ExplainBattery: Enhancing Battery Capacity Estimation with an Efficient LSTM Model and Explainability Features

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Abstract

Prognostic and Health Management (PHM) is essential for ensuring the reliable operation of machines by predicting failures and enabling preventive measures. In this context, accurately predicting the capacity of lithium-ion batteries, which power a wide range of applications, is crucial due to their inevitable degradation over time. Battery Management Systems (BMS) play a pivotal role in monitoring and managing battery health throughout their lifecycle. We propose a novel Long Short-Term Memory (LSTM) neural network model for lithium-ion battery capacity prediction. Our model is designed to be more efficient than state-of-the-art models, particularly in terms of the number of trainable parameters, making it suitable for deployment on low-resource devices commonly found in BMS. Utilizing the *Li-ion Battery Aging Dataset* provided by the *NASA Ames Prognostics Center of Excellence*, we demonstrate that our LSTM model offers accurate and reliable capacity predictions. To complement the proposed model, this paper introduces *ExplainBattery*, a web application that allows users to interact with our efficient LSTM. This tool enables users to visualize predictions for different batteries and explore the most influential attributes through an explainable dashboard. ExplainBattery enhances both the usability and transparency of our model, providing an accessible platform for further research and practical application in PHM and BMS environments.

Keywords

Long-Short Term Memory, Lithium-ion Battery, Capacity Estimation, Remaining Useful Life, Explainability

1. Introduction

The growing integration of lithium-ion batteries across a wide range of applications [2], including electric vehicles, renewable energy storage systems, and consumer electronics, emphasizes their key role in advancing sustainable energy solutions. However, the performance and longevity of these batteries are constrained by their gradual degradation over time, which leads to a reduction in their overall capacity and efficiency. Consequently, accurately predicting battery capacity is fundamental to maintaining optimal performance, enhancing safety, and preventing unexpected failures, particularly in critical applications. This challenge forms a core aspect of *Prognostic and Health Management* (PHM) [3, 4], a multidisciplinary field dedicated to predicting the health and remaining useful life of systems, thereby enabling proactive maintenance and reducing operational risks.

Battery Management Systems (BMS) [5] are at the forefront of this effort, as they are responsible for continuously monitoring and controlling battery health parameters, ensuring the safe and efficient operation of lithium-ion batteries throughout their lifecycle. Within the BMS framework, accurate capacity prediction is essential for estimating the *state of health* (SOH) and *state of charge* (SOC) of the battery, which directly influences the reliability and efficiency of the devices it powers. However,

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predicting battery capacity is a non-trivial task, given the complex electrochemical dynamics of lithium-ion batteries and the multitude of factors, such as temperature, charging rates, and usage patterns, that influence their degradation over time.

Traditional modeling techniques, including *physics-based* [6, 7, 8, 9] and *data-driven* [10, 11, 12] approaches, have been extensively explored for battery capacity prediction. While physics-based models offer insights into the underlying degradation mechanisms, they often require detailed knowledge of battery chemistry and are computationally intensive. In contrast, data-driven approaches, particularly those based on machine learning, have emerged as a more practical solution. They can learn complex patterns directly from historical data without requiring explicit modeling of electrochemical processes. Among these, *Recurrent Neural Networks* (RNNs) [13, 14, 15, 16] have shown promise due to their inherent ability to model temporal dependencies in sequential data. However, standard RNNs are prone to the vanishing gradient problem, which limits their effectiveness in capturing long-term dependencies and thus compromises prediction accuracy.

Long Short-Term Memory (LSTM) [17, 18, 19] networks have been introduced as a superior alternative, overcoming the limitations of traditional RNNs by incorporating memory cells and gating mechanisms that enable the retention of long-term dependencies in sequential data. This capability makes LSTM networks particularly well-suited for modeling the complex, time-dependent degradation behavior of lithium-ion batteries. Nevertheless, existing LSTM-based models in the literature often suffer from high computational complexity and a large number of trainable parameters, making them less practical for deployment in BMS environments where computational resources and energy efficiency are constrained.

To address these limitations, this paper proposes a novel LSTM-based neural network architecture tailored for lithium-ion battery capacity prediction, focusing on achieving a balance between accuracy and efficiency. Our approach builds upon the architecture proposed by Ansari et al. [20], but with a critical modification, i.e., replacing traditional RNN layers with LSTM layers, to leverage the strengths of LSTM in capturing long-term dependencies while ensuring an efficient parameter structure. This results in a model that not only achieves high predictive accuracy but also maintains a reduced computational footprint, making it more suitable for real-time applications in BMS.

We conducted a comprehensive evaluation of the proposed model using the *Li-ion Battery Aging Dataset* provided by the *NASA Ames Prognostics Center of Excellence*, a widely recognized benchmark in the battery research community. The experimental results demonstrate that our LSTM-based model outperforms existing state-of-the-art models, particularly those developed by Choi et al. [21] and Park et al. [22], in terms of prediction accuracy. Remarkably, this performance is achieved with a significantly lower number of trainable parameters, indicating that the model is not only more accurate but also more efficient and potentially deployable in resource-constrained BMS environments.

