management applications.

The remainder of this paper is organized as follows. Section II reviews related works on SoC estimation using model-based and data-driven approaches. Section III presents the proposed physically-informed Bi-LSTM framework. Section IV describes the experimental setup and discusses the obtained results. Finally, Section V concludes the paper and outlines future research directions.

II. RELATED WORK

SoC estimation is a key component of reliable battery management systems (BMS). Early research mainly relied on model-based approaches such as Coulomb counting and observer-based methods including Kalman filters. These techniques provide physically interpretable SoC estimates by relying on electrochemical or equivalent circuit models of the battery. However, their performance strongly depends on accurate model parameters and precise system identification, which can be difficult to maintain under aging, temperature variations, and dynamic operating conditions [7].

To overcome these limitations, recent studies have explored data-driven approaches based on deep learning. Neural networks are capable of learning complex nonlinear relationships directly from battery measurements without requiring explicit physical modeling. In particular, recurrent neural networks (RNNs), and especially Long Short-Term Memory (LSTM) networks, have demonstrated strong performance for SoC estimation because they can effectively capture the temporal dependencies present in battery signals such as voltage, current, and temperature. Bidirectional LSTM (BiLSTM) architectures further improve the modeling capability by processing the time sequence in both forward and backward directions, allowing a richer representation of battery dynamics [8] [6].

Despite their strong predictive performance, purely data-driven models may generate SoC predictions that are not fully consistent with the physical behavior of lithium-ion batteries [9]. In practical BMS applications, such physically inconsistent predictions may lead to unreliable SoC trajectories under unseen operating conditions. To address this issue, physics-informed learning approaches have been proposed to integrate battery physics into deep learning models [10].

Physical knowledge can be incorporated into neural networks through several strategies:

- **Physics-constrained loss functions**: Physical relationships governing battery behavior are included in the training objective. For example, the SoC evolution can be constrained using the Coulomb counting equation that links SoC variation to the time integral of the current and the battery nominal capacity.
- **Hybrid physical–data models**: Neural networks are combined with simplified physical models such as equivalent circuit models (ECM), where the neural network estimates unknown parameters or compensates modeling errors.
- **Physics-informed neural networks (PINNs)**: The governing physical equations describing battery behavior are embedded directly into the learning process, allowing the model to simultaneously minimize prediction errors and violations of physical laws [11].

In the battery domain, early physics-informed approaches mainly focused on combining simplified electrochemical or equivalent circuit models with machine learning methods. For example, physical quantities derived from battery models, such as open-circuit voltage (OCV) or internal resistance, were used as additional inputs to learning algorithms in order to improve SoC estimation accuracy [12], [13]. Later studies extended this idea by integrating physical constraints directly into the training objective, enforcing fundamental battery laws such as charge conservation or lithium diffusion dynamics during learning [14].

More recent research has applied physics-informed principles to advanced deep learning architectures for SoC estimation. These approaches incorporate electrochemical knowledge such as Coulomb counting, OCV–SoC relationships, polarization effects, and diffusion dynamics derived from simplified electrochemical models like the Single Particle Model (SPM). For instance, Transformer-based models and hybrid cascade neural networks have shown that embedding physical constraints within the feature representation or the training loss can significantly reduce estimation errors while improving robustness under varying operating conditions [14], [15].

Nevertheless, among the different deep learning architectures investigated, recurrent neural networks remain the most widely used for SoC estimation due to their ability to model sequential battery behavior. In particular, physics-constrained LSTM models have demonstrated improved stability and physical consistency by enforcing relationships derived from Coulomb counting or electrochemical dynamics between successive SoC states. By constraining the predicted SoC trajectory to respect these physical principles, such models reduce physically implausible fluctuations and improve estimation reliability under dynamic operating conditions [16].

Motivated by these observations, this work proposes a physics-informed BiLSTM framework for SoC estimation. In the proposed approach, the BiLSTM network captures the temporal dependencies of battery measurements, while physical knowledge is incorporated through an updated loss function that enforces consistency with battery charge conservation. By integrating Coulomb-counting-based physical constraints into the training process, the proposed model aims to improve estimation accuracy while ensuring physically consistent SoC predictions.

