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Article

Developing an Innovative Seq2Seq Model to Predict the Remaining Useful Life of Low-Charged Battery Performance Using High-Speed Degradation Data

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Abstract: This study introduces a novel Sequence-to-Sequence (Seq2Seq) deep learning model for predicting lithium-ion batteries' remaining useful life. We address the challenge of extrapolating battery performance from high-rate to low-rate charging conditions, a significant limitation in previous studies. Experiments were also conducted on commercial cells using charge rates from 1C to 3C. Comparative analysis of fully connected neural networks, convolutional neural networks, and long short-term memory networks revealed their limitations in extrapolating to untrained conditions. Our Seq2Seq model overcomes these limitations, predicting charging profiles and discharge capacity for untrained, low-rate conditions using only high-rate charging data. The Seq2Seq model demonstrated superior performance with low error and high curve-fitting accuracy for 1C and 1.2C untrained data. Unlike traditional models, it predicts complete charging profiles (voltage, current, temperature) for subsequent cycles, offering a comprehensive view of battery degradation. This method significantly reduces battery life testing time while maintaining high prediction accuracy. The findings have important implications for lithium-ion battery development, potentially accelerating advancements in electric vehicle technology and energy storage.

Keywords: lithium-ion battery; remaining useful life (RUL); sequence-to-sequence (Seq2Seq); acceleration of battery degradation

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1. Introduction

The rapid transition to electric vehicles is driving extensive research into predicting the remaining lifespan of lithium-ion batteries (LIBs) [1,2]. Accurate forecasting of battery lifespan is crucial for ensuring the safety and reliability of electric vehicles and electronic devices, as well as for managing battery replacement and maintenance costs effectively [3]. However, the degradation of LIBs is influenced by various operational conditions, such as charge/discharge cycles and temperature fluctuations, which makes accurate prediction a challenging task [4,5].

In recent years, there has been a growing trend in employing artificial intelligence (AI) techniques to address the complexity of battery systems [6,7]. These approaches utilize changes in environmental variables and operational conditions to learn and predict intricate battery behavior patterns. Among the various machine learning models, the Fully Connected Neural Network (FNN) has been a commonly used early model for time-series data problems, including the prediction of remaining battery life [8]. FNN consists of multiple fully connected hidden layers between input and output layers and is primarily used for pattern recognition and handling complex data characteristics. However, as an early deep learning model, FNN often encounters issues with overfitting, where the model becomes overly adapted to the training data, reducing its ability to work well with new data. It also exhibits inefficiencies in data preprocessing.

The development of convolutional neural networks (CNNs) has dramatically enhanced image recognition and processing capabilities [9]. CNNs are particularly effective at grasping the spatial arrangement of images, identifying local patterns, and extracting hierarchical features. They are frequently utilized to visualize battery structures and conditions. However, they are also associated with increased model complexity and slower training speeds due to the need for extensive image datasets.

In recent times, time-series-based models like long short-term memory (LSTM) [10], a type of Recurrent Neural Network (RNN), have been used to capture the time-dependent traits of charge/discharge data [11]. LSTM is beneficial for modeling long-term patterns within time-series data, making it helpful in predicting current battery states by utilizing past charge/discharge histories. While LSTM models efficiently learn patterns in time-series data, such as voltage, current, and temperature variations, they may struggle to fully incorporate long-term electrochemical time-series characteristics and the diverse protocols involved in charging and discharging.

This study aims to overcome the limitations of RNNs and LSTMs by using a Sequence-to-Sequence model (Seq2Seq) [12]. This model handles various charge/discharge protocols and predicts LIBs' electrochemical and thermal behavior during high-speed charging. Unlike traditional FNN, CNN, and LSTM models, the Seq2Seq model provides insights into battery degradation and RUL under fast charging conditions [13,14]. It goes beyond predicting discharge capacity based on simple charge voltage, current, and temperature profiles. It forecasts sequential charge voltage, current, and temperature profiles based on the initial charge data [15].

The key innovation of our research lies in using the Seq2Seq model to predict low-rate charging behavior based on high-rate charging data. This approach addresses the critical issue of data scarcity for slow charging conditions, which has been a significant limitation for traditional models [16,17]. By conducting experiments on 21,700 actual cylindrical cells under high-speed degradation conditions (1.2C to 3C) [18], we aim to predict electrochemical characteristics and lifespan at slower rates (1C). This represents a significant advancement in developing a proactive model capable of simultaneously predicting both electrochemical input and output characteristics.

Our study's approach has the potential to significantly reduce the time and resources required for battery life testing while maintaining high prediction accuracy [19]. This could have far-reaching implications for developing and optimizing lithium-ion batteries, potentially accelerating the advancement of electric vehicles and other battery-dependent technologies [20,21]. In the following sections, we will detail our experimental setup, the architecture of our Seq2Seq model, and the results of our predictions, demonstrating the superior ability of our approach to extrapolate from high-speed to low-speed charging scenarios.

2. Experiment and Models

2.1. High-Speed Degradation Experiment for Cylindrical Cells

The high-speed degradation experiment for cylindrical cells was conducted to predict the degradation performance of lithium-ion batteries through accelerated aging using high-speed charging [22,23]. The experiment utilized Samsung SDI 21,700 commercial cells and involved six samples with charge rates ranging from 1C to 3C [24]. The charging protocol employed the Constant Current–Constant Voltage (CC-CV) method. Each sample underwent Constant Current (CC) charging followed by Constant Voltage (CV) charging at 4.2 V. A constant current rate of 1C was applied to all samples for discharging, with a lower voltage limit set to 2.5 V.

The six samples were tested under current rates of 1C, 1.2C, 1.5C, 2.0C, 2.5C, and 3.0C, respectively (Table 1). A 5 min intermediate rest period was implemented between each end of the charge and discharge cycle to measure voltage, current, and temperature [25]. The temperature was recorded at the external surface of the cell by attaching a sensor at the mid-point of the cylindrical cell. This temperature measurement method is crucial for understanding the thermal behavior of lithium-ion batteries during charge and discharge cycles. Thermocouples were attached to cylindrical cells to monitor temperature changes during cycling. This experimental setup allowed for collecting comprehensive data on battery degradation under various high-speed charging conditions, providing a foundation for subsequent analysis and prediction of battery performance and lifespan [26].

Table 1. Charging and discharging protocol of 21,700 cells for an acceleration of LIB degradation.

Sample	Charge	Discharge
1.0C	1.0C CC, 4.2 V CV	1.0C CC with 2.5 V cut-off
1.2C	1.2C CC, 4.2 V CV	
1.5C	1.5C CC, 4.2 V CV	
2.0C	2.0C CC, 4.2 V CV	
2.5C	2.5C CC, 4.2 V CV	
3.0C	3.0C CC, 4.2 V CV	

2.2. Artificial Neural Network Model for Predicting Discharge Capacity and Remaining Useful Life of LIBs

This study investigates the application of various artificial neural network architectures to predict the discharge capacity and remaining useful life (RUL) of LIBs. The models examined include FNN, CNN, and LSTM networks.