In addition to the development of the LSTM model, we recognize the importance of transparency, interpretability, and trustworthiness in the today's scientific context. This holds true for many domains, such as loan approval systems [23], user profiling [24, 25, 26, 27], e-commerce [28, 29], and especially for critical applications like battery health monitoring. Therefore, we developed *ExplainBattery*, a web-based application designed to facilitate interaction with the dataset, the proposed LSTM model, and the implemented explainability techniques, including *SHAP* [30, 31] and *Saliency Maps* [32]. ExplainBattery allows users to visualize battery capacity predictions, explore the model's decision-making process, and investigate the impact of various features on the predictions. This enables deeper insights into the model's behavior and enhances its applicability in real-world PHM and BMS environments.

This paper makes a contribution to the field of lithium-ion battery health management by presenting an accurate, efficient, and explainable LSTM-based model for capacity prediction, complemented by a user-friendly web application that encourages further research and practical deployment.

The structure of the paper is organized as follows: Section 2 provides a review of the background and related work in the domain of battery capacity prediction; Section 3 illustrates in detail the dataset adopted as the benchmark; Section 4 describes the methodology and architecture of the proposed LSTM model; Section 5 presents the experimental evaluation and results; Section 6 introduces *ExplainBattery*, detailing its features and functionality; finally, Section 7 concludes the paper and outlines potential directions for future research.

2. Background and Related Work

In this section, we discuss definitions and techniques for predicting the health status of batteries and explore explainability approaches specifically applied to RNNs, particularly LSTM networks.

2.1. State of Health and Remaining Useful Life

In the existing literature [22, 20, 21, 33], the *State Of Health* (SOH) and *Remaining Useful Life* (RUL) of a battery are often used interchangeably, despite exhibiting distinct differences alongside shared commonalities.

The estimation of a battery's SOH is primarily based on the assessment of its capacity, which is calculated from the battery's current capacity using the following formula:

$$SOH = \frac{C_k}{C_0} * 100 \tag{1}$$

where C_0 is the nominal capacity of the battery, and C_k is the capacity of the battery at the k^{th} cycle.

With the *End Of Life* (EOL) criterion of a battery defined as the threshold capacity value beyond which the battery's proper functioning is no longer guaranteed, the RUL can be formally defined as the difference between the total number of charge-discharge cycles elapsed when the battery's actual capacity drops to the threshold value (N_{EOL}) and the number of charge-discharge cycles performed thus far by the battery (N). Consequently, the RUL quantifies the number of remaining charge-discharge cycles available to the battery, after which its performance and proper functioning are no longer assured. In formula:

$$RUL = N_{EOL} - N \tag{2}$$

Given that the primary objective of existing techniques and studies for estimating SOH and RUL [22, 20, 21, 33] is the assessment of battery capacity, the model proposed in this work aims to estimate the capacity of lithium-ion batteries. This information will subsequently be utilized to evaluate the battery's health status, thereby providing valuable insights into its remaining lifespan and overall performance.

The techniques for estimating battery SOH fall into three main model categories: *experience-based*, *physics-based*, and *data-driven*.

Experience-based methods utilize expert knowledge and predefined rules to estimate SOH by analyzing stochastic deterioration patterns. While effective for less complex systems, they lack real-time monitoring capability and are heavily reliant on domain expertise, which limits their adaptability [34].

Physics-based models create mathematical representations of battery degradation using real-time data to update parameters [7]. They are suitable for accurate SOH prediction without requiring extensive historical data but are hindered by the absence of established models for battery aging behaviors and complexities in capturing failure modes [8]. Techniques such as Particle Filtering [9] and Kalman filtering [6] have been employed, yet challenges like particle degeneration limit their long-term accuracy.

Data-driven models, which rely on historical measurements of battery parameters (e.g., voltage, current, temperature), have shown the most promise due to their adaptability and efficiency. They do not require explicit physical models, making them versatile for different battery types. Early methods combined Ensemble Empirical Mode Decomposition (EEMD) with ARIMA [12] but faced limitations in capturing non-linear behaviors. More sophisticated techniques, such as Support Vector Machines (SVM) [10], Relevance Vector Machines (RVM) [11], and artificial neural networks (ANNs) [35], have been developed. Recently, RNNs, specifically LSTM networks, have gained prominence for their ability to handle time-series data effectively [36].

2.2. Recurrent Neural Networks vs. Long-Short Term Memory Networks

Recurrent Neural Networks (RNNs) [13, 14, 15, 16] are a class of ANNs designed to process sequential data by maintaining a form of memory through their recurrent connections, allowing information to persist over time. However, standard RNNs face challenges in learning long-term dependencies due to the vanishing gradient problem, which hampers the network's ability to propagate information over extended sequences. *Long Short-Term Memory* (LSTM) [17, 18, 19] networks address this limitation by incorporating a more sophisticated memory cell structure that includes gates (specifically, input, forget, and output gates) that regulate the flow of information. These gates enable LSTMs to retain or discard information as needed, making them significantly more efficient in capturing long-term dependencies in sequential data compared to traditional RNNs. Consequently, LSTMs exhibit superior performance in tasks involving lengthy sequences, such as time series prediction.