III. PROPOSED PHYSICS-INFORMED BILSTM ARCHITECTURE

To improve the accuracy and physical consistency of battery State of Charge (SoC) estimation, a physics-informed deep learning framework based on a Bidirectional Long Short-Term Memory (BiLSTM) network is proposed.

The approach integrates a physics-based model, namely the Coulomb Counting (CC) method, directly into the training process of the neural network through a hybrid loss function. This design enables the model to benefit from both the temporal learning capability of recurrent neural networks and the physical consistency imposed by electrochemical principles.

A. Battery Dataset

To evaluate the proposed approach, we rely on an experimental dataset originally gathered for battery characterization purposes at the Mobi Battery Center [17]. Key specifications of the tested cells are summarized in Table I.

The experimental setup comprised a battery cycler interfaced with a climate chamber, allowing precise thermal control throughout the testing campaign. As described in [18], the ambient temperature was systematically varied across experimental sequences. Two complementary protocols were carried out:

- **Capacity Test:** Repeated charge/discharge cycles were performed at different C-rates and controlled temperature levels, yielding information on capacity fade and overall electrochemical behavior over time.
- **Dynamic Discharge Pulse Test (DDPT):** The battery was excited with current profiles representative of actual electric vehicle usage, incorporating acceleration and regenerative braking patterns, thus offering a more operationally realistic perspective.

TABLE I
TESTED LI-ION BATTERY CHARACTERISTICS [19]

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

All measurements were logged as time-series CSV files at a one-second sampling rate. Four battery cells were involved in this study: three cells contributed to model development, partitioned into training and test subsets following an 80%/20% ratio, while the remaining cell was held out as a fully independent validation set. This deliberate separation ensures that the model's ability to generalize to unseen operating histories is assessed under rigorous conditions.

B. Physics-Informed Learning Framework for SoC Estimation

First, a physics-based SoC estimate is computed using the Coulomb Counting method. This estimate provides a physically meaningful reference that follows the charge conservation principle of the battery. However, this method is sensitive to accumulated errors caused by measurement noise, parameter uncertainties, and operating conditions. To overcome these limitations, a BiLSTM model is trained to learn the SoC directly from data while being constrained by the physical estimation.

The Coulomb Counting formulation is given by 1:

$$SoC_{CC}(t) = SoC_{CC}(t-1) + \frac{\eta I(t) \Delta t}{C} \tag{1}$$

where $I(t)$ is the measured current, C is the nominal battery capacity, η is the Coulombic efficiency, and Δt is the sampling interval.

Unlike residual learning approaches, the proposed model directly predicts the SoC while being guided by both the measured SoC and the physics-based estimate. The prediction of the neural network is expressed as:

$$SoC_{pred} = f_\theta(X_t) \tag{2}$$

where f_θ denotes the BiLSTM model and X_t represents the input sequence.

To enforce physical consistency, a hybrid physics-informed loss function involving the data loss and physic loss is introduced:

$$\mathcal{L} = \mathcal{L}_{data} + \lambda_{phy} \mathcal{L}_{physics} \tag{3}$$

with:

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^{N} (SoC_{true}^{(i)} - SoC_{pred}^{(i)})^2 \tag{4}$$

$$\mathcal{L}_{physics} = \frac{1}{N} \sum_{i=1}^{N} (SoC_{CC}^{(i)} - SoC_{pred}^{(i)})^2 \tag{5}$$

where λ_{phy} controls the contribution of the physical constraint. This formulation encourages the model to produce predictions that are consistent with both experimental measurements and the underlying physical behavior of the battery.

C. BiLSTM Network Architecture

The proposed neural network is designed to capture temporal dependencies in battery signals while maintaining a relatively simple and efficient structure as described in previous work [19]. The architecture consists of the following components:

- **Input Layer**
  The model receives multivariate time-series sequences composed of battery measurements such as current, voltage, and temperature. The input dimension is defined as $(seq\_length, n_{features})$.
- **Two Bidirectional LSTM Layer**
  - 32 LSTM units
  - Bidirectional processing
  - Return sequences: True
  - Captures short-term temporal dependencies in the input signals
- **Dense Layer**
  - 16 neurons
  - Activation function: ReLU
  - Transforms the extracted temporal features into a non-linear representation
- **Output Layer**
  - 1 neuron
  - Activation: Linear
  - Produces the predicted SoC value SoC_{pred}

As illustrated in Fig. 1, the proposed framework combines a physics-based SoC estimation with a BiLSTM network and a hybrid loss function in order to improve SoC prediction.

