Improving lithium-ion battery reliability through neural network remaining useful life prediction

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ABSTRACT

The reliable performance of lithium-ion batteries is crucial for the safe and efficient operation of electrical systems, particularly in electric vehicles. To mitigate the risk of battery failure due to degradation, accurate forecasting of the remaining useful life (RUL) is imperative. In this study, we propose employing various recurrent neural network (RNN) methods, including RNN, gated recurrent unit (GRU), and long short-term memory (LSTM), to enhance RUL prediction accuracy for lithium-ion batteries. Our approach aims to provide reliable, accurate, and simple estimates of remaining battery life, facilitating effective management of electric vehicle power systems and minimizing the risk of failure. Performance evaluation metrics such as mean absolute error (MAE), R-squared (R^2), mean absolute percentage error (MAPE), and root mean squared error (RMSE) are utilized to assess prediction accuracy. Experimental validation conducted using the NASA lithium-ion battery dataset demonstrates the superiority of LSTM in reducing prediction error and enhancing RUL prediction performance compared to alternative approaches. These findings underscore the potential of neural network methodologies in advancing battery management practices and ensuring the longevity and reliability of lithium-ion battery systems.

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1. INTRODUCTION

Electric vehicles powered by lithium-ion batteries have emerged as a promising solution to combat the escalating threat of air pollution and reduce CO_2 emissions stemming from global transportation systems [1]. These vehicles, heralded for their environmental benefits, rely on intricate battery packs to operate efficiently. However, as these batteries undergo continuous use, their performance undergoes changes, manifesting as capacity loss and increased resistance [2], [3]. The repercussions of such alterations extend beyond mere efficiency concerns, often culminating in severe catastrophes such as combustion or explosions within energy storage systems. These catastrophic events are largely precipitated by the heightened resistance within degraded batteries, which generates excessive heat. Consequently, the accurate estimation of battery lifespan assumes paramount importance, serving as a pivotal indicator of battery aging and damage status. Such insights are indispensable for ensuring the safety and reliability of electrified vehicles and energy storage systems alike. To navigate the complexities inherent in utilizing these batteries safely and effectively, the implementation of robust battery management systems (BMS) [4] becomes imperative. Recent years have witnessed a surge in research endeavors aimed at refining battery technologies, with a particular focus on empowering BMS to proficiently estimate battery parameters. Monitoring factors such as state of charge (SOC) [5], state of health (SOH) [6], remaining useful life (RUL), charge capacity, and internal resistance emerges as quintessential practices to uphold the efficient and secure utilization of lithium-ion batteries [7]. Among these, RUL emerges as a pivotal parameter, pivotal for fault diagnoses and early safety warnings throughout the life cycle of lithium-ion batteries in electrified vehicles. Moreover, the accurate prediction of RUL plays an instrumental role in quantifying battery life and forecasting the remaining mileage of electric vehicles [8]. Lithium-ion batteries, renowned for their high energy density, power density, low self-discharge rate, and extended lifespan, stand out as favored choices across diverse applications.

The concept of RUL, delineated as the remaining number of cycles to reach the failure threshold, has spurred the development of four distinct prediction methods: direct measurement, model-based, data-driven, and hybrid methodologies [9]. The direct measurement approach utilizes open-circuit voltage and electrochemical impedance spectroscopy to assess the capacity and impedance of battery cells. In contrast, the model-based method leverages various models, including electrochemical, equivalent circuit, and empirical models such as unscented Kalman filter (UKF) and particle filter (PF). Data-driven prediction methods, like gaussian processes (GP) [10], recurrent neural networks (RNN), long short-term memory networks (LSTM) [11], support vector regression (SVR) [12], grey models (GM), relevance vector machines (RVM) [13], and artificial neural networks (ANN) [14], are gaining increasing attention due to the abundance of data available from Li-ion batteries. These data-driven methods do not depend on complex chemical, physical, or mathematical models of battery capacity degradation, making them highly attractive for battery health prediction. In recent times, the prowess of neural networks, particularly RNNs, has garnered attention for its potential to enhance prediction accuracy. Leveraging their innate capacity for self-learning, RNNs hold promise in revolutionizing RUL prediction methodologies [15], [16]. Deep learning methods, already lauded for their success across various domains, offer further credibility to this approach, particularly in time-series prediction tasks. Proposing the utilization of diverse RNN methods in our study represents a concerted effort to augment the prediction accuracy of lithium-ion battery RUL, thereby advancing the frontier of battery management in electrified vehicles. The primary challenges faced in the context of RUL prediction in this study are multifaceted. Foremost among these challenges is the imperative to enhance the prediction accuracy of RUL, striving for high precision and minimizing prediction errors to ensure reliable prognostications. Additionally, the study grapples with the need to curb computational costs and reduce lengthy training times associated with complex prediction models, aiming to streamline processes and improve efficiency.

