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A Comparative Study of GRU-Based Architectures for State-of-Health and Remaining Useful Life Estimation in Lithium-Ion Batteries for Renewable Energy Storage

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Abstract

Lithium-ion batteries are widely adopted in electric vehicles and renewable energy storage systems due to their high energy density and long cycle life. Accurate prediction of State of Health (SOH) and Remaining Useful Life (RUL) is essential to ensure safety, reliability, and efficient battery management – key factors for accelerating the transition to clean energy and mitigating climate change. In this study, we systematically evaluate and compare the prediction performance of three deep learning architectures: Gated Recurrent Unit (GRU), a hybrid GRU–Deep Neural Network (GRU–DNN), and a hybrid Convolutional Neural Network–GRU–DNN (CNN–GRU–DNN). Experiments are conducted using the publicly available NASA PCoE dataset under consistent preprocessing and training protocols. The results show that the proposed CNN–GRU–DNN model achieves the lowest SOH prediction errors compared to models reported in the literature. Furthermore, compared with non-optimized models, the hybrid CNN–GRU–DNN consistently delivers substantial improvements, confirming its capability to capture both nonlinear features and temporal dependencies. These findings contribute to more reliable battery lifetime prediction, thereby enhancing the viability of renewable energy storage and supporting sustainable development goals.

I. Introduction

Lithium-ion batteries (LiBs) are widely used in electric vehicles (EVs), portable electronics, and renewable energy storage systems due to their high energy density, long cycle life, and relatively low self-discharge rates [1], [2]. In the context of climate change mitigation, the integration of LiBs with solar and wind power is critical for stabilizing the grid and enabling a transition away from fossil fuels. Despite these advantages, LiBs undergo gradual degradation over time, caused by mechanisms such as solid electrolyte interphase (SEI) growth, lithium plating, and electrode material degradation [3]. These aging processes reduce battery capacity and power output, making accurate estimation of State of Health (SOH) and Remaining Useful Life (RUL) essential for safe operation, optimal performance, and effective battery management — particularly for large-scale renewable energy storage, where unexpected battery failure can disrupt clean energy supply. Traditional model-based approaches, including equivalent circuit models and electrochemical models, have been used for SOH and RUL estimation [4], [5]. These models require detailed knowledge of battery chemistry and operating conditions, and often involve complex parameter identification. Moreover, their predictive accuracy can decrease when applied to cells under varying operating profiles. To support the reliable deployment of renewable energy systems, more robust and adaptive methods are needed. To overcome these limitations, data-driven methods have gained attention in recent years. Machine learning techniques, particularly deep learning, can capture complex nonlinear relationships from operational data, enabling more accurate and robust SOH and RUL predictions [6]. Recurrent neural networks (RNNs) have demonstrated strong performance in handling sequential data such as voltage, current, and temperature profiles. Among them, Gated

Recurrent Units (GRUs) provide efficient learning of temporal dependencies while mitigating vanishing gradient problems, making them suitable for battery prognostics [7]. Recent studies have also explored hybrid architectures, such as GRU combined with Deep Neural Networks (GRU–DNN) or Convolutional Neural Networks (CNN–GRU–DNN), which enhance feature extraction and improve predictive performance [8]. However, systematic comparisons of these architectures across multiple datasets and different battery types remain limited.

In this work, motivated by the need for reliable and long-lasting energy storage to support sustainable development goals (SDGs), we conduct a comparative study of GRU, GRU–DNN, and CNN–GRU–DNN architectures for SOH and RUL prediction. Experiments are carried out using one publicly available dataset: NASA PCoE [9]. A unified preprocessing pipeline, including cycle alignment, feature extraction, normalization, and sequence windowing, is applied to ensure consistency across datasets. The main contributions of this study are:

- A systematic comparison of GRU, GRU–DNN, and CNN–GRU–DNN architectures for SOH and RUL prediction.
- Demonstration that hybrid CNN–GRU–DNN models achieve superior predictive accuracy and reliability compared to baseline GRU.
- Providing insights for designing deep learning-based battery prognostics suitable for practical battery management systems in renewable energy storage applications.