The FNN represents basic neural network architecture. This model processes input features, such as charging current, voltage, and temperature curves, transforming them into a fixed input vector. Subsequently, this vector is processed through an output layer and one or more hidden layers. The output layer represents the discharge capacity of the respective cycle, thereby creating a model that predicts the discharge capacity based on the input vector of the corresponding cycle (Figure 1a).

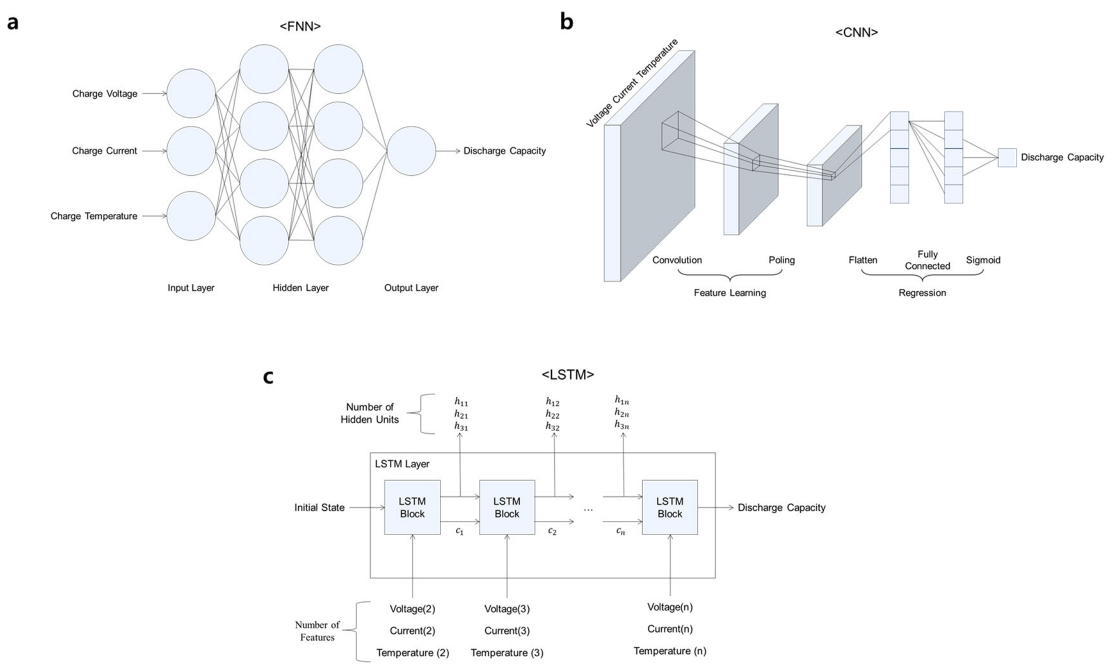

Figure 1. Various neural network models for prediction of the remaining useful life (RUL) of lithium-ion battery: (**a**) FNN, (**b**) CNN, (**c**) LSTM.

However, FNNs exhibit limitations in RUL prediction. Notably, they lack the ability to model time-dependent relationships in sequential data, which is crucial for understanding battery degradation patterns. Furthermore, FNNs may encounter difficulties when processing high-dimensional input data, potentially leading to overfitting and poor generalization to novel, unseen data.

CNN, while primarily utilized for image processing, has demonstrated efficacy in analyzing time-series data. The CNN model extracts salient features from the input data through multiple convolutional layers, subsequently employing these features to predict the time-series data. For instance, it can utilize input curves of charging voltage, current, and temperature to predict the discharge capacity of each cycle (Figure 1b). Despite their effectiveness, CNNs present certain drawbacks to RUL prediction. They may need to fully capture long-term dependencies in time-series data, which are essential for comprehending battery degradation over extended periods. CNN-based models, such as conditional score-based diffusion models, can capture time-dependency image data with self-supervised learning [27]. CNNs are computationally intensive and require substantial data for effective training, which may only sometimes be available in battery life prediction scenarios.

LSTM networks, a variant of RNN, are specifically designed to process sequential and time-series data. LSTM networks incorporate a gating mechanism to retain important information in time-series input data over extended periods. This mechanism allows LSTM networks to selectively keep or discard voltage, current, and temperature data characteristics over time [28]. Consequently, LSTM networks are valuable for making continuous predictions of the RUL of lithium-ion batteries (Figure 1c) [29,30]. While LSTM networks demonstrate power in time-series prediction, they also exhibit limitations in RUL prediction. They may need help to capture very long-term dependencies, particularly in cases where battery degradation occurs over hundreds or thousands of cycles. Additionally, LSTM models can be sensitive to noise in the input data and may encounter difficulties in generalizing new operating conditions or battery types not encountered during training. The details architectures of neural networks of FNN, CNN, and LSTM were summarized in Table 2. The LSTM unit consists of a memory cell, forget gate, input gate, and output gate, which works in concert to process sequential data and capture long-term dependencies. In this study, we employ the fundamental LSTM unit architecture as outlined by Park et al. [31].

Table 2. Comparison of FNN, CNN, LSTM, and Seq2Se1 network architectures of layers and parameters.

Model	Layers	Parameter
FNN	Input layer (dense) Hidden layer 1 (dense, 256 ReLU) Hidden layer 2 (dense, 64 ReLU) Output Layer (dense, Softmax for regression)	>10,000
CNN	Image input layer (kernel 1 × 30) Convulsion layer 1 (64 filters, kernel 1 × 30 ReLU) MaxPolling layer (pool size 1 × 30) Convulsion layer 2 (16 filters, kernel 1 × 4 ReLU) MaxPolling layer (pool size 1 × 4) Output layer (fully connected layer, Softmax for regression)	>50,000+
LSTM	Sequence input layer (kernel 1 × 30) LSTM layer 1 (100 units, return sequence = true) Output layer (fully connected layer, regression layer)	>40,000
Seq2Seq	Sequence input layer (4: capacity, voltage, current, temperature) LSTM layer 1 (128, encoder, output mode = sequence) Fully connected layer (64) Dropout layer (0.5) LSTM layer 2 (256, decoder) Fully connected layer (4) Regression layer	>45,000+

The limitations inherent in FNN, CNN, and LSTM models underscore the necessity for more advanced approaches, such as the Sequence-to-Sequence (Seq2Seq) model proposed in this study, to enhance the accuracy and reliability of RUL predictions for lithium-ion batteries. In this investigation, we developed a predictive model for the discharge capacity of the 1C slow-charged sample. We employed various neural network models trained on high-speed charged samples at rates of 1.2C, 1.5C, 2C, 2.5C, and 3C. Our methodology validated the superior performance of the time-series-based LSTM model, which subsequently led to the development of a Seq2Seq model aimed at improving RUL prediction accuracy.