Furthermore, the pursuit of an optimal solution presents challenges of its own, demanding high stability, rapid convergence speed, flexibility, and seamless implementation to effectively address the intricacies of RUL prediction in practical applications. Addressing these challenges is paramount to advancing the state-of-the-art in RUL prediction methodologies and ensuring their practical viability and efficacy. The key contributions of this paper revolve around the development of a predictive model for lithium-ion battery RUL prediction using a simple yet effective technique based on various RNN methods applied to univariate time series data. Furthermore, this work offers valuable insights into the efficacy of simple RNN methods in RUL prediction for lithium-ion batteries through comprehensive comparisons with other methodologies, including RNN, gated recurrent unit (GRU), and LSTM techniques employed in previous studies. Notably, our proposed LSTM method demonstrates outstanding performance, achieving exceptional predictive accuracy in RUL estimation and facilitating timely predictions based on previously estimated information. These advancements hold promise for enhancing battery lifetime control strategies and safety monitoring functions, thereby reducing the risk of catastrophic events.

The subsequent sections of this paper are structured as follows. Section 2 outlines the framework of our method and elucidates the process of predicting the RUL and introduces the tools and methodology employed for predicting the RUL of lithium-ion batteries using the proposed methods. In section 3, we present the RUL prediction results and compare them with existing prediction methods. Lastly, the paper concludes with a summary of findings.

2. METHOD

2.1. The recurrent neural network methods

Predicting the remaining life of lithium-ion batteries represents a multifaceted and crucial endeavor, particularly in domains like electric vehicles and portable electronics. In tackling this challenge, various neural network algorithms emerge as promising solutions, each offering distinct advantages contingent upon factors such as data nature, resource availability, and specific requirements. Among the array of proposed algorithms, RNNs, GRUs, and LSTMs networks, represented in Figures 1 to 3, stand out prominently.

RNNs excel in capturing temporal features by leveraging correlations between current capacity and previous inputs, facilitating realistic estimations for future predictions. However, they encounter challenges with long-distance dependencies, leading to issues like vanishing gradients. In contrast, LSTM addresses these concerns by regulating gradient propagation and maintaining parameter memory across time iterations. The

LSTM architecture comprises long-term and short-term states, harnessing input and activation values to compute hidden layer nodes effectively. On the other hand, GRU [17], characterized by its simplified architecture featuring two gates—update and reset—offers comparable performance to LSTM with fewer parameters [9], [18], [19].