The remainder of the paper is organized as follows: Section 2 introduces the problem formulation and defines SOH and RUL. Section 3 presents the datasets and preprocessing methods. Section 4 describes the deep learning architectures and training procedures. Section 5 discusses the experimental results and comparative analysis. Section 6 concludes the paper with key findings and future research directions.

II. Prediction Methodology

a. Problem Formulation

Reliable assessment of lithium-ion battery performance depends on two critical indicators: State of Health SOH and RUL. In the context of renewable energy storage systems, accurate prediction of these indicators is essential to ensure grid stability, optimize battery replacement schedules, and minimize the environmental impact of premature battery disposal. SOH is defined as the ratio of the current battery capacity to its nominal capacity, expressed as a percentage

$$SOH = \frac{\mathrm{Ct}}{\mathrm{Cnom}} * 100 \qquad (1)$$

where Ct is the measured capacity at cycle t and Cnom is the nominal capacity of the battery.

RUL represents the number of cycles remaining before the battery reaches its end-of-life threshold, typically defined as SOH≤80%. For renewable energy storage applications, extending RUL through accurate prognostics directly contributes to reducing electronic waste and lowering the carbon footprint of battery manufacturing.

- Input Features: Remaining capacity
- Prediction Targets: SOH and RUL at each cycle.

This formulation allows the models to learn both the degradation trend and temporal dependencies of battery operation. By enabling more accurate SOH and RUL estimation, the proposed approach supports the sustainable management of battery assets in solar, wind, and grid-scale storage systems, aligning with global climate action goals.

b. Models

In this study, three deep learning architectures [12], [13] are systematically evaluated for SOH and RUL prediction :

- GRU :

The GRU is a recurrent neural network variant designed to model sequential dependencies in time-series data such as voltage, current, and temperature. Its gating mechanism effectively preserves long-term information while mitigating vanishing gradient issues, making it a strong baseline for battery prognostics.

- GRU–DNN (Hybrid Model 1):

The GRU–DNN hybrid integrates the sequential learning capability of GRU layers with the regression strength of fully connected deep neural network layers. While GRU layers extract temporal features from battery degradation sequences, the DNN layers map these features into continuous SOH and RUL predictions. This architecture improves prediction accuracy by capturing both time-dependent and non-linear relationships.

- CNN–GRU–DNN (Hybrid Model 2):

The CNN–GRU–DNN framework extends the previous hybrid by adding convolutional layers as a preliminary feature extractor. CNN layers capture local degradation patterns and variable correlations in raw input signals, which are then processed by GRU layers to model long-term temporal dynamics. Finally, DNN layers perform regression to estimate SOH and RUL. This multi-stage design leverages spatial, temporal, and non-linear feature representations, resulting in superior accuracy, robustness, and generalization compared to simpler models.