2.3. Seq2Seq Model-Based Prediction Model for RUL of Slow-Charged LIBs

The Seq2Seq model employs an RNN-based encoder–decoder architecture to address the limitations of traditional deep learning models in predicting the RUL of LIBs [30]. This architecture consists of an encoder that converts the input sequence into a fixed-length vector, which is subsequently utilized by the decoder to generate the output sequence.

While Seq2Seq models are predominantly used in natural language processing tasks, this study innovatively applies the model to forecast later cycle charging data, specifically targeting 80% of the nominal battery capacity, using only fast-charged sample data (Figure 2). This approach represents a significant advancement in battery life prediction methodology [32].

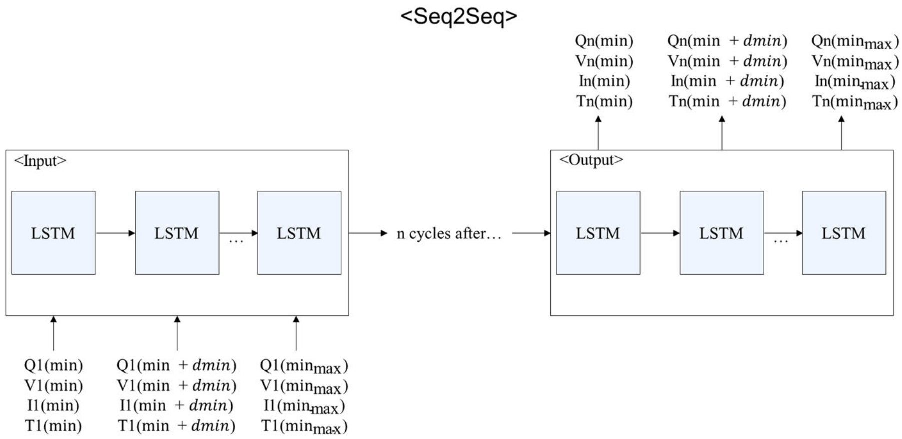

Figure 2. Schematic of the model structure of Seq2Seq for prediction of RUL of LIB.

The model was trained using charging voltage, current, and temperature for each cycle as input values, with the charging capacity, current, and temperature for the subsequent cycle serving as output values. This training strategy enabled the model to predict charging data for later cycles based solely on the initial charging data of high-speed charged samples.

By leveraging this predictive capability, this study successfully forecasted charging patterns for slow-charged samples, thereby facilitating a more accurate estimation of the battery's actual RUL. This methodology offers a novel solution to predict long-term battery performance using limited short-term data, potentially revolutionizing battery life prediction in electric vehicles and energy storage applications.

The Seq2Seq model's ability to extrapolate from high-speed charging data to predict slow-charging behavior addresses a critical gap in current battery modeling techniques [33]. This approach not only enhances the accuracy of RUL predictions but also provides valuable insights into battery degradation mechanisms under various charging conditions.

3. Results

3.1. Prediction of RUL for Slow-Charged LIBs

Various artificial neural network models, including FNN, CNN, and LSTM, investigated the prediction of RUL for slow-charged LIBs. The research methodology involved analyzing charge/discharge measurements of commercial cylindrical cells to determine their nominal condition based on cycle-dependent data in Figure 3. As expected, higher C-rates correlated with increased degradation rates of the cells. This study focused on identifying the cycle life at which cells retained 80% of their initial capacity (4 Ah) to predict RUL.

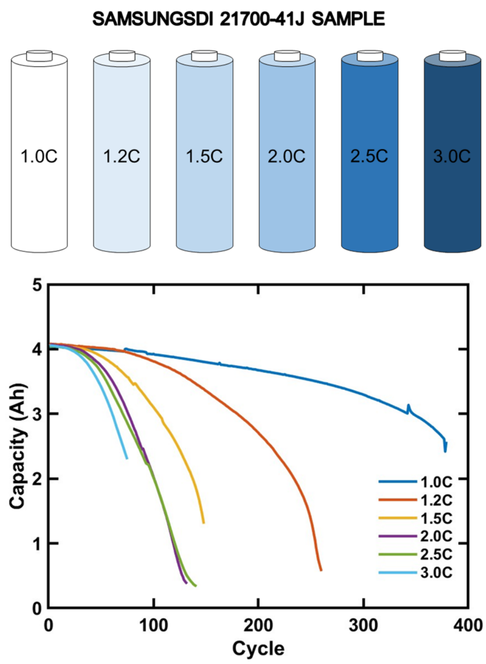

Figure 3. Experimentally measured cycle capability of 21,700 cylindrical cells for C-rate from 1C to 3C.

This study conducted performance analyses of various artificial neural network models (FNN, CNN, and LSTM) to predict the RUL of LIBs. The models were configured using measured lifespan data to predict discharge capacity based on input vectors comprising current, voltage, and temperature curves for each cycle [34]. The results showed that all models achieved a relatively high level of accuracy during training, with root mean square error (RMSE) values remaining below 3.5% of the nominal capacity for all samples (Figure 4b). This indicates good overall performance in fitting the training data.

