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State of Health Prediction for Lithium-Ion Batteries Using Partial Charging-Transformer-Based Deep Learning Models

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***Abstract* -** This study introduces a Partial Charging-Transformer model, which leverages partial charging data (3.6V – 4.0V) to estimate State of Health (SOH) effectively. The proposed approach extracts key degradation-related features, including total charging time, and total current charge, which provide valuable insights into battery aging trends. A series of experiments were conducted using the NASA battery dataset, where the proposed model was trained on individual battery data and tested across different battery cells. The results demonstrated that the Partial Charging-Transformer model achieved more than 66% lower RMSE compared to conventional deep learning methods, including LSTM, Multi-Layer Perceptron, standard Transformer, and CNN-LSTM architectures. Notably, the use of partial charging data did not compromise predictive accuracy, making the approach highly practical for Battery Management Systems (BMS). Additionally, this method enhances computational efficiency by reducing data requirements while maintaining robust performance. This research highlights the potential of partial charging data in real-world battery health monitoring and demonstrates the effectiveness of transformer-based architectures in capturing battery degradation trends. The findings pave the way for efficient and scalable SOH estimation models, which are essential for optimizing battery lifespan and performance in practical applications.

***Keywords*:** Lithium-ion battery, state of health, partial charging, transformer, battery degradation, machine learning

1. Introduction

The accurate prediction and estimation of battery health, often referred to as State of Health (SOH), are critical for ensuring the reliability, safety, and longevity of battery systems, particularly in electric vehicles (EVs). Traditionally, SOH estimation has relied on full charging cycles, where the battery is charged from a low State of Charge (SOC) to its maximum capacity. This approach leverages comprehensive data from the entire charging process, enabling the extraction of key features [1]-[3] such as capacity fade, internal resistance, and voltage profiles, which are essential for accurate health prediction. However, the reliance on full charging data poses significant challenges in real-world applications, particularly in EVs, where full charging cycles are not always feasible due to time constraints and user behaviour.

In real-world scenarios, EV users often engage in partial charging [4]-[6], where the battery is charged intermittently and not always to its full capacity. This behaviour introduces variability in the data available for SOH estimation, making it difficult to apply traditional methods that depend on complete charging cycles. Consequently, there is a growing need to develop robust methods for SOH estimation that can operate effectively with partial charging data. Partial charging data, while more challenging to analyse, offers the potential to provide real-time insights into battery health without requiring full charging cycles, thereby aligning more closely with real-world usage patterns.

Recent advancements in deep learning have led to the development of more sophisticated models for battery health prediction. LSTM networks [7]-[9] have been widely used for their ability to capture temporal dependencies in sequential data. For example, Ma et al. [8] proposed an LSTM-based model for SOH estimation using voltage, current profiles, Temperature and Impedance from full charging cycles. Similarly, RNNs have been applied to predict battery degradation by modelling the sequential nature of battery data [7], [10]-[11]. However, these models often struggle with long-term dependencies and require large amounts of labelled data for training, which can be challenging to obtain in real-world applications [12]-[13].

The limitations of LSTM and RNN models have prompted researchers to explore alternative approaches. For instance, Convolutional Neural Networks (CNNs) have been used to extract spatial features from battery data, while hybrid models combining CNNs and LSTMs [12], [14]-[15] have been proposed to capture both spatial and temporal dependencies. Despite these advancements, the performance of these models degrades when applied to partial charging data, highlighting the need for more robust methods.

Transformers, originally introduced for natural language processing, have emerged as a powerful alternative for handling sequential data [12]-[13]. Their self-attention mechanism allows them to capture long-range dependencies without being constrained by sequence length, making them particularly well-suited for tasks involving incomplete or variable-length data. In the context of battery health prediction, Transformers offer the potential to overcome the limitations of traditional sequence-based models by effectively modelling the complex patterns in partial charging data.

Several studies have begun to explore the application of Transformers in battery-related tasks. For example, Gu et al. [12] proposed transformer and CNN-Transformer-based model for predicting the SOH of batteries using full charging data. Their results demonstrated the superior performance of Transformers compared to traditional models, particularly in capturing long-term dependencies. However, the application of Transformers for SOH estimation using partial charging data remains largely unexplored, presenting a significant opportunity for further research.

To address these limitations, this study proposes the use of Transformer models for battery health prediction using partial charging data. Transformers, originally developed for natural language processing, have shown remarkable success in handling sequential data with long-range dependencies. Their self-attention mechanism allows them to capture complex patterns in data without being constrained by sequence length, making them particularly well-suited for partial charging scenarios. By leveraging the Transformer architecture, this research aims to develop a more accurate and robust method for SOH estimation that can operate effectively with partial charging data.

