

Enhanced State of Charge Prediction for Lithium-Ion Batteries Using Informer-LSTM Fusion*

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Abstract

State of Charge (SoC) estimation plays a vital role in optimising Battery Management Systems (BMS), particularly for electric vehicles and renewable energy storage applications. However, traditional SoC estimation techniques often struggle to capture modern lithium-ion batteries' complex, non-linear behaviours. This paper introduces a deep learning hybrid model integrating Long Short-Term Memory (LSTM) with Informer model to enhance SoC estimation accuracy. The LSTM component captures short-term temporal dependencies, while the Informer addresses long-term dependencies, improving the overall robustness and accuracy of the system. The model is evaluated on real-world datasets, including UDDS, FUDS, and US06 driving cycles. Experimental findings indicate that the proposed hybrid model outperforms standalone LSTM and Informer models, attaining a Root Mean Square Error (RMSE) of 1.593% and a peak Mean Absolute Error (MAE) of 1.395%. This work demonstrates the potential of combining Informer and LSTM for real-time SoC estimation in battery management systems, offering a robust solution for the future of energy management.

Keywords

Battery Management System, State-of-Charge Estimation, Informer, LSTM, Informer

1. Introduction

The rapid growth of electric mobility and renewable energy systems has increased the need for advanced and intelligent battery management solutions. A key component of Battery Management Systems (BMS) is the precise estimation of the State of Charge (SoC), which delivers crucial information about the remaining energy capacity of a battery [1-3]. This estimation plays a key role in ensuring optimal battery performance, enhancing lifespan, and preventing issues such as overcharging that can result in battery degradation or safety risks [4].

With the increasing complexity of modern battery technologies, traditional methods for SoC estimation have not been very effective, especially under diverse operating conditions such as varying temperatures and different charge/discharge cycles. The challenges in achieving accurate SoC estimation are further compounded by factors such as battery ageing, environmental variations, and the inherent variability in performance across different battery types and usage scenarios [5-6].

The Informer model, a state-of-the-art architecture designed for handling long-term dependencies in sequential data, offers an elegant solution to this challenge [7]. By integrating the strengths of LSTM and Informer models, we propose a hybrid approach that addresses the limitations of traditional methods. The LSTM component of the model focuses on learning immediate temporal

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relationships. Whereas the Informer model captures broader trends over extended periods, thus improving CEUR-WS's LibreOffice template provides a consistent style for use across CEUR-WS publications. This document will explain the major features of the template. If you are new to publishing with CEUR-WS, this document is a valuable guide to the process of preparing your work for publication.

This paper proposes a hybrid Informer-LSTM model for SoC estimation of lithium-ion batteries. We evaluate the performance of this model using real-world datasets, including those from standard driving cycles and under different temperatures. The results demonstrate that our hybrid approach outperforms both the standalone LSTM and Informer models in terms of accuracy and robustness, marking notable progress in battery management systems.

2. Deep Learning Forecast Models

2.1. Long Short-Term Memory (LSTM) Network

LSTMs are well-suited for capturing short-term temporal dependencies in battery data, such as voltage, current, and temperature fluctuations during charging and discharging cycles [11]. These short-term variations are critical for accurate SoC estimation, as they directly influence the battery's operational behaviour at any given moment. The LSTM model uses its memory cells to store relevant information from earlier time steps, which can then predict the battery's current state [12]. This allows the network to adapt to changes in battery performance over time, providing more accurate estimations of the SoC during dynamic battery operation.

However, LSTM networks, while effective at modelling short-term dependencies, may have difficulty capturing long-term relationships in the data. As the sequence length increases, LSTMs may lose crucial contextual information from earlier time steps, leading to suboptimal performance when capturing long-term dependencies, essential for accurate SoC predictions over extended periods [13- 14].

2.2. Informer Model

The Informer model is a robust deep-learning architecture explicitly designed to address the difficulty of capturing long-range dependencies in sequential data [15]. Unlike traditional transformer-based models, Informer incorporates a more efficient attention mechanism that focuses on the most significant parts of the input sequence, reducing the computational burden. This mechanism, known as the "probabilistic linear complexity self-attention," selectively attends to important information, making it particularly useful for time-series forecasting tasks, such as battery SoC estimation.

The Informer model captures long-term trends and patterns spanning multiple steps. By integrating positional encoding into the attention mechanism, the Informer can preserve the temporal relationships between data points, even over extended periods [16]. Focusing on long-term dependencies allows the Informer to make more accurate predictions about battery behaviour, such as anticipating SoC levels several steps ahead [17-19].