2.3. Single-Channel vs. Multi-Channel Input Profiles

Machine learning models employing a *Single-Channel Input* (SCI) profile are characterized by their use of a dataset from a single battery, typically split into training and testing sets. Such models rely on a single battery parameter (e.g., voltage or capacity) as the input feature for predicting the SOH or RUL. This univariate approach often results in high error rates due to the low dimensionality and lack of comprehensive information inherent in the dataset. Consequently, SCI models struggle to capture the complex degradation dynamics of batteries, leading to suboptimal accuracy in SOH and RUL predictions.

In contrast, the adoption of a *Multi-Channel Input* (MCI) profile represents a significant advancement in training methodologies. MCI models leverage datasets from multiple batteries, incorporating a range of parameters—such as voltage, current, temperature, and capacity, across various charge-discharge cycles. This multivariate approach enables the model to capture more intricate patterns of battery degradation, including the phenomenon of capacity regeneration, which SCI models often fail to represent adequately. The inclusion of multiple channels of input data allows for a more holistic understanding of the battery's health, thereby improving the model's predictive accuracy.

Literature on battery RUL prediction [22, 20, 21, 37] consistently demonstrates the superiority of MCI methodologies over SCI approaches in terms of accuracy and robustness. MCI models not only provide a more nuanced representation of the battery's operational profile but also enhance the model's ability to generalize across different battery conditions. Therefore, in line with these findings, this work employs an MCI methodology to train the proposed model, aiming to achieve more reliable and precise predictions of battery SOH and RUL.

2.4. Explainable Artificial Intelligence

As machine learning models increasingly inform critical decisions in battery SOH estimation, explainability becomes a key concern. Trust in these models hinges on transparency, distinguishing between *trusting individual predictions* and *trusting the model's overall behavior* [38]. Building this trust is crucial, particularly in applications where safety and operational efficiency are paramount.

In the domain of lithium-ion batteries, XAI techniques offer a pathway to understand and validate model predictions, ensuring safe deployment in energy management systems. However, research on the explainability of RNNs remains limited. Schlegel et al. [39] investigated XAI methods for time-series data, revealing that techniques like SHAP, Saliency Maps, DeepLIFT, and Layer-wise Relevance Propagation (LRP) offer valuable insights but vary in effectiveness based on model architecture. For RNNs, SHAP proved consistent across models, while other techniques showed performance fluctuations, indicating the need for further exploration of XAI methods in this field.

Advancing data-driven SOH estimation with optimized RNN architectures, coupled with rigorous XAI techniques, becomes essential for developing trustworthy, efficient battery management solutions.

3. Li-ion Battery Aging Dataset

The benchmark dataset used in the presented work, which is the main dataset adopted in the literature [22, 20, 21] to estimate the capacity of a lithium-ion battery, is the **Li-on Battery Aging Dataset**[1]

[1]https://catalog.data.gov/dataset/li-ion-battery-aging-datasets. Accessed October 28, 2024.

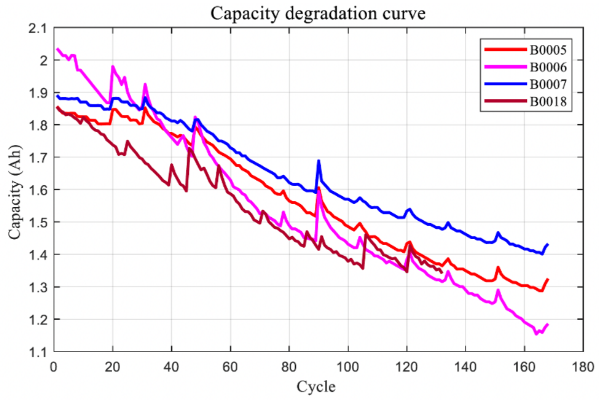


Figure 1: Capacity degradation curve of the batteries included in the *Li-ion Battery Aging Dataset* with increasing charge-discharge cycles.

provided by the *NASA Ames Prognostic Center of Excellence*. The dataset contains the lifecycle data of four custom-built lithium-ion batteries (identified as B0005, B0006, B0007, and B0018), each with a nominal capacity of 2 Ah, which were subjected to and monitored under three different operational profiles at room temperature: *charge*, *discharge*, and *impedance*.

The batteries were charged in constant current (CC) mode at 1.5 A until the battery voltage reached 4.2 V, followed by constant voltage (CV) mode until the charge current dropped to 20 mA. The batteries' discharge was carried out at a constant current (CC) level of 2 A until the battery voltage dropped to 2.7 V, 2.5 V, 2.2 V, and 2.5 V for batteries B0005, B0006, B0007, and B0018, respectively. Impedance measurement, which indicates the ease with which alternating current passes through the electrical circuit, was performed by frequency scanning using the technique of Electrochemical Impedance Spectroscopy (EIS) from 0.1 Hz to 5 kHz.

Repeated charge and discharge cycles lead to accelerated aging of the batteries, while impedance measurements provide information on internal battery parameters that change as aging progresses. Figure 1 shows the capacity degradation curve of the various batteries due to the repeated charge-discharge cycles performed on them.