The contributions of this research are twofold. First, it explores the use of partial charging data for battery health prediction, addressing a significant gap in existing methods that rely on full charging cycles. Second, it introduces the application of Transformer models for SOH estimation, offering a novel approach that overcomes the limitations of traditional sequence-based models. The proposed method is validated using three different cells, demonstrating its potential for practical implementation in EVs and other battery-powered systems.

2. Methodology

2.1. Nasa Dataset

This study uses data from the NASA Battery Aging Dataset [16]-[17], which tracks the degradation of lithium-ion batteries over time. Three 18650 Lithium-Ion batteries, labelled B05, B06, and B07, each with a 2 Ah capacity, were tested. The experiments involved repeated charge-discharge cycles: (1) discharging at 2 A until reaching specific cutoff voltages (2.7 V, 2.5 V, and 2.2 V for B05, B06, and B07, respectively); (2) charging with a constant current of 1.5 A until the current dropped to 0.02 A; and (3) repeating these cycles until the batteries degraded significantly. All tests were conducted at room temperature (around 24°C), and the dataset includes detailed measurements of voltage, current, temperature, and capacity. This dataset is ideal for developing SOH prediction models, especially for partial charging scenarios, as it reflects real-world battery aging behaviour.

2.2. Partial Charging Data Feature Extraction

In this study, the extraction of partial charging data features focuses on the voltage range of 3.6-4 volts. This range was chosen because it covers the most informative phase of lithium-ion battery charging in terms of degradation and battery health. Within this voltage range, the battery transitions from the Constant Current (CC) charging phase to the Constant Voltage (CV) charging phase, where changes in internal battery characteristics, such as capacity and charging efficiency, can be more clearly observed.

Two main features were extracted: Total Charging Time (F1) and Total Current Charge (F2). F1 is calculated as the total time required to charge the battery from 3.6 to 4 volts. While charging time generally tends to increase with battery degradation due to rising internal resistance, in this dataset, it was observed that charging time decreases as the number of cycles increases. This phenomenon can be explained by several factors, such as a reduction in battery capacity, which means less charge is required to reach 4 volts, or changes in charging behaviour due to the degradation of electrode and electrolyte materials. Although internal resistance data is not available, Total Charging Time remains a relevant feature as it reflects the dynamics of battery charging within the specified voltage range.

F2 is calculated as the integral of the charging current over the 3.6-4-volt range. This feature represents the total charge that the battery can accept within this voltage range. A decrease in Total Current Charge indicates a loss of active battery capacity, which is a sign of ageing and degradation. Even though charging time becomes shorter, a decline in Total Current Charge suggests that the battery can no longer hold as much charge as before, consistent with capacity reduction over increasing cycles.

The selection of the 3.6-4-volt range is based on the consideration that this phase is critical in battery charging, where small changes in battery characteristics can provide important insights into battery health. Additionally, this range is more accessible in everyday use, as batteries are not always charged to their maximum voltage. By focusing on this range, the proposed method can be more relevant for real-world applications, such as in electric vehicles, where partial charging occurs more frequently than full charging. The partial charging curves and partial charging features representation can be seen in Figure 1.

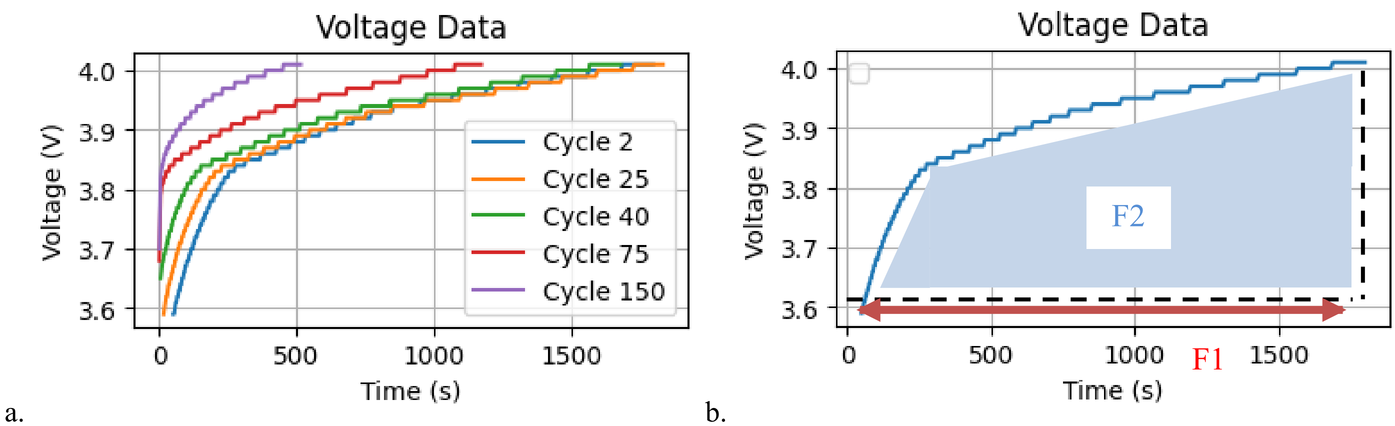

Fig. 1: a) Partial Charging Curves at different cycles and b) Partial Charging Features Representation