However, while the Informer model is highly effective for long-term dependency modelling, it does not inherently account for short-term fluctuations in the data, which are also critical for accurate SoC estimation. So, combining the Informer model and LSTM can provide a more comprehensive solution, with each model focusing on the dependencies best suited to capture.

2.3. Hybrid LSTM-Informer Model

To address the limitations of individual models, we introduce a hybrid model that leverages the advantages of LSTM and Informer networks. This hybrid model is developed to effectively capture both short-term and long-term dependencies in battery data, enhancing the accuracy and reliability of SoC estimation. Figure 1 illustrates our proposed model, which consists of four main components.

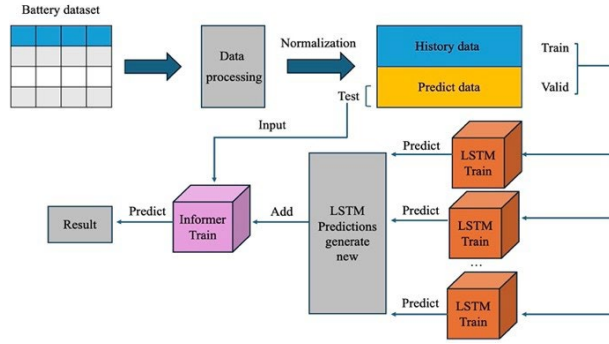


Figure 1: SoC estimation architecture based on Informer-LSTM model.

Preprocessing and Data Normalization: The raw input data, including key features such as voltage, current, and temperature, undergoes preprocessing to standardise and normalise the values. This step ensures that all features play an equal role in the model's contribution. Mitigating any potential bias introduced by features with more extensive numerical ranges. Min-max normalisation is applied to scale the data within a consistent range, ensuring that all input variables are treated relatively during model training.

Short-Term Dependency Modeling with LSTM: The preprocessed data is first fed into the LSTM network, which learns the short-term temporal dependencies within the battery data. The LSTM operates on overlapping data windows, processing these windows sequentially to detect immediate trends and fluctuations in the battery's performance. By learning from these short-term patterns, the LSTM network generates new features that reflect the battery's current state, including its response to recent voltage, current, and temperature changes.

Long-Term Dependency Modeling with Informer: The features generated by the LSTM network are then passed to the Informer model, which captures the long-term dependencies in the data. The Informer's attention mechanism allows the model to concentrate on critical historical data, maintaining meaningful temporal relationships over long periods. This enables the hybrid model to make accurate predictions about the SoC in the future, considering both immediate and long-term factors that influence battery behaviour.

Final SoC Prediction: The output from the Informer model represents the final SoC prediction. This prediction results from the combined efforts of the LSTM and Informer networks, each contributing to the model's ability to capture different aspects of the temporal dynamics in the battery's operational data. The final model output is a more accurate and robust SoC estimate for short- and long-term battery behaviour fluctuations.

By integrating these two models, the proposed hybrid architecture effectively combines the strengths of LSTM's short-term memory and Informer's long-term attention mechanism, resulting in a well-suited model for accurate and reliable SoC estimation in lithium-ion batteries under diverse operational conditions.

3. Experiment and Results

3.1. Datasets

To assess the effectiveness of the proposed hybrid Informer-LSTM model for SoC estimation, we utilised the publicly available LG 18650HG2 Li-ion battery dataset. This dataset, which has been widely used in battery research, contains data from various battery discharge tests performed under different temperature variations and driving cycles. The dataset comprises essential battery parameters, including voltage, current, and temperature, all measured at a frequency of 0.1 seconds during discharge cycles [20].

The battery data was collected across three distinct temperature settings (0°C, 10°C, 25°C) and several drive cycles, including the US06, FUDS and UDDS cycles. These conditions simulate real-

world usage scenarios, ensuring the model can be tested under various environmental and operational factors influencing battery behaviour.

The dataset was divided into training, validation, and test sets, following a typical split of 70%, 10%, and 20%, respectively. This split enables us to use most of the data for training while reserving a portion for validating and testing the model's performance on unseen data. Additionally, we preprocessed the data by applying normalisation techniques, ensuring that all features, such as temperature, current, and voltage, were scaled to a uniform range. This step ensures that no feature dominates due to differences in magnitudes.

3.2. Model Training and Testing Procedures

The training of the proposed hybrid model followed several essential steps to ensure effective learning from the given data. We first split the dataset into three segments: training, validation, and test sets, ensuring that each set contained diverse battery operating conditions and temperature variations. This enabled the model to learn how to estimate the SoC accurately across different scenarios, improving its robustness and adaptability.