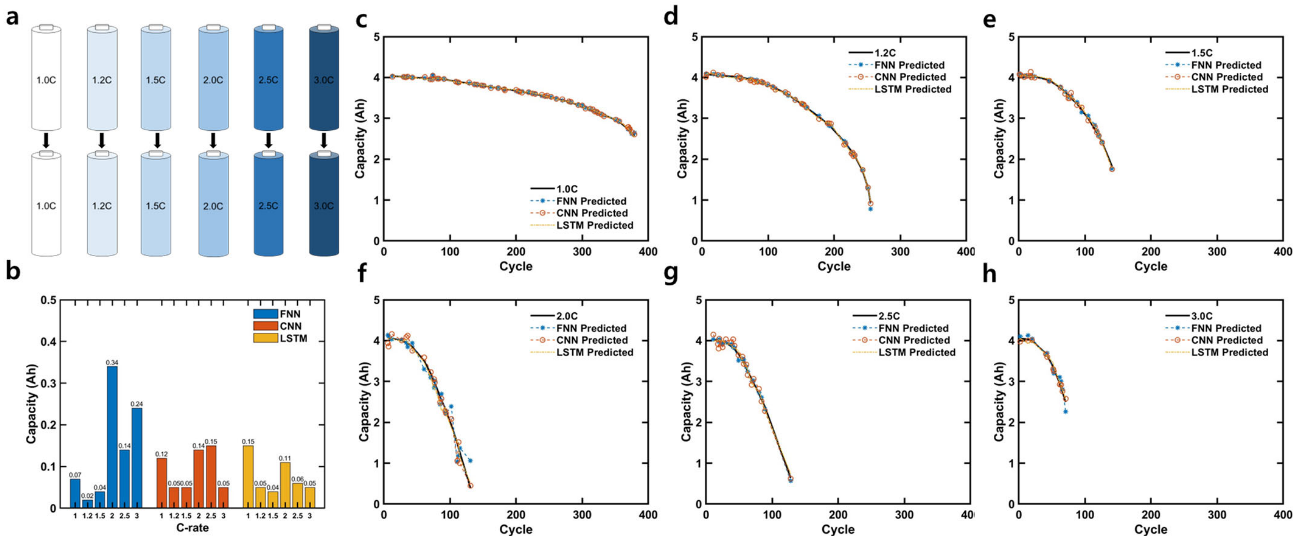

Figure 4. (**a**) Discharge capacity prediction and (**b**) RMSE of cylindrical 21,700 cells using FNN, CNN, and LSTM with various C-rates: (**c**) 1C, (**d**) 1.2C, (**e**) 1.5C, (**f**) 2C, (**g**) 2.5C, (**h**) 3C.

When comparing the performance of the models, we observed significant differences. The CNN and LSTM models showed higher accuracy compared to the FNN model. This improved performance can be attributed to their ability to incorporate time-related effects in the data, which is crucial for capturing the temporal dependencies in battery degradation patterns [35]. In contrast, the FNN model displayed higher RMSE values and provided less accurate discharge capacity estimations. This poorer performance of the FNN model was likely due to its inability to effectively capture temporal relationships in the data, coupled with inadequate training data from the high-speed degradation experiment.

These observations are illustrated in Figure 4c–h, which show the comparative performance of the three models across different scenarios. The superior performance of the CNN and LSTM models underscores the importance of considering temporal dependencies in battery life prediction tasks. Their ability to capture time-related effects makes them more suitable for modeling the complex, time-dependent processes involved in battery degradation.

Figure 5b,g display the projected discharge capacity plotted against the cycle, utilizing FNN, CNN, and LSTM with two sets of cycling data. The first set includes 1.0C, 1.5C, 2.0C, 2.5C, and 3.0C, shown in Figure 5a, while the second set comprises 1.2C, 1.5C, 2.0C, 2.5C, and 3.0C, illustrated in Figure 5b. These models utilized respective cycles' voltage, current, and temperature curves as input vectors. The RMSE for all samples remained below 2% of the nominal capacity during training, indicating high accuracy. The performance differences between FNN, CNN, and LSTM networks in predicting 1.2C data in Figure 5d can be attributed to their distinct architectural characteristics and ability to process time-series data.

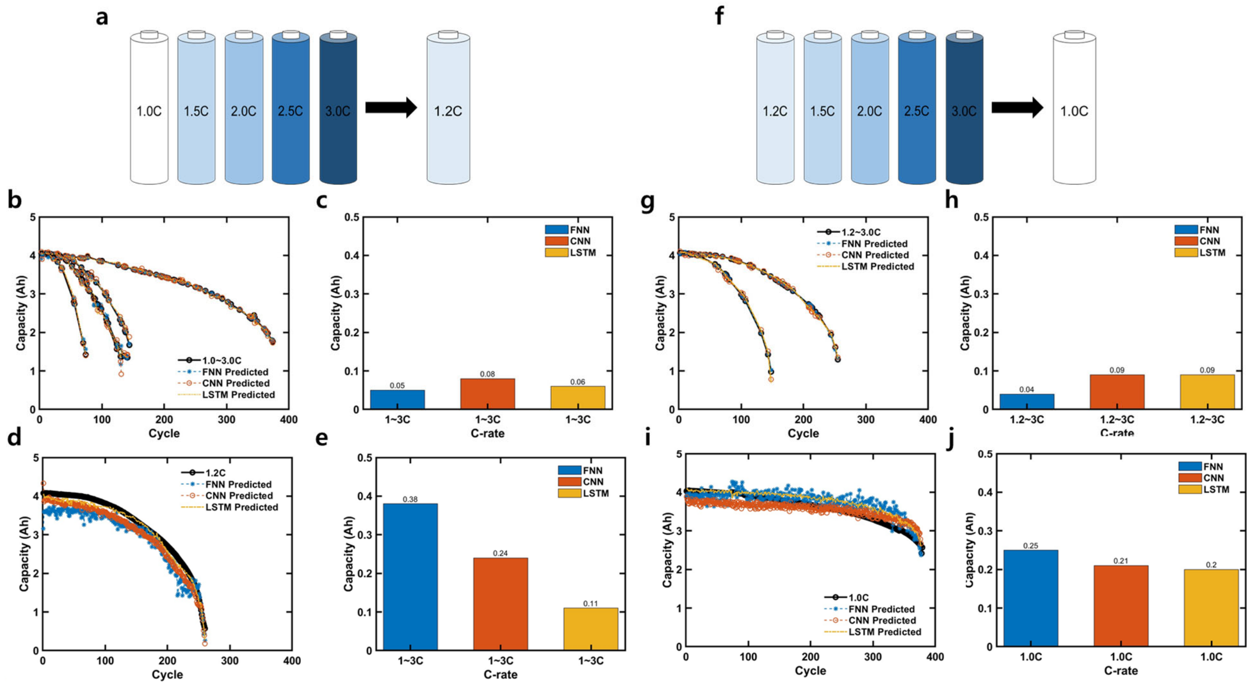

Figure 5. Prediction of the discharge capacity of cell samples at (**a**) 1.2C and (**f**) 1C using other data for training data with FNN, CNN, and LSTM. (**b**,**c**) Prediction of discharge capacity of training sample sets for 1.2C prediction and (**d**,**e**) prediction of discharge capacity of 1.2C test sample. (**g**,**h**) Prediction of discharge capacity of training sample sets for 1.0C prediction and (**i**,**j**) prediction of discharge capacity of 1.0C test sample.

While capable of handling complex, non-linear relationships, FNNs have limitations in capturing temporal dependencies inherent in time-series data. In the context of battery data, where past information significantly influences current and future states, FNNs struggle to learn these temporal relationships effectively. This limitation is particularly evident when dealing with interpolated data of 1.2C, where the temporal patterns are crucial for accurate predictions.

CNNs, primarily designed for spatial feature extraction, face challenges in directly modeling temporal dependencies. While they excel in image processing and can be adapted for time-series data, they may not fully capture the long-term dependencies crucial for understanding battery degradation over extended periods. This limitation becomes apparent when dealing with the complex temporal patterns in 1.2C charging data.

In contrast, predicting a discharge capacity of 1.2C using LSTM networks shows the lowest value of RMSE (Figure 5e). LSTMs are specifically designed to handle sequential and time-series data. Their architecture, featuring a gating mechanism, allows them to learn and retain important information over long periods effectively. This capability is particularly advantageous for modeling the long-term patterns inherent in battery charge/discharge cycles, including those at 1.2C rates.