2.3. Transformer Model for Battery Health Prediction

The Transformer architecture, known for its success in handling sequential data, is well-suited for predicting battery health using partial charging data. Its self-attention mechanism captures long-range dependencies, making it ideal for analysing incomplete charging cycles. In this study, we propose a Transformer-based model to estimate SOH of lithium-ion batteries by leveraging features like Total Charging Time and Total Current Charge extracted from partial charging data.

The Transformer encoder consists of multiple layers, each with a Multi-Head Self-Attention mechanism and a Position-wise Feed-Forward Network. The self-attention mechanism computes attention scores between all positions in the input sequence $X = (x_1, x_2, \ldots, x_n)$ using the formula:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

where Q, K, and V are the query, key, and value matrices derived from X, and d_k is the dimensionality of the key vectors. Multi-head attention extends this by applying multiple attention heads in parallel:

$$MultiHead(Q,K,V) = Concat(head_1, head_2, \ldots, head_h)W^O \tag{2}$$

where each head is computed as $head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$, and W_i^Q, W_i^K, W_i^V, and W^O are learned parameters. The output is passed through a feed-forward network:

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2 \tag{3}$$

where W_1, W_2, b_1, and b_2 are learned weights and biases. Layer normalization and residual connections are applied to stabilize training:

$$LayerNorm(x + Sublayer(x)) \tag{4}$$

where $Sublayer(x)$ represents either the multi-head attention or feed-forward network.

For battery health prediction, the input sequence consists of features like Total Charging Time and Total Current Charge within the 3.6-4-volt range. The Transformer encoder processes these features to capture temporal dependencies, even in incomplete charging cycles. The final SOH prediction is obtained through a fully connected layer:

$$SOH = Linear(TransformerEncoder(X)) \tag{5}$$

where X is the input sequence. The model is trained using Mean Squared Error (MSE) loss:

$$Loss = \frac{1}{N}\sum_{i=1}^{N}\left(SOH_{predicted}^{i} - SOH_{true}^{i}\right)^2 \tag{6}$$

where N is the number of samples. By leveraging the Transformer's ability to handle partial data and model long-term dependencies, this approach provides a robust solution for real-world battery health prediction.

Table 1: Caption for table goes at the top.

Battery	Metric	Training	B5	B6	B7	Time
B5	R-squared	0.9893	0.9928	0.9414	0.9865	17.6300
B5	RMSE	0.0089	0.0084	0.0274	0.0095	
B6	R-squared	0.9818	0.9907	0.9884	0.9873	20.8
B6	RMSE	0.0133	0.0096	0.0122	0.0092	
B7	R-squared	0.9784	0.9868	0.9768	0.9861	11.22
B7	RMSE	0.0104	0.0114	0.0173	0.0096	

3. Results and Discussion
3.1. Results Analysis

In this study, a transformer-based model was developed to predict the SOH of lithium-ion batteries using partial charging data (3.6V–4.0V). The modelling process involved three different batteries from the NASA Battery Aging Dataset (B5, B6, and B7), where each battery was used both as a training and testing dataset. Before training, data preprocessing steps were applied, including data cleaning, outlier analysis, and normalization, to ensure consistency and robustness in the predictive modelling. Furthermore, the evaluation was conducted using two key metrics: R-squared (R^2) for goodness-of-fit and Root Mean Square Error (RMSE) for prediction accuracy. The complete experimental results for all models are presented in Table 1, while the prediction performance for the Transformer model is visualized in Figure 2 for B5, Figure 3 for B6, and Figure 4 for B7.

The transformer model was first trained on B5 and then tested on B5, B6, and B7 to evaluate its generalization capability. The results showed that the model performed well, achieving $R^2 = 0.9893$ on the training data, while maintaining high accuracy on B5 (0.9928) and B7 (0.9865). However, its performance on B6 ($R^2 = 0.9414$) was slightly lower, indicating that differences in degradation characteristics between batteries may influence generalization. Similarly, the RMSE values remained low, with the lowest error recorded when tested on B5 (0.0084) and slightly higher on B6 (0.0274).