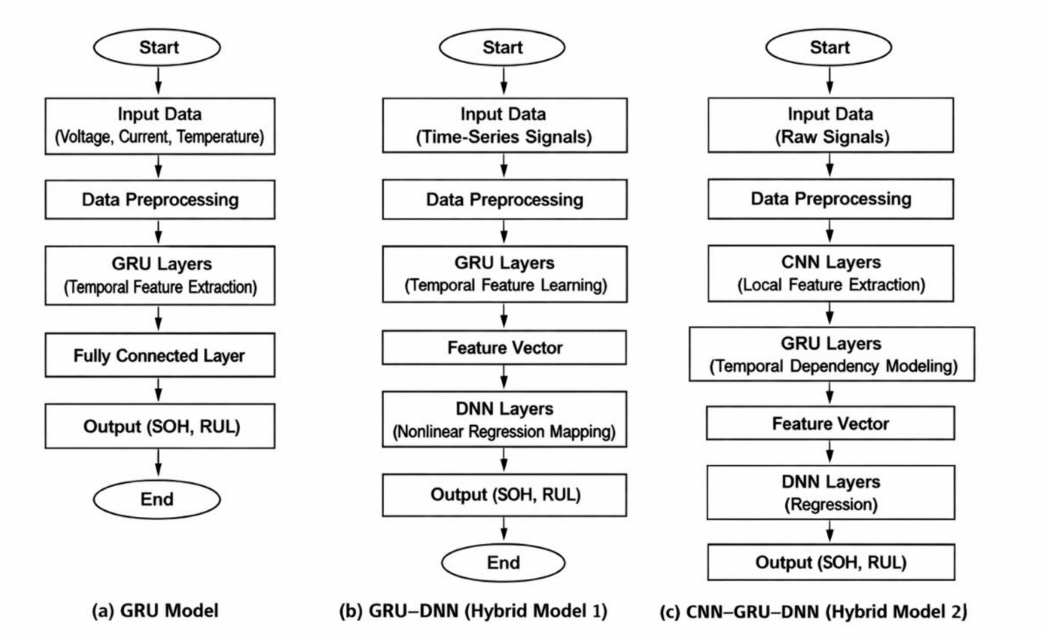

Figure 1. Three deep learning architectures

Although GRU models have been widely used for battery SOH and RUL estimation, few studies systematically compare their performance with hybrid architectures like GRU–DNN and CNN–GRU–DNN. Our work aims to fill this gap by evaluating these models under consistent datasets and preprocessing pipelines, highlighting the advantages of hybrid approaches for practical battery management applications.

c. Experimental Setup

- **Datasets:**

A publicly available datasets is used to evaluate the proposed models. The NASA PCoE dataset [9] provides Li-ion battery aging data under controlled cycling conditions.

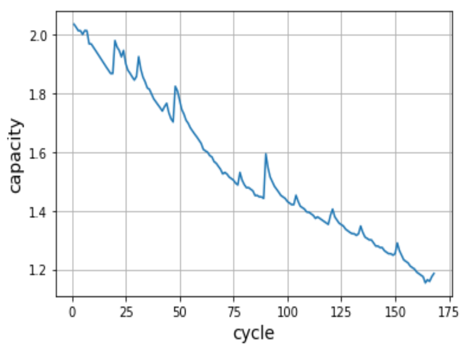

Figure 2. Capacity degradation curve of B0006

- **Data Preprocessing and Training Configuration:**

Raw battery datasets are preprocessed to ensure consistency and suitability for model input. Charge–discharge cycles are segmented to align sequential measurements, and sliding windows are applied to generate input samples for time-series learning. The dataset is then divided into training and testing subsets to evaluate generalization performance on unseen data.

All models are trained using the Mean Squared Error (MSE) loss function, which penalizes larger deviations between predicted and actual SOH/RUL values. The Adam optimizer is adopted to achieve efficient convergence. Training is conducted over 100–200 epochs with a batch size of 32–64, depending on dataset size and model complexity. To mitigate overfitting, early stopping is employed, ensuring reliable generalization.

- **Evaluation Metrics:**

The predictive performance of the models is evaluated using multiple metrics [10], [14], [15]:

- Absolute Error (AE): measures the pointwise deviation between predicted and actual values for each sample.
- Mean Absolute Error (MAE): computes the average of AE values across all samples, providing an overall measure of accuracy that is less sensitive to outliers.
- Root Mean Square Error (RMSE): captures the magnitude of prediction errors, penalizing larger deviations more heavily.
- Coefficient of Determination (R^2): indicates how well the predicted values approximate the actual values, reflecting the model's goodness-of-fit.

Together, these metrics provide a comprehensive evaluation of accuracy, robustness, and reliability in SOH and RUL prediction.

$$MAE = \sum_{k=1}^{k} |y_k - \widehat{y_k}| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_k - \widehat{y_k})^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{K=1}^{n} (y_k - \widehat{y_k})^2}{\sum_{K=1}^{n} (y_k - \widehat{\overline{y_k}})^2} \quad (4)$$

$$\text{AE} = |\text{RULreal} - \text{RULpredicted}| \quad (5)$$

Here, y_k represents the true value, $\widehat{y_k}$ indicates the estimated value of the actual battery capacity, and N denotes the total number of observations. Lower MAE and RMSE values, coupled with an R^2 value closer to 1, indicate higher model accuracy and robustness in SOH estimation.