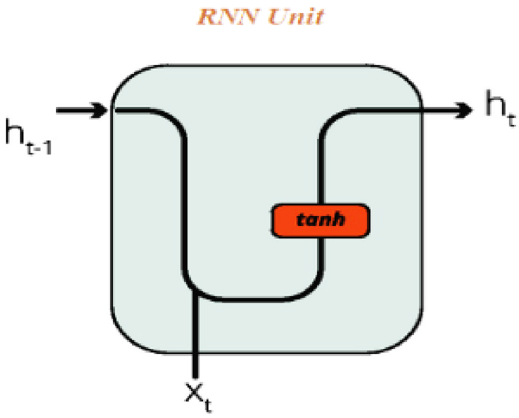


Figure 1. The RNN architecture

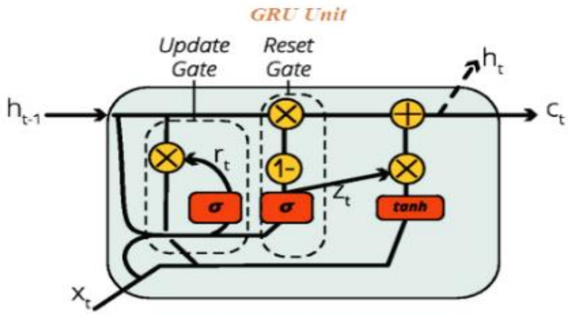


Figure 2. The GRU architecture

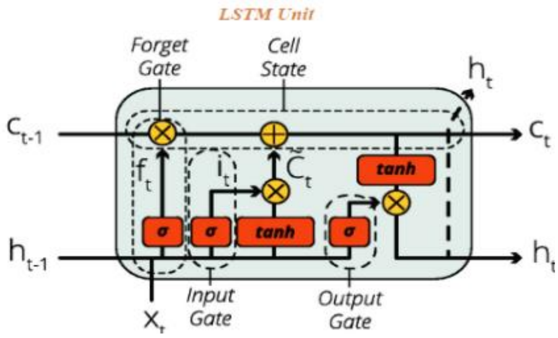


Figure 3. The LSTM architecture

The selection of the most suitable algorithm hinges on dataset characteristics, computational resources, and desired accuracy levels. Leveraging the strengths of each algorithm, our method, as depicted in Figure 4, is meticulously crafted to capitalize on these diverse benefits, ensuring optimal performance in predicting lithium-ion battery RUL. To achieve optimal performance in predicting the RUL of lithium-ion batteries. To further enhance accuracy, we adhered to a well-defined process for RUL prediction, which is detailed in Figure 5. This systematic approach ensures a robust and efficient prediction model.

Figure 4. The proposed framework to predict RUL of battery lithium-ion

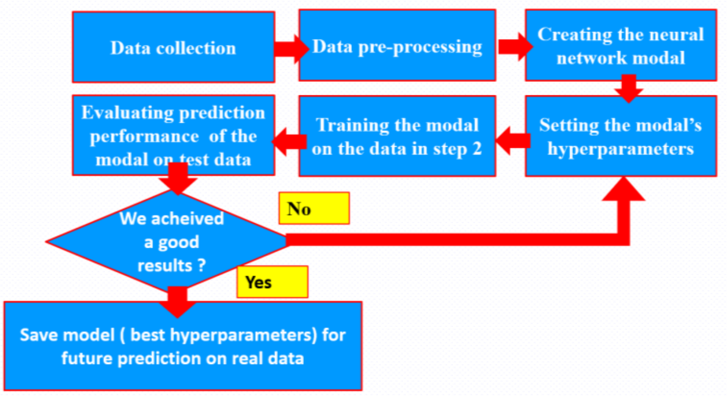


Figure 5. The process for predicting RUL of battery lithium-ion

2.2. Battery dataset

The study validates its findings using experimental data sourced from the NASA [20] of excellence, focusing on aging data for 18650 lithium-ion batteries. The dataset includes three distinct modes: charging, where the battery is charged with a constant current until reaching 4.2 V, followed by a constant voltage phase; discharge, where the battery is discharged with a constant current until reaching 2.5 V; and termination, occurring when the battery's actual capacity drops below 70% of its rated capacity (2 Ah). Analysis is conducted using the dataset for the B0006 battery showing in Figure 6.

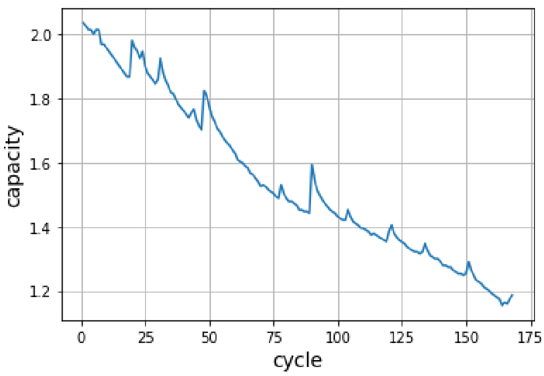


Figure 6. Capacity degradation curve of B0006 battery

2.3. System configuration and evaluation criteria of performance

The hardware and software environment and hyper-parameters shown in Table 1 was used to implement the three methods, i.e. RNN, GRU, and LSTM, respectively. The Adam optimizer and Huber loss are utilized, as well as the rectified linear unit (ReLU) activation function. In addition, we utilize the mean absolute error (MAE) [21], root mean square error (RMSE), R square (R^2) [22], and mean absolute percentage error (MAPE) [23] to evaluate the methods of RUL prediction performance.

$$MAE = \frac{1}{K}\sum_{k=1}^{k}|y_k - \widehat{y_k}| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_k - \widehat{y_k})^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{K=1}^{n}(y_k - \widehat{y_k})^2}{\sum_{K=1}^{n}(y_k - \overline{\widehat{y_k}})^2} \tag{3}$$

$$MAPE = \frac{1}{K}\sum_{k=1}^{k}\left|\frac{y_k - \widehat{y_k}}{y_k}\right| \times 100\% \tag{4}$$

Where y_k stands for the genuine capacity of the battery, $\widehat{y_k}$ for the estimated capacity, and $\overline{y_k}$ for the actual capacity average. The capacity forecast accuracy is greater when the MAE, MAPE, and RMSE are near to zero. When it comes to R^2, a number near to one means more accurate RUL predictions. The Detailed flowchart steps for predicting RUL based on the proposed model are illustrated in Figure 7.