When the transformer model was trained on B6, the results demonstrated strong predictive accuracy across all datasets. The model achieved $R^2 = 0.9818$ on the training data, with high generalization to B5 (0.9907) and B7 (0.9873), as well as maintaining consistency on its own test set (0.9884). The RMSE values also reflected this strong performance, with errors remaining below 0.0133 in most cases. Training the model on B6 took the longest time (20.8s), indicating potential variations in dataset complexity.

Lastly, when trained on B7, the transformer model achieved $R^2 = 0.9784$ on the training set, while generalizing well to B5 (0.9868) and B6 (0.9768). The model's RMSE values remained low, similar to the other training configurations. Interestingly, training on B7 resulted in the shortest training time (11.22s), suggesting that the B7 dataset might contain more structured or less noisy data compared to B5 and B6.

The consistent high R^2 values (>0.97) across all test scenarios confirm the Transformer architecture's effectiveness in learning meaningful patterns from partial charging data. The relatively low RMSE values (<0.03) further validate the model's precision in SOH estimation. The variation in performance across different training-test combinations suggests that battery-specific characteristics may influence model generalization, though the overall strong results indicate the Transformer's robustness to these variations. The results suggest that Transformer models can effectively leverage partial charging data for accurate battery health prediction, with potential applications in real-world battery management systems where complete charging cycles are often unavailable.

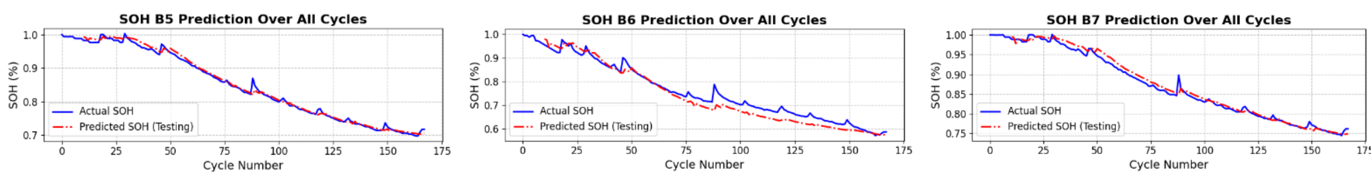

Fig. 2: Performance evaluation of the B5-based Transformer model across test batteries B5-B7.

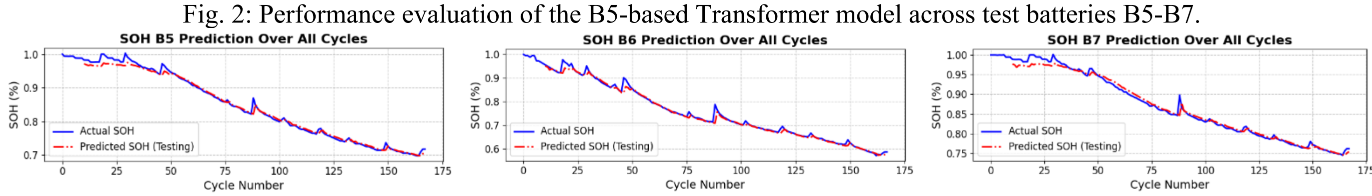

Fig. 3: Performance evaluation of the B6-based Transformer model across test batteries B5-B7.

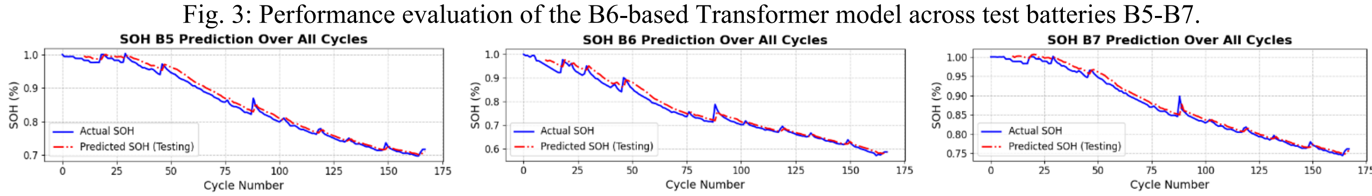

Fig. 4: Performance evaluation of the B7-based Transformer model across test batteries B5-B7.

3.2. Discussion

The results from the transformer-based modelling for SOH prediction demonstrate the feasibility of using partial charging data (3.6V–4.0V) to estimate battery degradation with high accuracy. Compared to traditional full-cycle SOH estimation approaches, this method offers a more practical solution, as real-world battery usage rarely involves complete charge-discharge cycles. The findings highlight key observations related to model performance, generalization across different battery datasets, and the implications for real-world applications.