III. Results and discussion

This section presents a detailed evaluation of SOH and RUL prediction performance using the three investigated deep learning models: GRU, GRU–DNN, and CNN–GRU–DNN. The experiments were conducted on benchmark datasets from NASA ensuring consistent preprocessing and training configurations. The goal is to assess the models' predictive capability under both stable and fluctuating degradation behaviors.

The results are presented through error metrics (RMSE, MAE, R^2) and visual comparisons between true and predicted degradation trajectories. Figures 3, 4 and 5 illustrate the prediction results, where the actual battery measurements are shown in blue and the predicted values in orange. These visualizations enable a clear comparison of each model's ability to follow the degradation and life cycle trends.

a. Prediction Results

From the results in Fig. 3–5, it is clear that all three models capture the overall degradation trajectory of the B0006 battery, but with varying levels of accuracy. The GRU model (Fig. 3) follows the general trend but exhibits noticeable deviations around sudden capacity drops and underestimates SOH near the end of life. The GRU–DNN hybrid model (Fig. 4) provides a closer fit to the ground truth, reducing fluctuations and aligning better with sharp changes in degradation, especially around cycles 75–125. Finally, the CNN–GRU–DNN model (Fig. 5) demonstrates the most stable and accurate predictions, with minimal deviation from the actual SOH curve throughout the entire cycle range. This improvement is attributed to the CNN's ability to extract local features before temporal modeling by GRU, combined with the regression capability of DNN layers.

In terms of RUL estimation, the GRU model shows early misalignment with the true end-of-life point, while GRU–DNN achieves better prediction of the crossing cycle at the 70% SOH threshold. The CNN–GRU–DNN hybrid yields the closest match to the actual failure point, demonstrating both lower error in SOH prediction and higher reliability in RUL forecasting.

Overall, the results confirm that while simple GRU can model long-term temporal dependencies, its performance is limited by sensitivity to local fluctuations. The addition of fully connected layers in GRU–DNN improves regression accuracy, but the integration of CNN in the CNN–GRU–DNN hybrid provides the best balance of spatial, temporal, and regression learning, leading to the most accurate and robust predictions among the three approaches.