During the training phase, we employed the Adam optimiser, a well-established optimisation algorithm known for its efficiency in training deep learning models. We selected a learning rate of 0.00001 to guarantee that the model converged smoothly without overshooting the optimal solution. Additionally, we applied the Huber loss function as the evaluation metric due to its ability to balance between quadratic and linear loss functions, making it particularly useful for scenarios where there are outliers in the data, which is common in battery datasets.

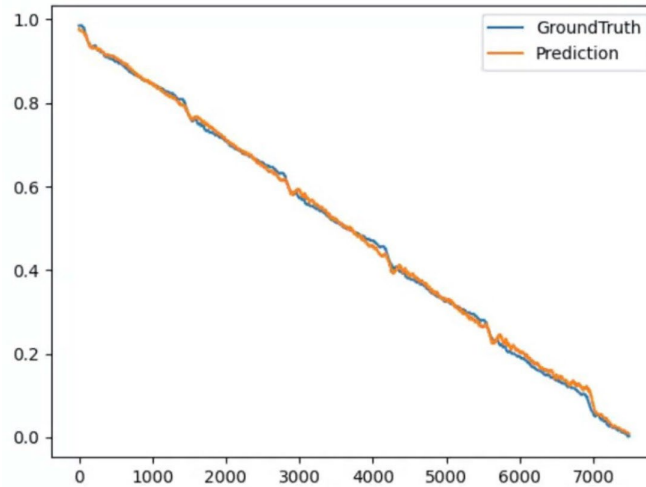


Figure 2: Prediction curve of SoC at 25 degrees.

3.3. Analysis and Discussion of Experiment Results

The SoC estimation results from the proposed model at 25°C are illustrated in Figure 2. The plot above compares the actual and forecasted SoC values for a lithium-ion battery over time. The blue line depicts the actual SoC values, representing the ground truth, while the orange line indicates the predicted SoC values generated by the hybrid Informer-LSTM model. Both lines exhibit a close match, indicating that the model's predictions closely follow the actual values, demonstrating its high accuracy. The model effectively tracks the battery's discharge process, with minimal errors observed, even as the SoC approaches lower values. This indicates the model's robustness in predicting the battery's performance under varying conditions, showcasing its potential for practical use in BMS.

Table 1 provides a detailed comparative analysis of prediction errors across several models, specifically focusing on the performance of the proposed Informer-LSTM hybrid network and the standalone LSTM model. The results demonstrate that the Informer-LSTM network outperforms the

LSTM model regarding prediction accuracy across different datasets, as evidenced by the significantly lower error values observed for the hybrid model. Notably, the Informer-LSTM network achieves a maximum RMSE of 0.01593 and an MAE of 0.01395, highlighting its ability to make precise SoC predictions with minimal deviation from the ground truth.

Table 1

Prediction errors at different temperatures

Degree	Dataset	LSTM		Informer-LSTM	
		RMSE	MAE	RMSE	MAE
25	US06	0.01405	0.01187	0.01397	0.01178
	FUDS	0.01325	0.01096	0.01312	0.01094
10	US06	0.02467	0.02143	0.01572	0.01393
	FUDS	0.02288	0.01994	0.01343	0.01167
0	US06	0.02075	0.01543	0.01593	0.01395
	FUDS	0.01947	0.01484	0.01377	0.01109

In contrast, the pure LSTM model exhibits higher error rates, with a maximum RMSE of 0.02467 and an MAE of 0.02143, reflecting its relatively poorer performance in comparison. These substantial differences in error metrics underline the superiority of the Informer-LSTM hybrid model, which provides more accurate SoC predictions and demonstrates enhanced robustness across various testing conditions. The lower error values the hybrid model achieves indicate its excellent stability and reliability, reinforcing its potential for practical implementation in BMS where accuracy is critical. This comparison emphasises the advantages of combining the Informer’s long-term dependency modelling with LSTM’s ability to capture short-term fluctuations. This results in a more comprehensive and practical approach to battery SoC estimation.

4. Conclusion

This study introduces a hybrid deep learning model combining LSTM and Informer architectures for precisely estimating lithium-ion battery SoC. The proposed model outperforms traditional methods in accuracy and robustness by effectively modelling both short-term and long-term dependencies. The results demonstrate that the Informer-LSTM hybrid network holds significant promise for enhancing BMS, offering potential applications in electric vehicles. Future research will refine the model and extend its capabilities to other battery systems and operational conditions.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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