The model framework depend as model inputs are the current and previous capacity vector [C(t − i), . . ., C(t)]. While model outputs are C(t + 1), which can be predicted after employing the proposed method. We use a recursive prediction procedure where the previously forecast capacity as the next input of the model to predict new capacity value until the battery's EOL is arrived, then new RUL can estimated.

Table 1. Environment of hardware and software and best values of hyper-parameters

Hardware ENVIRONMENT	Software ENVIRONMENT	hyperparameters (size)	hyperparameters
RAM 8G	Python with Tensorflow	Window: 8	Epochs: 1500
1.80 GHz CPU	Windows 10 professional edition	Batch: 8	learning_rate: 8e-4
Intel(R) HD Graphics Family		shuffle_buffer: 1000	Regularization: without

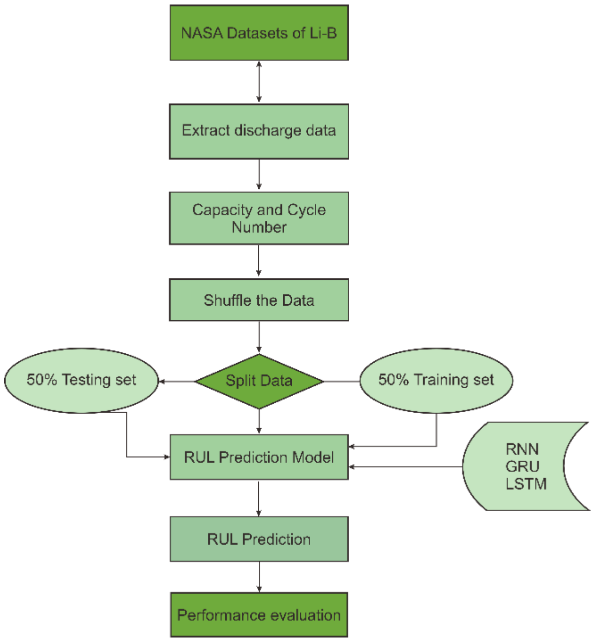
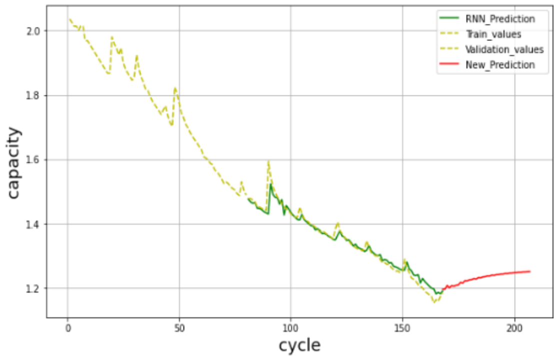