After the data collection process, a predictive model will be trained utilizing the dataset to estimate battery capacity. Notably, the dynamic nature of the discharge process, characterized by rapid variations in current over time, renders the accurate measurement or calculation of internal battery parameters challenging. Furthermore, the parameters governing the discharge process in real-world scenarios can exhibit significant variability, contingent upon the specific usage patterns of the battery owner and user. In contrast, the charging process is typically governed by manufacturer-defined protocols and parameters embedded in the battery charger device, thereby facilitating the measurement and comparison of battery performance during successive charging cycles. To elucidate the evolution of internal battery parameters throughout its lifespan, this study will primarily focus on exploiting data related to voltage, current intensity, and battery temperature recorded during charge cycles. Figures 2, 3, and 4 illustrate the trends of voltage, current intensity, and temperature values for batteries B0005, B0006, B0007, and B0018 during the charging phase, as a function of increasing charge-discharge cycles.

An examination of the voltage, current intensity, and temperature profiles measured during the charging phase reveals distinct characteristics of batteries in advanced stages of aging, having undergone numerous charge-discharge cycles. Specifically, the following trends are observed: (1) The threshold voltage of 4.2 V is attained significantly earlier in aged batteries, as compared to their relatively newer counterparts; (2) The current intensity diminishes more rapidly in aged batteries; and (3) The maximum temperature is reached more expeditiously in aged batteries. These observations collectively indicate that the voltage, current intensity, and temperature values measured during the charging phase are strongly influenced by the battery's health condition, which is, in turn, a function of its degree of aging.

Based on these findings, it can be inferred that a correlation exists between the measured charging phase parameters and the battery's state of health. This relationship will be leveraged in subsequent

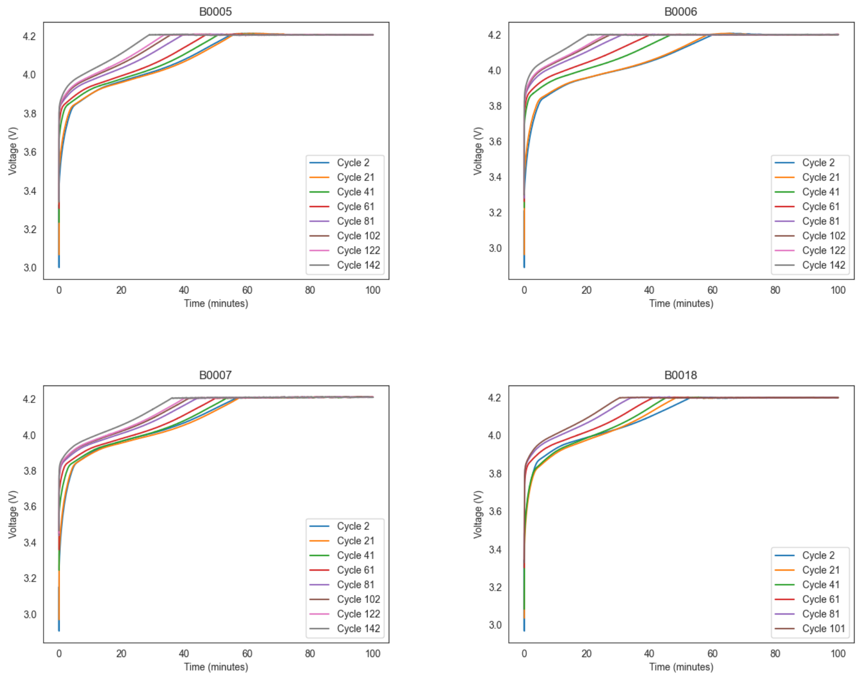


Figure 2: Voltage trend over time for the batteries included in the *Li-ion Battery Aging Dataset*.

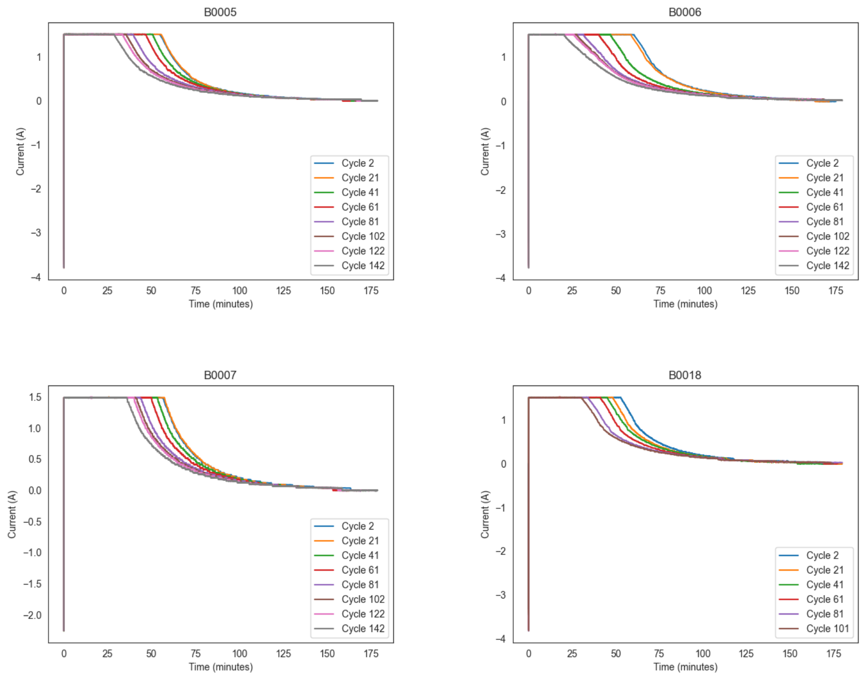


Figure 3: Current intensity trend over time for the batteries included in the *Li-ion Battery Aging Dataset*.

chapters to train a predictive model for estimating the capacity of lithium-ion batteries. To further elucidate the evolution of internal battery parameters throughout its lifespan, the capacity measured during the preceding discharge cycle will also be taken into account. By integrating these data, a more comprehensive understanding of the aging process and its impact on battery capacity can be achieved.