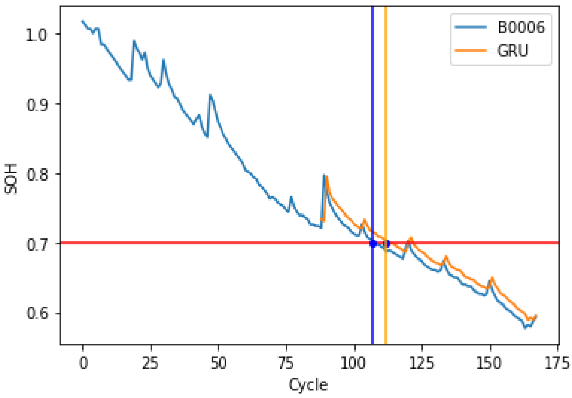

Figure 3. RUL and SOH Prediction Results by GRU

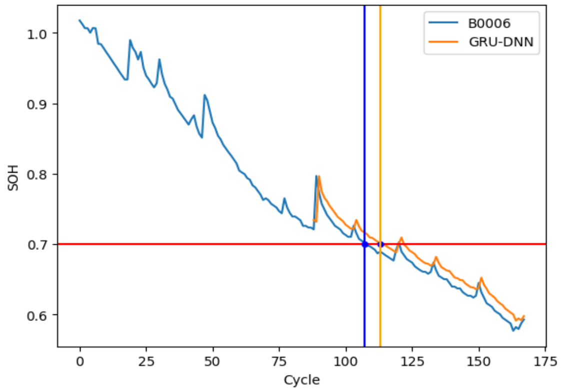

Figure 4. RUL and SOH Prediction Results by GRU -DNN

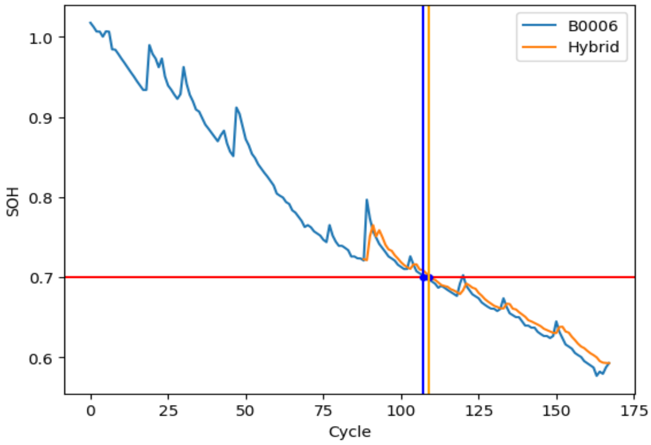

Figure 5. RUL and SOH Prediction Results by CNN- GRU-DNN

These findings emphasize that while simple GRU networks may suffice for basic monitoring tasks, hybrid models, particularly CNN–GRU–DNN, are more reliable for safety-critical applications such as electric vehicle battery management and grid-scale energy storage. The consistent improvements across different datasets confirm the adaptability of hybrid deep learning architectures to diverse battery aging behaviors.

b. Evaluation of Prediction Performance

Table 3 summarizes the RUL prediction performance for battery B0006 under an 50% data split, comparing GRU, GRU-DNN, and CNN-GRU-DNN methods.

Table 1. RUL and SOH Prediction Results

		RUL			SOH		
Batteries	**Methods**	**RULpredict**	**RULtrue**	**RULerror**	**RMSE**	**MAE**	**R^2**
B0006	GRU	112	107	5	0.0154	0.0137	0.747
	GRU-DNN	113	107	6	0.0167	0.0151	0.689
	CNN- GRU-DNN	109	107	2	0.0131	0.0095	0.861

Overall, the hybrid CNN-GRU-DNN method achieves the best performance, with the lowest RUL prediction error (2 cycles), RMSE (0.0131), and MAE (0.0095). It also yields the highest R^2 value of 0.861, indicating stronger agreement between predicted and actual values compared to GRU ($R^2 = 0.747$) and GRU-DNN ($R^2 = 0.689$). While GRU and GRU-DNN show acceptable results, they produce larger prediction errors of 5 and 6 cycles, respectively, and lower correlation with the true degradation trend.

These findings demonstrate that the integration of CNN layers with GRU-DNN enhances feature extraction and temporal learning, leading to more accurate and robust RUL prediction. The consistent reduction in error metrics highlights the superiority of the proposed CNN-GRU-DNN approach in capturing the complex nonlinearities of battery degradation and improving reliability in lithium-ion battery prognostics.

IV. Conclusion

In this study, we presented a comparative evaluation of three deep learning architectures—GRU, GRU–DNN, and CNN–GRU–DNN—for lithium-ion battery State of Health (SOH) and Remaining Useful Life (RUL) prediction. The models were tested on publicly available benchmark datasets from NASA, ensuring a rigorous and reproducible experimental framework. The results demonstrate that while the standard GRU provides acceptable short-term predictions, it struggles to capture the nonlinear and long-term degradation dynamics. The GRU–DNN hybrid model significantly improves prediction accuracy by leveraging nonlinear feature interactions, thereby offering a more reliable alternative for practical deployment. The CNN–GRU–DNN model achieved the highest overall performance, with superior accuracy and robustness across both SOH and RUL tasks. Its ability to integrate spatial feature extraction with temporal sequence modeling enables precise and stable predictions, even under fluctuating degradation conditions. These findings highlight the potential of hybrid deep learning models for advanced battery health management. In particular, the CNN–GRU–DNN architecture provides a promising solution for applications requiring high reliability, such as electric vehicles and energy storage systems. Future work will focus on extending this study to larger, more diverse datasets.

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