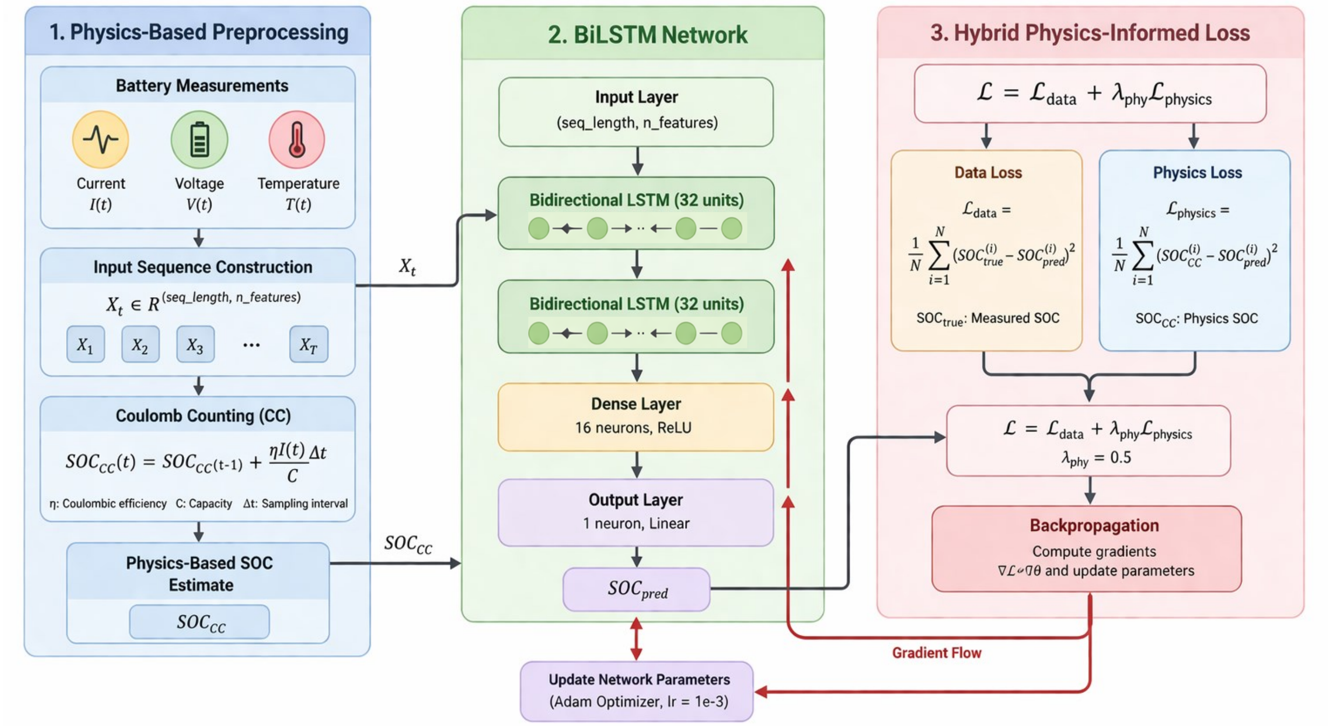

Fig. 1. Architecture of the proposed Physics-Informed BiLSTM model

D. Model Hyperparameters

The main hyperparameters used in the proposed model are summarized in Table II. These parameters were determined empirically after several experiments and iterative adjustments. Different configurations of the network architecture, learning rate, batch size, and physics constraint weight were evaluated to provide the best performance in terms of SoC estimation accuracy and training stability.