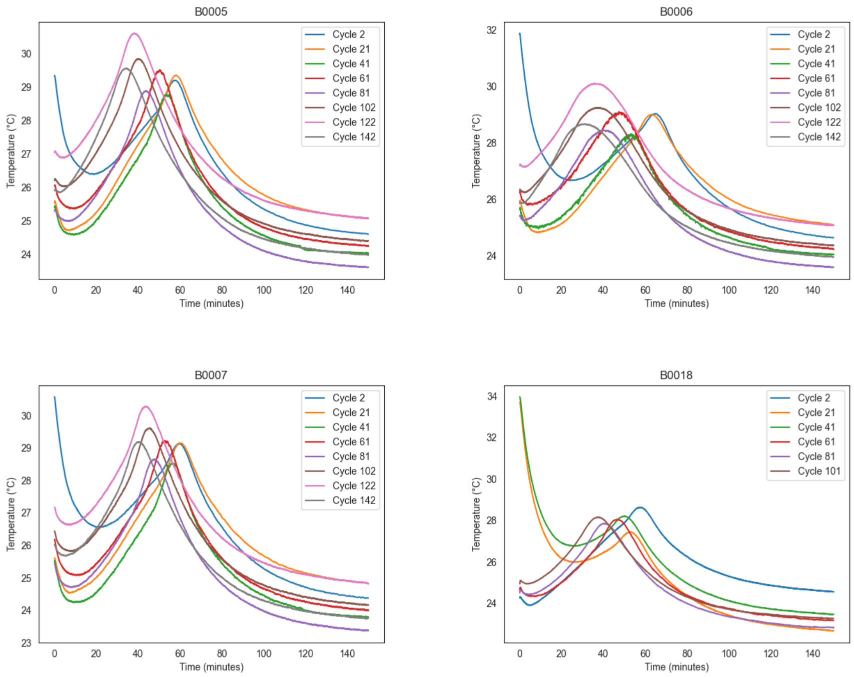


Figure 4: Temperature trend over time for the batteries included in the *Li-ion Battery Aging Dataset*.

4. System Design and Implementation

In the field of lithium battery capacity estimation, accurate and efficient prediction models are crucial for ensuring reliable operation and longevity of battery systems. Recent advancements have led to the development of state-of-the-art models by Choi et al. [21], Park et al. [22], and Ansari et al. [20], each contributing unique strengths to the domain. A critical analysis of these models reveals an opportunity to enhance predictive performance by combining their most effective elements.

The models proposed by Choi et al. [21] and Park et al. [22] utilize LSTM-based architectures, which excel in capturing the temporal dependencies and nonlinear degradation patterns inherent in battery capacity data. Their sophisticated LSTM frameworks have demonstrated high predictive accuracy, making them benchmarks for the industry. However, these models are computationally intensive, with complex architectures that may be less practical for implementation in systems with limited computational resources, such as BMS.

In contrast, Ansari et al. [20]'s model adopts a more efficient approach by employing a simpler RNN-based architecture. This model offers faster training and inference times, making it more suitable for real-time applications and deployment on hardware with restricted processing capabilities. Nevertheless, this model's reduced complexity results in lower predictive accuracy compared to Choi et al. [21] and Park et al. [22]'s LSTM-based models, limiting its effectiveness in capturing battery degradation behaviors.

Recognizing the strengths and limitations of these approaches, our system design strategy aims to integrate the efficiency of Ansari et al. [20]'s model with the predictive capabilities of LSTM architectures. Specifically, we adopt this model architecture as a foundational framework due to its computational efficiency and replace the standard RNN layers with LSTM layers. This hybrid approach seeks to leverage the superior sequence-learning ability of LSTMs, allowing the model to capture long-term dependencies in battery data more effectively, as demonstrated in Choi et al. [21] and Park et al. [22]'s work. By incorporating LSTM layers within a less complex architecture, our objective is to achieve a balance between computational efficiency and predictive accuracy, resulting in a model that can be deployed in real-world BMS applications while maintaining high performance in battery capacity estimation. This design choice represents a strategic synthesis of existing methodologies. It aims to