Figure 7. Flowchart steps for predicting RUL

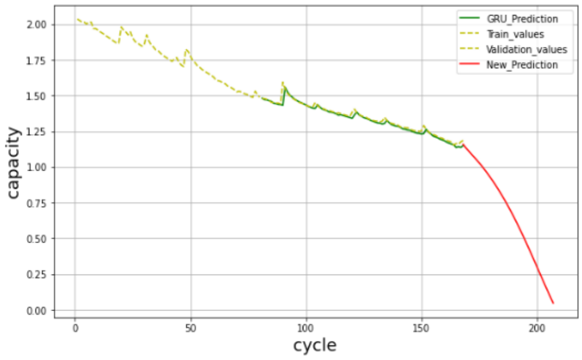
3. RESULTS AND DISCUSSION

3.1. Remaining useful life prediction with the various methods

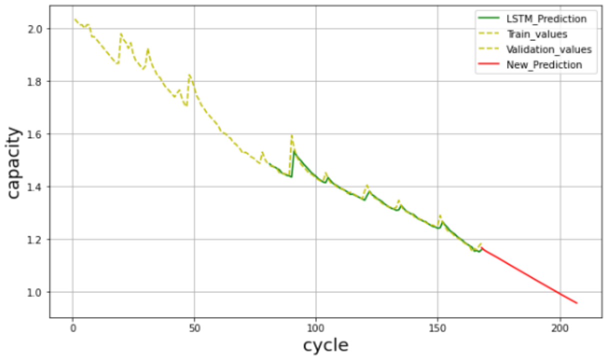
In this section, we present the results of our experimentation on predicting RUL using three distinct methods RNN, GRU, and LSTM. Each method comprises four key steps: data pre-processing, training over 80 cycles, validation prediction over 88 cycles, and 40 new prediction cycles (from 169 to 208). The RUL prediction results for each method are delineated, with real values depicted in yellow, predictions in green (beginning at cycle 80), and new predictions in red. First, employing the RNN method for lithium-ion batteries RUL prediction reveals close alignment between validation and true values as shown in Figure 8(a), indicative of effective learning. However, its performance in new predictions is suboptimal. Conversely, the GRU method as shown in Figure 8(b) exhibits improved accuracy during the validation phase, yet new prediction performance remains inadequate. The LSTM method, on the other hand, not only enhances RUL prediction accuracy for lithium-ion batteries but notably achieves satisfactory performance in new predictions. The consistency between estimates and true values is evident as shown in Figure 8(c), with significant improvement in new prediction accuracy. Furthermore, the loss curve of the LSTM method consistently converges towards zero, demonstrating continual learning and reduced perturbation compared to RNN and GRU methods as shown in Figures 9(a) to 9(c). These findings underscore the superiority of LSTM in achieving high estimation accuracy and robust performance in predicting new RUL, thus solidifying its status as the most accurate method for lithium-ion batteries RUL prediction. The subsequent section provides a summary of numeric RUL prediction errors and contextualizes them against other leading methods in the literature.



(a)

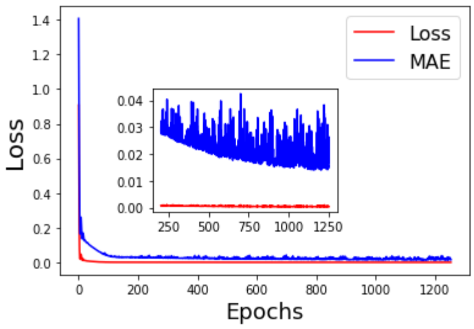


(b)

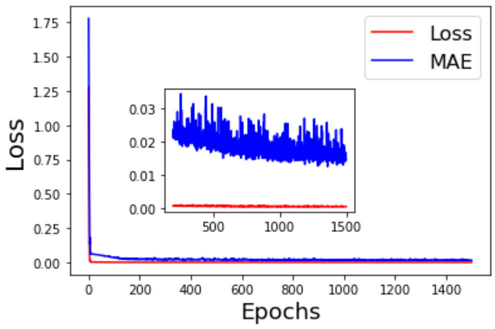


(c)

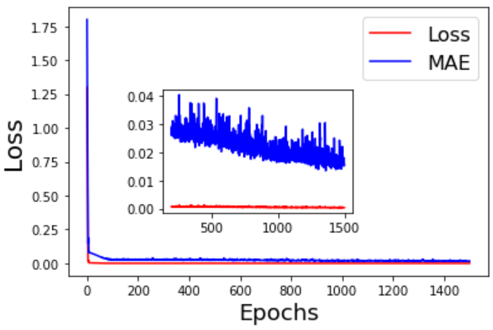
Figure 8. RUL prediction results using: (a) RNN, (b) GRU, and (c) LSTM



(a)



(b)



(c)

Figure 9. RUL training performance: (a) RNN, (b) GRU, and (c) LSTM

3.2. Comparative results analysis

3.2.1. Remaining useful life validation and the evaluation criteria

In the preceding section, our focus was on evaluating the extrapolation capabilities of the LSTM model through RUL prediction tests conducted on the B0006 battery case. Subsequently, the prediction results for this battery were plotted, accompanied by the presentation of accuracy indicators. To ensure comprehensive capacity information inclusion during the training process, the initial 80 data points from the capacity degradation curve, constituting a near-even split, were utilized as the training sets. Subsequent to model training, predictions of future capacity across remaining cycles were made, emphasizing the significance of early-cycle RUL prediction for battery management. In this section, our attention shifts towards scrutinizing the recursive prediction performance and the robustness of our proposed method. The experiments conducted affirm the ability of the proposed method to effectively capture the dynamic nature of lithium-ion batteries. Evaluation of prediction performance was conducted using four key indicators: MAE, R^2, MAPE, and RMSE, with detailed results presented in Table 2.