TABLE II
HYPERPARAMETERS OF THE PHYSICS-INFORMED BILSTM

Parameter	Value
Architecture Type	Physics-Informed BiLSTM
Number of BiLSTM Layers	2
Neurons per BiLSTM Layer	32 / 32
Dense Layer	16 neurons (ReLU)
Output Neurons	1 (SoC prediction)
Output Activation	Linear
Optimizer	Adam
Learning Rate	1×10^{-3}
Loss Function	Physics-informed loss (data + physics)
Physics Weight λ_{phy}	0.5
Batch Size	20
Epochs	30
Input Features	Current, Voltage, Temperature
Sequence Length	Sliding window (seq_length)
Physics Model	Coulomb Counting (SoC_{CC})
Prediction Strategy	Direct SoC prediction with constraint

IV. Results

In this section, we evaluate the performance of the proposed physics-informed BiLSTM model and compare it with a purely data-driven BiLSTM approach. The goal is to analyze how the integration of physical knowledge influences the accuracy and robustness of battery State of Charge (SoC) estimation.

Table III presents the performance comparison between the purely data-driven Bi-LSTM model and the proposed physics-informed Bi-LSTM approach. The obtained results demonstrate that integrating physical constraints into the learning process significantly improves the SoC estimation accuracy. In particular, the proposed model achieves an average RMSE about 1.5% during the testing phase, indicating a reliable prediction performance.

In contrast, the fully data-driven Bi-LSTM model exhibits higher error values, highlighting the benefit of incorporating battery physics to guide the learning process and improve model generalization.

TABLE III
PERFORMANCE COMPARISON OF SOC ESTIMATION MODELS ON THE TESTING DATASET

Model	MAE	RMSE
Data only Bi-LSTM	2.0695%	2.8324%
Physically informed Bi-LSTM	1.1999%	1.6969%

Figure 2 illustrates the SoC estimation results obtained using both the purely data-driven BiLSTM model and the proposed physics-informed BiLSTM model, compared with the measured SoC during the validation phase.

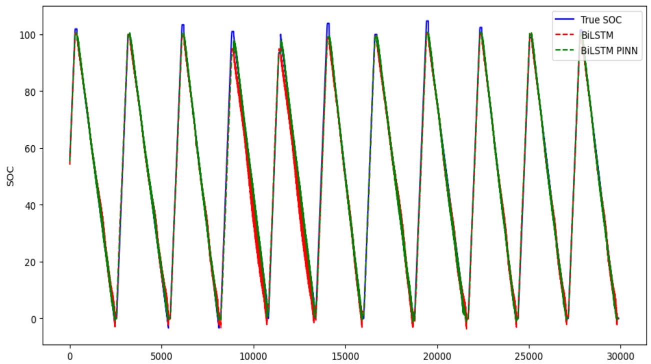

Fig. 2. Comparison between the estimated SoC obtained using the purely data-driven BiLSTM model and the proposed physics-informed BiLSTM model against the measured SoC.

The validation was carried out over several charge and discharge cycles at different C-rates. The discharge profile includes pulsed current patterns, allowing the evaluation of the models under demanding operating conditions where diffusion phenomena inside the battery are strongly excited. The obtained results are promising, showing improved tracking of the real SoC when physical knowledge is incorporated into the learning process.

V. Conclusion and Future Work

This paper presented a physics-informed deep learning approach for SoC estimation by combining the Coulomb Counting method with a BiLSTM network. The proposed model leverages both the physical principles governing battery charge conservation and the ability of deep learning to capture nonlinear temporal patterns in battery measurements. By integrating physics-based estimation with data-driven learning, the framework improves the reliability and accuracy of SoC prediction compared to purely data-driven approaches.

The results highlight the benefit of incorporating physical knowledge into machine learning models. While the Coulomb Counting equation provides a physically meaningful reference for SoC evolution, the BiLSTM network learns complex behaviors and compensates for errors caused by noise, parameter uncertainty, and varying operating conditions. This hybrid approach therefore offers a more stable and consistent SoC estimation.

Future work will focus on improving the generalization capability of the model by incorporating additional operating profiles and driving cycles. Another important direction is the integration of more advanced electrochemical constraints, such as voltage dynamics or internal resistance behavior, to further guide the learning process. Additionally, extending the framework to different battery chemistries will allow the method to be applied across a wider range of energy storage technologies. Ultimately, developing a more generic physics-informed framework capable of adapting to different batteries and operating conditions remains an important goal for future research.

References

[1] G. L. Plett, "Extended kalman filtering for battery management systems of lipb-based hev battery packs: Part 2. modeling and identification," *Journal of Power Sources*, vol. 134, no. 2, pp. 262–276, 2004.