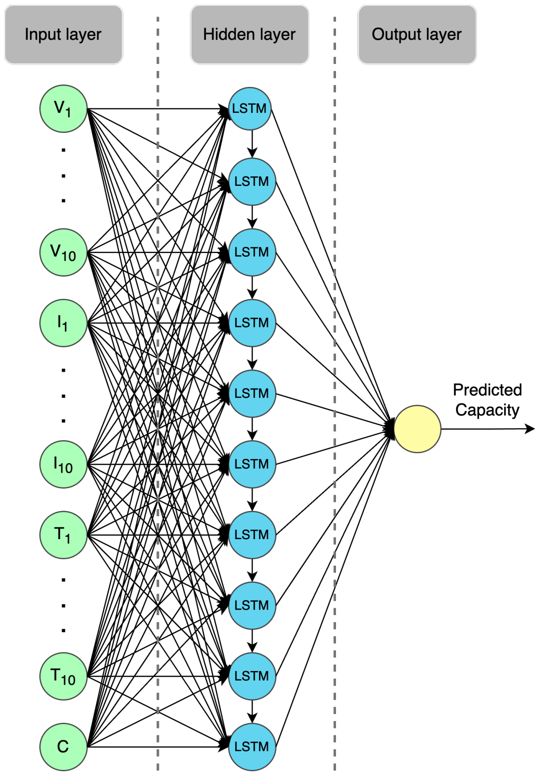


Figure 5: Architecture of the proposed LSTM-based model.

achieve the predictive robustness of LSTM-based models while retaining the operational efficiency necessary for practical applications. Through this integrated approach, we aim to enhance the overall reliability and applicability of lithium battery capacity estimation in energy management systems.

Given the above motivation, the resulting proposed architecture, whose structure is shown in Figure 5, is constructed with the *input layer* of 31 nodes, a *hidden layer* of 10 LSTM neurons, and the *output layer* for estimating the battery capacity.

5. Evaluation

In this section, we describe the proposed model's training process, the experimental setting to compare it with the existing models, and finally, discuss the experimental results.

5.1. Training process

For the training of the proposed LSTM-based neural architecture, we employed a technique called *systematic sampling* [40, 41]. It is a sampling strategy that involves extracting samples at regular intervals from an ordered reference population. In our specific case, data related to voltage, current intensity, and temperature during a charging cycle, as well as the capacity recorded during the previous discharge cycle, are used to estimate the battery's current capacity. Specifically, for each charging cycle, 10 values for voltage, 10 values for current intensity, and 10 values for temperature are extracted using the systematic sampling technique to form the input vector, which consists of 31 features, along with the capacity recorded during the previous discharge cycle.

Given its demonstrated efficacy, as discussed in Section 2.3, we train our model with an MCI profile which entails that, in each iteration, data from three batteries are used as training datasets, with the fourth serving as the testing dataset.

Figure 6 illustrates the described training process, including systematic sampling and the MCI profile.

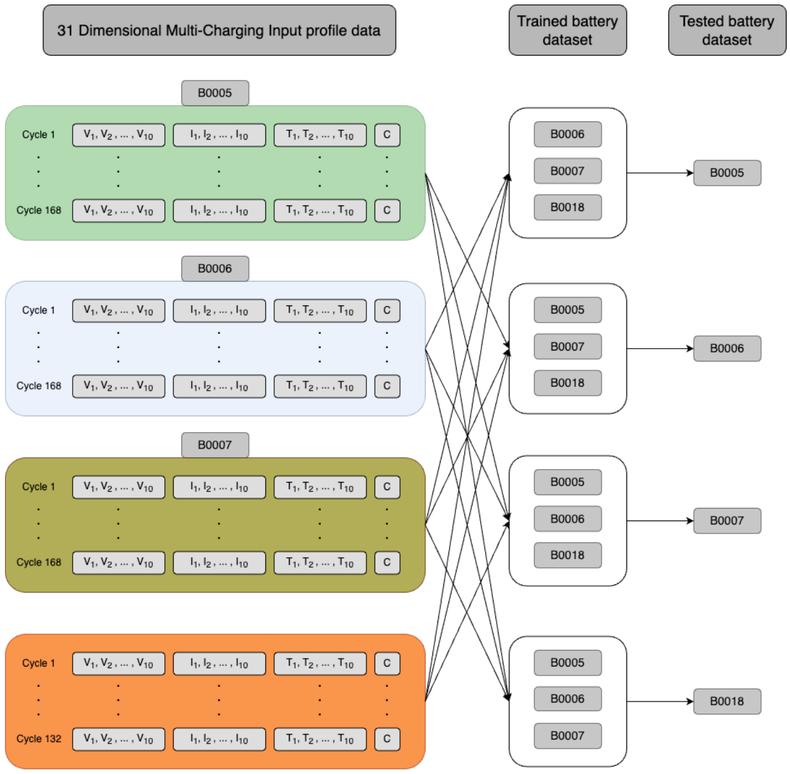


Figure 6: Training process of the proposed model, constituted by systematic sampling and a Multi-Channel Input (MCI) profile.

Model	Parameters	Performance Metrics Mean			
		MSE (↓)	RMSE (↓)	MAE (↓)	MAPE (↓)
Choi et al. [21]	17472	6.052×10^{-4}	0.0246	0.0104	0.0159
Park et al. [22]	2772	$\underline{5.227 \times 10^{-4}}$	<u>0.0198</u>	<u>0.0103</u>	<u>0.0145</u>
Ansari et al. [20]	**491**	8.378×10^{-4}	0.0278	0.0139	0.0157
Proposed model	<u>1578</u>	$\mathbf{2.797 \times 10^{-4}}$	**0.0156**	**0.0089**	**0.0093**

Table 1
Comparison between the *performance metrics* and *complexity* (expressed as the number of *trainable parameters*). The down arrow (↓) indicates that lower values are better. Bold indicates the best value for each metric, while underlined is the second best.