One notable observation is the strong predictive performance of the transformer model across all training scenarios. When trained on B5, B6, or B7, the model consistently achieved high R^2 values (>0.97), demonstrating its capability to capture long-term battery degradation trends even with limited charging data. This suggests that critical degradation features are present within the selected partial charging data range (3.6V–4.0V), reinforcing the idea that a reduced dataset can still provide meaningful insights into battery health. The low RMSE values further confirm the reliability of the transformer model, indicating minimal deviation between predicted and actual SOH values.

However, variations in model performance across different test sets reveal some interesting insights. For instance, the model trained on B5 exhibited slightly lower R^2 (0.9414) when tested on B6, compared to when tested on B7 (0.9865). Similarly, when trained on B6, the model generalized well to both B5 (0.9907) and B7 (0.9873), suggesting that B6's degradation characteristics may be more representative of other datasets. These variations indicate that different batteries, despite being of the same chemistry and capacity, may exhibit unique aging patterns due to factors such as manufacturing inconsistencies, usage conditions, or different degradation mechanisms.

Another key finding is the difference in training time across datasets. The transformer model trained on B7 had the shortest training time (11.22s), while training on B6 required the longest time (20.8s). This discrepancy could be attributed to differences in data complexity, noise levels, or cycle-to-cycle variations in the SOH trends. Despite these differences, the training times remain relatively low, highlighting the computational efficiency of transformer-based architectures compared to traditional recurrent neural networks (RNNs) such as LSTMs or GRUs, which typically require longer training due to sequential processing constraints.

From an application perspective, these results support the viability of partial charging-based SOH estimation in practical Battery Management Systems (BMS). Since electric vehicle (EV) batteries and energy storage systems rarely undergo full charge-discharge cycles, the ability to extract meaningful SOH information from a limited voltage window (3.6V–4.0V) presents a significant advantage. This approach not only reduces data collection complexity but also minimizes battery stress, as deep charge-discharge cycles can accelerate degradation. In summary, the transformer-based model effectively learns battery degradation patterns from partial charging data, offering a robust and scalable solution for real-world SOH estimation.

3.3. Comparison with Other Methods

To evaluate the effectiveness of the Partial Charging-Transformer model, we compared its performance with several deep learning models, including CNN-LSTM, standard Transformer, LSTM, and DNN. The comparison was based on Root Mean Squared Error (RMSE) and R-squared (R^2) scores, which assess predictive accuracy and model reliability.

The Partial Charging-Transformer model achieved the best performance with an RMSE of 0.01 and an R^2 of 0.99, demonstrating its ability to accurately capture battery degradation trends using only partial charging data. The CNN-LSTM model followed with an RMSE of 0.03 and an R^2 of 0.92, indicating strong predictive performance but slightly lower accuracy. The standard Transformer model and LSTM model had RMSE values of 0.05 and 0.06, respectively, with corresponding R^2 scores of 0.82 and 0.75, showing moderate effectiveness in learning battery aging patterns. The DNN model, however, had the lowest performance with an RMSE of 0.02 and an R^2 of 0.58, suggesting that fully connected architectures may struggle to capture long-term dependencies in battery degradation.

Overall, these results highlight the superiority of the Partial Charging-Transformer model in leveraging limited charging data for accurate battery health prediction, making it a promising approach for real-world battery management systems. The summary of all model results is presented in Table 1**.**

Table 2: Performance comparison model.

Model	**RMSE**	**R2**
Partial Charging-Transformer*	0.01	0.99
CNN-LSTM[12]	0.03	0.92
Transformer [12]	0.05	0.82
LSTM [12]	0.06	0.75
DNN	0.02	0.58

4. Conclusion

This study explored the application of Transformer-based models for predicting the State of Health (SOH) of lithium-ion batteries using partial charging data in the 3.6V–4.0V range. Unlike conventional approaches that rely on full charge-discharge cycles, our method utilizes Total Charging Time and Total Current Charge as key features. The results demonstrate that the Transformer model effectively captures long-term dependencies in battery degradation, achieving high predictive accuracy across different battery datasets (B5, B6, and B7). Comparison with other machine learning and deep learning methods showed that the Partial Charging-Transformer model provides competitive performance, making it a viable alternative for real-world battery management systems (BMS). Its ability to predict battery health using only partial charging data reduces the reliance on full charge-discharge cycles, which is often impractical in real-world applications. Future research directions could explore the model's performance under more diverse operating conditions and its integration with other prognostic approaches for even more robust battery health monitoring.

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