[2] H. He, R. Xiong, and J. Fan, "State-of-charge estimation of the lithium-ion battery using an adaptive extended kalman filter based on an improved thevenin model," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 4, pp. 1461–1469, 2011.

[3] X. Hu, F. Sun, and Y. Zou, "A comparative study of equivalent circuit models for li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.

[4] C. Zhang, J. Jiang, and W. Zhang, "A review of state of charge estimation methods for lithium-ion batteries," *Journal of Power Sources*, vol. 196, no. 15, pp. 6007–6014, 2018.

[5] E. Chemali, P. J. Kollmeyer, M. Preindl, and A. Emadi, "Long short-term memory networks for accurate state-of-charge estimation of li-ion batteries," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6730–6739, 2018.

[6] I. Baccouche and N. Essoukri Ben Amara, "A comprehensive overview of ai based methods for soc estimation of li-ion batteries in ev," in *2024 10th International Conference on Control, Decision and Information Technologies (CoDIT)*. IEEE, 2024, pp. 1885–1890.

[7] M. Hossain, M. Haque, and M. T. Arif, "Kalman filtering techniques for the online model parameters and state of charge estimation of the li-ion batteries: A comparative analysis," *Journal of Energy Storage*, vol. 51, p. 104174, 2022.

[8] N. Mehraj, C. Mateu, H. Bastida, Y. Li, Y. Ding, A. Sciacovelli, and L. F. Cabeza, "Artificial intelligence in state of charge estimation: Pioneering approaches across energy storage systems," *Energy*, vol. 335, p. 138166, 2025.

[9] H. T. J. Chan, J. Rubeša-Zrim, F. Pichler, A. Salihi, A. Mourad, I. Šimić, K. Časni, and E. Veas, "Explainable artificial intelligence for state of charge estimation of lithium-ion batteries," *Applied Sciences*, vol. 15, no. 9, 2025.

[10] F. Wang, Z. Zhai, Z. Zhao, Y. Di, and X. Chen, "Physics-informed neural network for lithium-ion battery degradation stable modeling and prognosis," *Nature Communications*, vol. 15, no. 1, p. 4332, 2024.

[11] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.

[12] X. Chen, Y. Li, and Z. Wang, "Physics-informed deep learning for lithium-ion battery state-of-charge estimation," *Applied Energy*, vol. 335, p. 120746, 2023.

[13] Y. Wu, D. Bai, K. Zhang, Y. Li, and F. Yang, "Advancements in the estimation of the state of charge of lithium-ion batteries: A comprehensive review of traditional and deep learning approaches," *Journal of Materials Informatics*, vol. 5, no. 2, 2025.

[14] H. Zhang, J. Liu, and M. Chen, "Cascade physics-informed neural network for lithium-ion battery state-of-charge estimation," *Energy*, vol. 289, p. 129902, 2024.

[15] Y. Zhao, H. Liu, J. Wang, and L. Chen, "Physics-informed transformer for lithium-ion battery state-of-charge estimation," *Energy*, vol. 310, p. 131650, 2025.

[16] S. Wang, Q. Zhang, Y. Li, and F. Sun, "Physics-constrained lstm network with kalman filtering for lithium-ion battery state-of-charge estimation," *Applied Energy*, vol. 358, p. 122512, 2026.

[17] A. Nikolian, J. Jaguemont, J. de Hoog, S. Goutam, N. Omar, P. Van Den Bossche, and J. Van Mierlo, "Complete cell-level lithium-ion electrical ecm model for different chemistries (nmc, lfp, lto) and temperatures (5°c to 45°c) – optimized modelling techniques," *International Journal of Electrical Power Energy Systems*, vol. 98, pp. 133–146, 2018.

[18] I. Baccouche, S. Jemmali, B. Manai, A. Nikolian, N. Omar, and N. Essoukri Ben Amara, "Li-ion battery modeling and characterization: an experimental overview on nmc battery," *International Journal of Energy Research*, vol. 46, no. 4, pp. 3843–3859, 2022.

[19] I. Baccouche and N. B. A. Essoukri, "A combined bi-lstm and self-attention approach for li-ion battery soc estimation under varying temperatures," in *2025 11th International Conference on Control, Decision and Information Technologies (CoDIT)*, vol. 1, 2025, pp. 1939–1944.