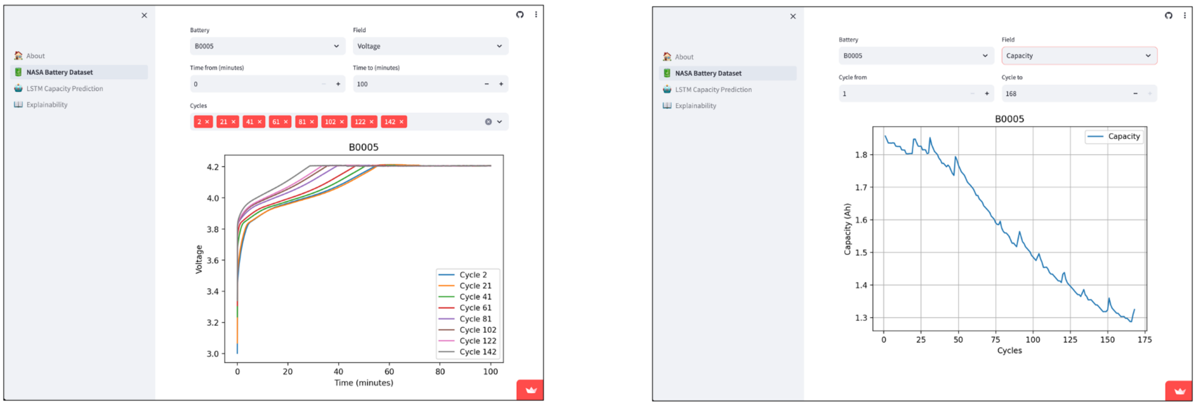
5.2. Experimental Setting

We assess the effectiveness of the proposed model on the *Li-ion Battery Aging Dataset* (Section 3) comparing the results against the state-of-the-art models already mentioned in this paper, namely, Choi et al. [21] (2019), Park et al. [22] (2020), and Ansari et al. [20] (2021). The metrics adopted for the performance evaluation are *Mean Squared Error* (MSE), *Root Mean Squared Error* (RMSE), *Mean Absolute Error* (MAE), and *Mean Absolute Percentage Error* (MAPE). Moreover, the *trainable parameters* are also calculated and reported to provide a measure of the complexity of the different models to relate them to their potential efficiency for implementation on a BMS.

For the training phase, we adopt the same MCI profile (see Section 5.1) for all the models, iterating at each stage for 1000 epochs, employing a learning rate of 0.001 and an Adam optimizer.

5.3. Experimental Results

The results of the conducted experiments are presented in Table 1. Due to the MCI profile employed for the training-testing process, the performance metric scores are reported as the mean values of the individual experiments carried out on each battery, while the number of trainable parameters remains



(a) Voltage trend over time for different charge cycles shown for battery B0005.

(b) Capacity trend over time shown for battery B0005, from cycle 1 to cycle 168.

Figure 7: ExplainBattery - NASA Battery Dataset page

constant throughout the entire evaluation.

A comprehensive analysis of the results reveals that the proposed model consistently outperforms the most effective state-of-the-art model, as presented by Park et al. [22]. Specifically, our model achieves substantial improvements across multiple evaluation metrics, with reductions of 46.45% in MSE, 21.21% in RMSE, 13.59% in MAE, and 35.86% in MAPE. Notably, these enhancements are achieved while simultaneously reducing the complexity of the neural architecture, demonstrated by a 75.67% decrease in trainable parameters. Regarding efficiency, the increase in the number of trainable parameters relative to the model proposed by Ansari et al. [20] amounts to 68.88%, indicating a judicious trade-off. This augmentation is justified by the significantly enhanced performance achieved, which substantially surpasses the improvements observed in the original model.

6. ExplainBattery Web Application

To facilitate exploration of the *Li-ion Battery Aging Dataset* used for training the proposed LSTM-based neural architecture, as well as to enable interaction with the model for accuracy verification and experimentation with explainability techniques for independent reliability assessment, the **ExplainBattery** web application has been developed (using *Streamlit*[2]) and published[3]. This tool serves as a foundation for further exploration and investigation into explainability techniques applied to lithium-ion battery capacity estimation using LSTM networks.

The developed web application is structured with the four distinct pages illustrated below, accessible via a dedicated sidebar menu.

About This page functions as ExplainBattery's homepage, describing the scientific research conducted and offering instructions on how to navigate and interact with the web application.

NASA Battery Dataset On this page, users can explore the *Li-ion Battery Aging Dataset* (illustrated in detail in Section 3). After setting the desired parameters, a chart configured according to the selected values will be generated and displayed on the page. Figure 7 presents examples of this page in use.

LSTM Capacity Prediction This page allows interaction with the proposed LSTM model implemented in this study, enabling verification of the prediction accuracy. Once the parameters are set, a table displaying the accuracy metrics (MSE, RMSE, MAPE, MAE) of the LSTM model, using the

[2] https://streamlit.io/. Accessed October 28, 2024.
[3] https://explainbattery.streamlit.app/. Accessed October 28, 2024.