The inclusion of 1C slow-charging data in the training set and interpolation of 1.2C data resulted in improved accuracy and better fit for the LSTM. The LSTM model, incorporating time-dependent characteristics, demonstrated the lowest RMSE and highest accuracy in predicting discharge capacity, suggesting its suitability for time-series data and potential for predicting RUL of untrained lithium-ion batteries [35].

To predict the slow degradation of discharge capacity, the second set of training cycle data (Figure 5f) shows similarly low values of RMSE compared to the first set of training cases, as shown in Figure 5h. When predicting 1C data, all three models exhibited high error rates in Figure 5j, highlighting the challenge of forecasting low-degradation characteristics using data obtained from high-speed degradation experiments (<1.2C). Additionally, discrepancies between the training and prediction electrochemical curves contributed to elevated errors across all models in Figure 5i.

While the LSTM model demonstrated proficiency in predicting discharge capacity for interpolated data within the range of its training set, it exhibited significant limitations when extrapolating to new, untrained input curves. Specifically, the LSTM model performed well in scenarios where it could interpolate between known data points, such as predicting 1.2C data when trained on both 1C and 1.5C data. However, when tasked with extrapolating to entirely new patterns or conditions not represented in the training data, such as predicting 1C behavior based solely on higher C-rate data, the LSTM model's performance deteriorated markedly.

This limitation in extrapolation highlights the challenges traditional RNN-based machine learning models face in accurately forecasting battery behavior under novel operational conditions. More advanced approaches like the Seq2Seq model need to be proposed for forecasting RUL in a slow charging rate with a fast-cycling degradation dataset. To address this, the research suggested the use of a Sequence-to-Sequence (Seq2Seq) model-based time-series artificial neural network model capable of accurately predicting untrained extrapolated data and input vectors, thereby enhancing RUL prediction accuracy for lithium-ion batteries.

3.2. Performance of Seq2Seq Model for Charging Profile Prediction and Lifespan Prediction

Figure 6 illustrates the conceptual framework of the Seq2Seq network developed in this study. The model was designed to predict subsequent cycles' voltage, current, and temperature curves based on the initial cycle's data. Specifically, the Seq2Seq network utilizes the current, voltage, and temperature profiles from the first cycle as input to forecast the corresponding curves for the next cycle [35]. This process is then repeated sequentially, with each prediction as input for the subsequent cycle's forecast. To optimize the model's performance, we conducted extensive hyperparameter tuning [36].

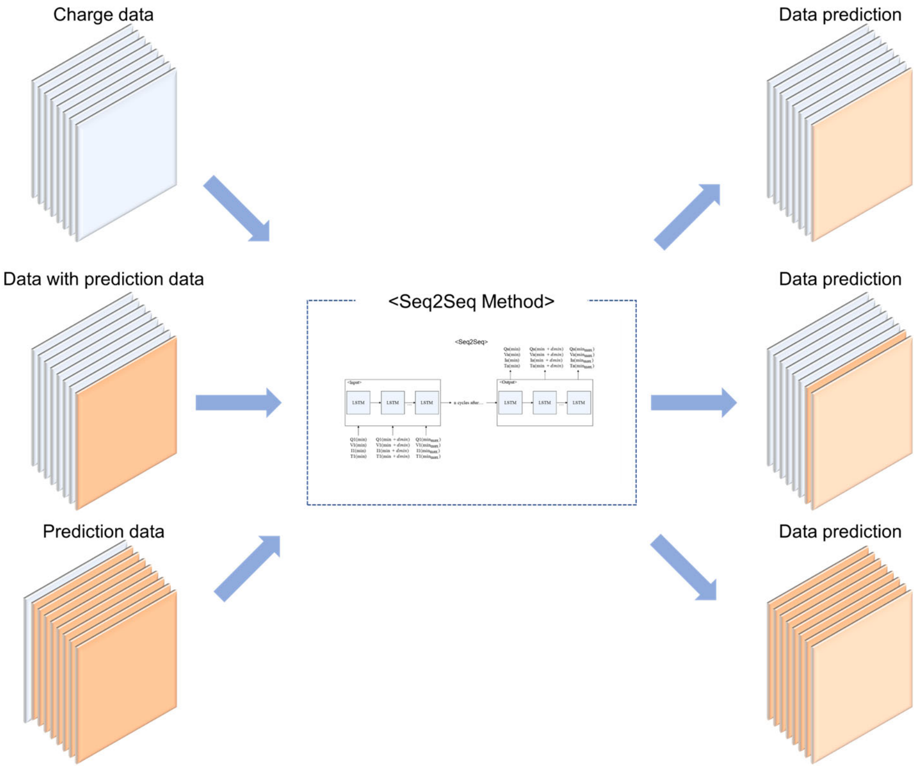

Figure 6. Schematic of Seq2Seq model for predicting RUL of LIBs using charging profiles of voltage, current, and temperature.

Following the hyperparameter optimization, we extended the model's capability to predict discharge capacity for each charge/discharge cycle. We incorporated the predicted voltage, current, and temperature curves into a discharge capacity estimation module within the Seq2Seq framework to accomplish this.

This approach addresses a significant limitation of prior models, such as FNN, CNN, and LSTM, which could not predict discharge capacity without existing input vectors. This innovative approach allows for the prediction of battery performance over multiple cycles, using only the initial cycle data as a starting point. By iteratively applying the Seq2Seq model, we can comprehensively forecast the battery's behavior throughout its lifespan, including the electrochemical parameters (voltage, current, temperature) and the critical performance metric of discharge capacity.

The Seq2Seq model in Figure 7b shows high accuracy by achieving an RMSE of less than 1% when predicting the final cycle's charging data corresponding to 379 cycles for 1.0C, 260 cycles for 1.2C, 148 cycles for 1.5C, 132 cycles for 2.0C, 141 cycles for 2.5C, and 75 cycles for 3.0C. These data represent 80% of the nominal capacity across all data points for the prediction of each C rate sample. Among the input parameters, it is noteworthy that temperature demonstrated a slightly higher RMSE in comparison to voltage and current, indicating a relatively lower degree of fit, as depicted in Figure 7b.

The model effectively predicts the RUL by using charging parameters like capacity, current, and temperature. It does this without needing repetitive experimental trials. In the 3C sample (Figure 7h), the RMSE was slightly higher because the model faced challenges predicting final cycle data based only on the first cycle data. This is a common limitation shared with other neural network models when dealing with insufficient and shorter time-series data compared to the lower C rate samples.