Table 2, along with Figures 8 and 9, provide a comprehensive insight into the performance evaluation of the proposed methodologies, all based on the B0006 battery's testing set with identical starting points. Notably, MAE, MAPE, and RMSE values associated with the LSTM method are notably lower compared to those of the RNN and GRU methods, while the R^2 values are correspondingly higher. These findings underscore the considerable enhancement in RUL prediction facilitated by the suggested approach. Particularly noteworthy are the significant improvements observed in MAE and RMSE metrics as shown in Figure 10 when transitioning from LSTM to GRU, indicating improvements of 29.2% and 10.8%, respectively. Such outcomes highlight the efficacy and superiority of the proposed LSTM method in enhancing predictive accuracy and precision for lithium-ion battery RUL prediction.

Table 2. RUL prediction results for B0006

Methods	Start point	MAE	R^2 (%)	RMSE	MAPE
RNN	80	0.01287	94.70	0.02321	0.9810
GRU	80	0.01206	94.86	0.02286	0.9473
LSTM	80	0.00854	95.91	0.02038	0.7861

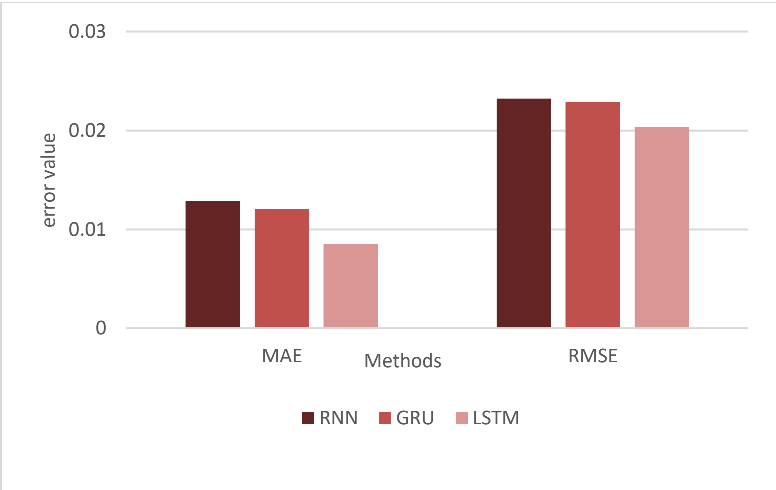


Figure 10. Comparing RUL estimation results by MAE and RMSE

3.2.2. Results analysis and comparison

This section compares the accuracy of RUL estimates across various methodologies from existing literature. single methods emerge as sufficient for handling time series data, as supported by the results in Table 3 and the accompanying analysis. Additionally, to offer a broader comparison encompassing various neural network prediction methodologies, we collate performance results from other studies utilizing the same NASA dataset and performance metrics, alongside commencing predictions from identical starting points. As delineated in Table 3, the LSTM method notably outperforms its single counterparts in terms of accuracy, affirming the efficiency and efficacy of LSTM as evidenced in this article. Specifically, the LSTM method demonstrates a demonstrable reduction in MAE and RMSE. The cumulative findings underscore the high-accuracy estimation capabilities of the proposed LSTM RUL prediction method, positioning it as a superior choice in the realm of predictive modeling.

Table 3. RUL prediction results of B0006 for various papers

Methods	Start point	MAE	RMSE
RNN	78		0.1131
LSTM [24]			0.0784
UKF	80	0.0994	0.1275
AUKF [22]		0.0371	0.0489
RVM	80		0.0667
GM [13]			0.0634
SVR [12]	80		0.0477
LSTM	70		0.0311
RNN [25]			0.0799
RVM			0.0682
RNN	80	0.01287	0.02321
GRU		0.01206	0.02286
LSTM		0.00854	0.02038

4. CONCLUSION

In conclusion, this study introduces the LSTM method as a novel approach for predicting the RUL of lithium-ion batteries, offering significant advancements over established methodologies such as RNNs and GRU. Leveraging a dataset sourced from NASA, our proposed approach undergoes rigorous experimental validation, affirming its exceptional predictive capabilities for lithium-ion battery RUL. Empirical findings unequivocally demonstrate the superior accuracy of the LSTM method compared to alternative approaches. Through comprehensive evaluation using four performance indices, LSTM emerges as the clear frontrunner, surpassing RNN, GRU, and other contemporary methodologies in predictive accuracy. These results underscore the significance of our proposed LSTM-based approach in advancing RUL prediction methodologies for lithium-ion batteries, with promising implications for enhancing battery management practices and ensuring operational efficiency and reliability in various applications.

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