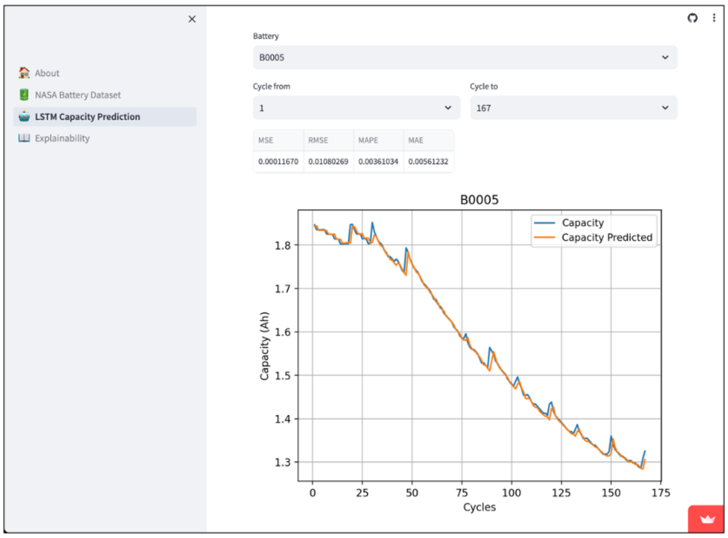
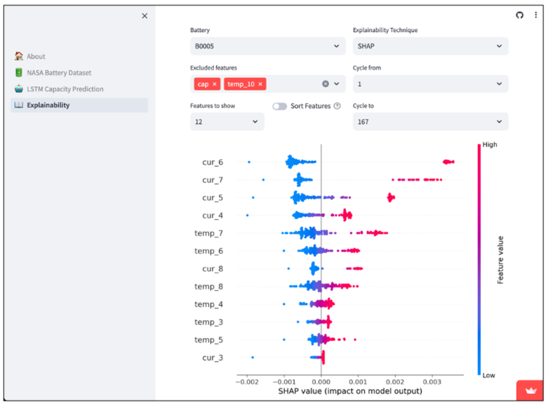
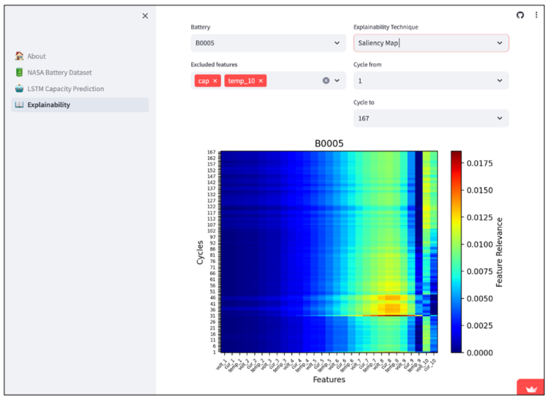


Figure 8: ExplainBattery - LSTM Capacity Prediction page. The accuracy metrics for the model using battery B0005 as the test battery are displayed. Additionally, a chart is shown comparing the actual capacity values with the estimated capacity values for battery B0005, from cycle 1 to cycle 167.



(a) *SHAP*. The top 12 features are displayed in order of relevance.



(b) *Saliency Map*.

Figure 9: ExplainBattery - Explainability page. In both cases, an explanation chart is generated for the model using battery B0005 as the test battery for cycles from 1 to 167. The features `cap` and `temp_10` are excluded.

selected battery as the test battery, will be shown. Subsequently, a chart comparing the actual capacity values with the estimated values generated by the LSTM model for the selected cycles will be displayed. Figure 8 illustrates an example of this page in use.

Explainability This page enables experimentation with two explainability techniques, *SHAP* [30, 31] and *Saliency Maps* [32], applied to the proposed LSTM-based neural network, allowing independent verification of their reliability. For the SHAP technique, users can select the number of features to display and choose to either order the features chronologically (from those related to the most recent discharging cycle to the least recent) or rank them by relevance. For both explainability methods, users can also choose which features to exclude from the visualization, thereby gaining insights into the influence of all the features by means of the displayed charts. Once these parameters are configured, an explanation chart based on the selected values will be generated and displayed on the page. Figure 9 provides examples of how the Explainability page can be utilized.

7. Conclusion

In this study, we addressed the challenges of developing a neural model for accurately and efficiently estimating the capacity of lithium-ion batteries. We implemented a novel neural architecture based on the model proposed by Ansari et al. [20], replacing standard RNN layers with LSTM layers to enhance the model's ability to capture complex temporal dependencies. The evaluation was conducted using NASA's Li-ion Battery Aging Dataset, providing a robust benchmark for assessing the model's performance.

The experimental results demonstrated that the proposed model outperformed state-of-the-art models, specifically those by Choi et al. [21] and Park et al. [22], achieving superior accuracy with a less complex architecture. This reduced complexity suggests that the model is not only more efficient but also potentially more suitable for deployment in BMS.

To further facilitate interaction with the developed model, we implemented a web application named *ExplainBattery*. This tool allows users to explore the dataset, verify the model's accuracy, and experiment with explainability techniques, such as SHAP and Saliency Maps, to gain deeper insights into the model's decision-making process.

Future work will involve an extended evaluation using additional datasets and models to further validate the robustness and generalizability of the proposed approach, ensuring its applicability in a broader range of real-world scenarios.

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