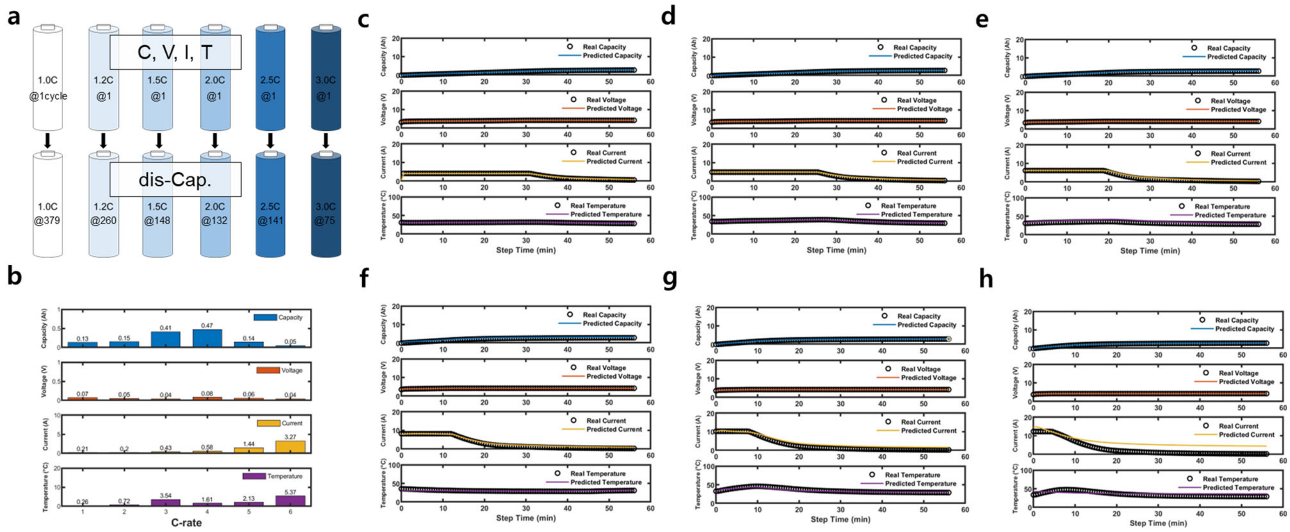

Figure 7. Prediction of the final voltage, current, and temperature charging profiles based on the initial cycle profiles. (**a**) Overview of the model training process. (**b**) Training results showing the RMSE. (**c**–**h**) Comparison of the experiment and prediction of final cycle profiles of voltage, current, and temperature at different C rates: 1.0C, 1.2C, 1.5C, 2.0C, 2.5C, and 3.0C.

To enhance accuracy, further training with additional samples at the same charging rate or fine-tuning the model's hyperparameters may be necessary. Despite this, the model has shown high accuracy in samples with sufficient cycle data at various C rates, indicating a promising potential for RUL prediction using this approach [37].

Figure 8 shows the performance of the Seq2Seq model in predicting low-rate, untrained data using high-rate charging training data. The analysis reveals that the model achieved low RMSE values for both untrained 1C and 1.2C data, demonstrating its capability to interpolate and extrapolate from high-rate to low-rate charging scenarios.

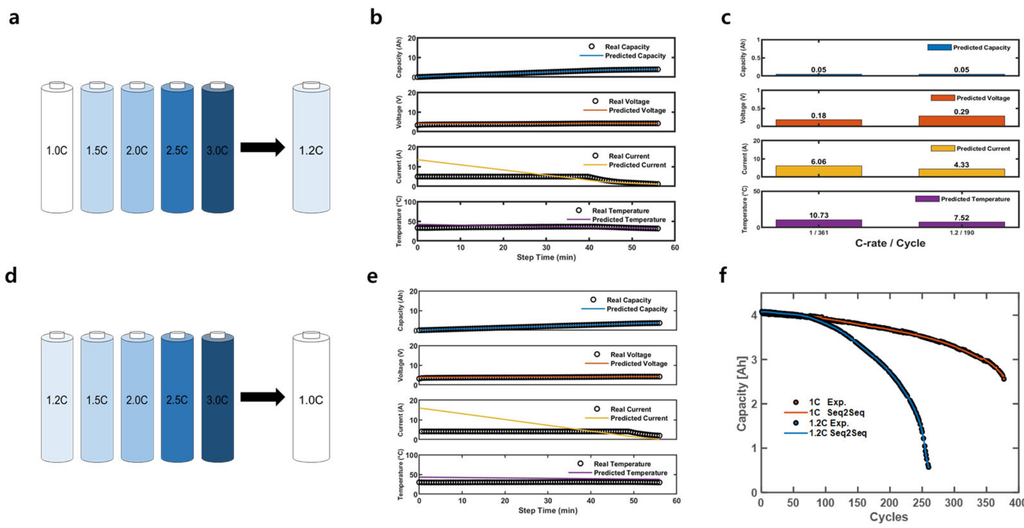

Figure 8. Prediction of charging profiles at (**a**) 1.2C and (**d**) 1C cell samples using other sample data with the Seq2Seq model. Predicted curves of capacity, voltage, current, and temperature of (**b**) 1.2C and (**e**) 1C with (**c**) RMSE. (**f**) Prediction of the discharge capacity of cell samples at 1.2C and 1C using other data for training data with the Seq2Seq model.

Specifically, the Seq2Seq model accurately predicted capacity, voltage, and current profiles for the untrained 1C (Figure 8b) and 1.2C (Figure 8c) conditions. These parameters exhibited similar patterns across different C-rates and cycles, enabling the model to capture and predict their temporal evolution effectively.

However, the model encountered challenges in accurately fitting temperature profiles during operation for both 1C and 1.2C conditions with relatively higher RMSE. This limitation can be attributed to the unique characteristics of temperature curves, which vary significantly between cycles and exhibit distinct thermal properties depending on the charging rate. Unlike capacity, voltage, and current, which maintain relatively consistent patterns across different C-rates, temperature profiles show more significant variability, making them more challenging to predict for untrained conditions [26].

Compared to previous FNN, CNN, and LSTM models, the Seq2Seq model demonstrated superior performance in predicting the untrained 1C sample, achieving lower RMSE values and higher curve-fitting accuracy. This improvement indicates the Seq2Seq model's enhanced capability for reliable lifespan prediction. A key advantage of the Seq2Seq model in the context of RUL prediction is its ability to forecast not only the discharge capacity for a specific cycle but also to predict subsequent cycle data. This feature significantly expands its applicability compared to prior models, enabling more comprehensive long-term battery performance predictions.

Despite these advancements, the Seq2Seq model faces challenges, particularly in potential data loss during normalization when handling input vectors of uniform dimensions. However, this limitation could be addressed by incorporating data transformation techniques inspired by CNN-based image learning models, which may help preserve important features during normalization.

4. Conclusions

This study presents a novel approach to predicting the RUL of LIBs using advanced ML techniques, focusing on the Seq2Seq model. Our research addresses critical challenges in battery life prediction, especially the extrapolation from high-rate to low-rate charging conditions, which has been a significant limitation in previous studies [38]. A comprehensive comparative analysis of neural network models, including FNN, CNN, and LSTM networks, was conducted to evaluate their performance in predicting battery discharge capacity. While all models demonstrated high accuracy for interpolation tasks, the LSTM model showed superior performance in capturing the time-dependent characteristics of battery degradation. However, even LSTM showed significant limitations when extrapolating to new, untrained conditions, particularly when predicting low-rate (1C) charging behavior or extrapolated profiles based on high-rate charging data [39].

To overcome these limitations, we proposed and implemented a Seq2Seq model, demonstrating remarkable capability in predicting charging profiles and discharge capacity for untrained, low-rate conditions using only high-rate charging data. The Seq2Seq model achieved low RMSE values and high curve-fitting accuracy for both 1C and 1.2C untrained data, surpassing the performance of traditional models. A key innovation of our Seq2Seq model is its ability to predict not only discharge capacity but also complete charging profiles (voltage, current, temperature) for subsequent cycles. This comprehensive approach offers a more holistic view of battery degradation over time. While the model showed high accuracy in predicting voltage and current profiles, we observed slightly lower accuracy in temperature predictions, indicating an area for future improvement.

Our research represents a significant advancement in battery life prediction, with far-reaching implications for developing and managing lithium-ion batteries. By enabling accurate long-term predictions based on short-range operation and accelerated testing data, our approach significantly reduces the time and resources needed for battery life testing. This can potentially expedite the development of LIBs for energy storage systems and electric vehicles. The Seq2Seq model's ability to extrapolate from high-speed to low-speed charging scenarios addresses a critical gap in current battery modeling techniques, offering valuable insights into battery degradation mechanisms under various charging conditions. Furthermore, the ability to predict RUL under different charging conditions enhances battery management strategies, improving safety and reliability. Future research may involve refining the model, expanding its application to other battery types, and integrating it into real-time battery management systems [40–44]. Ultimately, this study has the potential to revolutionize battery development and management strategies across various industries, paving the way for more efficient, reliable, and sustainable energy storage solutions.

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Data Availability Statement: Dataset available on request from the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Hu, X.; Li, S.E.; Yang, Y. Advanced Machine Learning Approach for Lithium-Ion Battery State Estimation in Electric Vehicles. *IEEE Trans. Transp. Electrif.* **2016**, *2*, 140–149. [CrossRef]
2. Dubarry, M.; Liaw, B.Y. Identify capacity fading mechanism in a commercial $LiFePO_4$ cell. *J. Power Sources* **2009**, *194*, 541–549. [CrossRef]
3. Liu, K.; Li, K.; Peng, Q.; Zhang, C. A brief review on key technologies in the battery management system of electric vehicles. *Front. Mech. Eng.* **2019**, *14*, 47–64. [CrossRef]
4. Xiong, R.; Cao, J.; Yu, Q.; He, H.; Sun, F. Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles. *IEEE Access* **2018**, *6*, 1832–1843. [CrossRef]
5. Berecibar, M.; Gandiaga, I.; Villarreal, I.; Omar, N.; Van Mierlo, J.; Van den Bossche, P. Critical review of state of health estimation methods of Li-ion batteries for real applications. *Renew. Sustain. Energy Rev.* **2016**, *56*, 572–587. [CrossRef]
6. Severson, K.A.; Attia, P.M.; Jin, N.; Perkins, N.; Jiang, B.; Yang, Z.; Chen, M.H.; Aykol, M.; Herring, P.K.; Fraggedakis, D.; et al. Data-driven prediction of battery cycle life before capacity degradation. *Nat. Energy* **2019**, *4*, 383–391. [CrossRef]
7. Lipu, M.S.H.; Hannan, M.A.; Hussain, A.; Saad, M.H.M.; Ayob, A.; Blaabjerg, F. State of Charge Estimation for Lithium-Ion Battery Using Recurrent NARX Neural Network Model Based Lighting Search Algorithm. *IEEE Access* **2018**, *6*, 28150–28161. [CrossRef]
8. Ren, L.; Zhao, L.; Hong, S.; Zhao, S.; Wang, H.; Zhang, L. Remaining Useful Life Prediction for Lithium-Ion Battery: A Deep Learning Approach. *IEEE Access* **2018**, *6*, 50587–50598. [CrossRef]
9. Ng, M.-F.; Zhao, J.; Yan, Q.; Conduit, G.J.; Seh, Z.W. Predicting the state of charge and health of batteries using data-driven machine learning. *Nat. Mach. Intell.* **2020**, *2*, 161–170. [CrossRef]
10. Hochreiter, S.; Schmidhuber, J. Long Short-Term Memory. *Neural Comput.* **1997**, *9*, 1735–1780. [CrossRef]
11. Zhang, Y.; Xiong, R.; He, H.; Pecht, M.G. Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries. *IEEE Trans. Veh. Technol.* **2018**, *67*, 5695–5705. [CrossRef]
12. Sutskever, I.; Vinyals, O.; Le, Q.V. Sequence to Sequence Learning with Neural Networks. *Adv. Neural Inf. Process. Syst.* **2014**, *27*, 3104–3112.
13. Li, X.; Yuan, C.; Wang, Z. Multi-time-scale framework for prognostic health condition of lithium battery using modified Gaussian process regression and nonlinear regression. *J. Power Sources* **2020**, *467*, 228358. [CrossRef]
14. Saha, B.; Goebel, K.; Poll, S.; Christophersen, J. Prognostics Methods for Battery Health Monitoring Using a Bayesian Framework. *IEEE Trans. Instrum. Meas.* **2009**, *58*, 291–296. [CrossRef]
15. Tian, Y.; Lai, R.; Li, X.; Tian, J. State-of-charge estimation for lithium-ion batteries based on attentional sequence-to-sequence architecture. *J. Energy Storage* **2023**, *62*, 106836. [CrossRef]
16. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Emadi, A. State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach. *J. Power Sources* **2018**, *400*, 242–255. [CrossRef]
17. Xia, F.; Wang, K.; Chen, J. State of health and remaining useful life prediction of lithium-ion batteries based on a disturbance-free incremental capacity and differential voltage analysis method. *J. Energy Storage* **2023**, *64*, 107161. [CrossRef]
18. Waldmann, T.; Scurtu, R.-G.; Richter, K.; Wohlfahrt-Mehrens, M. 18650 vs. 21700 Li-ion cells—A direct comparison of electrochemical, thermal, and geometrical properties. *J. Power Sources* **2020**, *472*, 228614. [CrossRef]
19. Waag, W.; Fleischer, C.; Sauer, D.U. Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles. *J. Power Sources* **2014**, *258*, 321–339. [CrossRef]
20. Vetter, J.; Novák, P.; Wagner, M.R.; Veit, C.; Möller, K.-C.; Besenhard, J.O.; Winter, M.; Wohlfahrt-Mehrens, M.; Vogler, C.; Hammouche, A. Ageing mechanisms in lithium-ion batteries. *J. Power Sources* **2005**, *147*, 269–281. [CrossRef]

21. Feng, Y.; Dong, Z.; Jiang, Y.; Jiang, J.; Zhang, C. A comprehensive review of lithium-ion battery state estimation methods: From shallow learning to deep learning. *Energy Storage Mater.* **2023**, *57*, 428–449.
22. Birkl, C.R.; Roberts, M.R.; McTurk, E.; Bruce, P.G.; Howey, D.A. Degradation diagnostics for lithium ion cells. *J. Power Sources* **2017**, *341*, 373–386. [CrossRef]
23. Lee, M.; Shin, Y.; Chang, H.; Jin, D.; Lee, H.; Lim, M.; Seo, J.; Band, T.; Kaufmann, K.; Moon, J.; et al. Diagnosis of Current Flow Patterns Inside Fault-Simulated Li-Ion Batteries via Non-Invasive, In Operando Magnetic Field Imaging. *Small Methods* **2023**, *7*, 2300748. [CrossRef] [PubMed]
24. Schmitt, J.; Rehm, M.; Karger, A.; Jossen, A. Capacity and degradation mode estimation for lithium-ion batteries based on partial charging curves at different current rates. *J. Energy Storage* **2023**, *59*, 106517. [CrossRef]
25. Richardson, R.R.; Osborne, M.A.; Howey, D.A. Gaussian process regression for forecasting battery state of health. *J. Power Sources* **2017**, *357*, 209–219. [CrossRef]
26. Zhang, Z.; Zhang, W.; Yang, K.; Zhang, S. Remaining useful life prediction of lithium-ion batteries based on attention mechanism and bidirectional long short-term memory network. *Measurement* **2022**, *204*, 112093. [CrossRef]
27. Tashiro, Y.; Song, J.; Song, Y.; Ermon, S. CSDI: Conditional Score-based Diffusion Models for Probabilistic Time Series Imputation. *Adv. Neural Inf. Process. Syst.* **2021**, *34*, 24804–24816.
28. Kim, S.W.; Oh, K.-Y.; Lee, S. Novel informed deep learning-based prognostics framework for on-board health monitoring of lithium-ion batteries. *Appl. Energy* **2022**, *315*, 119011. [CrossRef]
29. Chen, G.; Peng, W.; Yang, F. An LSTM-SA model for SOC estimation of lithium-ion batteries under various temperatures and aging levels. *J. Energy Storage* **2024**, *84*, 110906. [CrossRef]
30. Xu, J.; Qu, J.; Xu, H. Capacity estimation of lithium-ion batteries with automatic feature extraction and graph-enhanced LSTM. *J. Energy Storage* **2024**, *85*, 111131. [CrossRef]
31. Park, K.; Choi, Y.; Choi, W.J.; Ryu, H.-Y.; Kim, H. LSTM-Based Battery Remaining Useful Life Prediction with Multi-Channel Charging Profiles. *IEEE Access* **2020**, *8*, 20786–20798. [CrossRef]
32. Chen, D.; Zhang, W.; Zhang, C.; Sun, B.; Chen, H.; Yang, S.; Cong, X. A Novel Sequence-to-Sequence Prediction Model for Lithium-Ion Battery Capacity Degradation Based on Improved Particle Swarm Optimization. *Batteries* **2023**, *9*, 414. [CrossRef]
33. Feng, X.; Weng, C.; He, X.; Han, X.; Lu, L.; Ren, D.; Ouyang, M. Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine. *IEEE Trans. Veh. Technol.* **2019**, *68*, 8583–8592. [CrossRef]
34. Kim, S.W.; Kwak, E.; Kim, J.-H.; Oh, K.-Y.; Lee, S. Modeling and prediction of lithium-ion battery thermal runaway via multiphysics-informed neural network. *J. Energy Storage* **2023**, *60*, 106654. [CrossRef]
35. Li, Y.; Liu, K.; Foley, A.M.; Zülke, A.; Berecibar, M.; Nanini-Maury, E.; Van Mierlo, J.; Hoster, H.E. Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review. *Renew. Sustain. Energy Rev.* **2019**, *113*, 109254. [CrossRef]
36. Tang, T.; Yuan, H. An indirect remaining useful life prognosis for Li-ion batteries based on health indicator and novel artificial neural network. *J. Energy Storage* **2022**, *52*, 104701. [CrossRef]
37. Yang, D.; Zhang, X.; Pan, R.; Wang, Y.; Chen, Z. A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve. *J. Power Sources* **2018**, *384*, 387–395. [CrossRef]
38. Zhang, Y.; Tang, Q.; Zhang, Y.; Wang, J.; Stimming, U.; Lee, A.A. Identifying degradation patterns of lithium ion batteries from impedance spectroscopy using machine learning. *Nat. Commun.* **2020**, *11*, 1706. [CrossRef]
39. Lucu, M.; Martinez-Laserna, E.; Gandiaga, I.; Camblong, H. A critical review on self-adaptive Li-ion battery ageing models. *J. Power Sources* **2018**, *401*, 85–101. [CrossRef]
40. Tian, H.; Qin, P.; Li, K.; Zhao, Z. A review of the state of health for lithium-ion batteries: Research status and suggestions. *J. Clean. Prod.* **2020**, *261*, 120813. [CrossRef]
41. Chang, H.; Park, Y.; Kim, J.-H.; Park, S.; Kim, B.G.; Moon, J. Data-driven designs and multi-scale simulations of enhanced ion transport in low-temperature operation for lithium-ion batteries. *Korean J. Chem. Eng.* **2023**, *40*, 539–547. [CrossRef]
42. Park, S.; Lee, H.; Scott-Nevros, Z.K.; Lim, D.; Seo, D.-H.; Choi, Y.; Lim, H.; Kim, D. Deep-learning based spatio-temporal generative model on assessing state-of-health for Li-ion batteries with partially-cycled profiles. *Mater. Horiz.* **2023**, *10*, 1274–1281. [CrossRef] [PubMed]
43. Kim, S.; Jung, H.; Lee, M.; Choi, Y.Y.; Choi, J.-I. Model-free reconstruction of capacity degradation trajectory of lithium-ion batteries using early cycle data. *eTransportation* **2023**, *17*, 100243. [CrossRef]
44. Bose, B.; Garg, A.; Panigrahi, B.K.; Kim, J. Study on Li-ion battery fast charging strategies: Review, challenges and proposed charging framework. *J. Energy Storage* **2022**, *55*, 105507. [CrossRef]