GRU-GAN for State of Health Estimation in Lithium-Ion Batteries

Sri Kashyap Dongari
srdo24@student.bth.se
Blekinge Institute of Technology
Karlskrona, Sweden

Akhil Goud Rachakonda
akra24@student.bth.se
Blekinge Institute of Technology
Karlskrona, Sweden

ABSTRACT

Estimating the State of Health (SOH) of lithium-ion batteries accurately is essential for ensuring their reliability, safety, and longevity. However, conventional methods for predicting SOH often have difficulty recognizing the complex degradation behaviors of batteries, leading to less reliable predictions.This study introduces a deep learning approach that combines Gated Recurrent Units (GRU) with Generative Adversarial Networks (GAN) to enhance SOH estimation. The GRU model effectively learns sequential dependencies in battery performance, while the GAN framework improves prediction accuracy by refining the model's outputs through adversarial learning. The proposed GRU-GAN model achieves lower prediction errors and a higher coefficient of determination (R^2) compared to a standard GRU model. These results indicate that integrating adversarial learning with recurrent architectures can provide more reliable SOH predictions, supporting better battery health monitoring and management in practical applications.

KEYWORDS

State of Health, Lithium-Ion Batteries, Deep learning, Generative Adversarial Networks(GAN), Recurrent neural networks

1 INTRODUCTION

Lithium-ion (Li-ion) batteries have become the dominant energy storage technology for various applications, including electric vehicles, renewable energy systems, and consumer electronics [1, 8].Over time, these batteries undergo degradation, leading to capacity fade and reduced efficiency. Accurate State of Health (SOH) estimation is essential for ensuring battery reliability, safety, and performance optimization.

Traditional state of health (SOH) estimation methods for lithium-ion batteries often rely on electrochemical models or machine learning techniques, but these approaches can struggle to capture complex temporal dependencies of battery degradation [7].In this study, we propose a GRU-GAN-based approach for SOH prediction using real battery cycle data.GRU has proven effective in modeling sequential dependencies for battery SOH prediction, capturing non-linear degradation patterns better than traditional methods like SVMs and LSTMs, with higher accuracy and efficiency [5, 9].Additionally, a Generative Adversarial Network (GAN) is employed to refine these predictions, improving their reliability by distinguishing between real and estimated SOH values.

By leveraging real-time operational data, specifically from the NASA battery dataset, this approach enhances the accuracy of SOH forecasting, making it applicable to various industries that depend on battery health monitoring. The proposed model offers a scalable, data-driven solution for predicting battery degradation patterns, ultimately contributing to improved energy management and battery lifespan optimization.

2 RELATED WORK

Researchers have explored various neural network techniques for State of Health (SOH) estimation in lithium-ion batteries. A comparative analysis by [2] examined different neural network architectures, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), 1D-Convolutional Neural Networks (1D-CNN), and CNN-LSTM. Their findings indicate that while data-driven neural networks perform well in SOH estimation, 1D-CNN provides the most accurate predictions with the lowest variance. In contrast, LSTM models exhibit higher variance, while GRU and CNN-LSTM tend to overestimate and underestimate SOH, respectively. These findings highlight the strengths and limitations of different architectures and emphasize the need for further refinement in SOH estimation models.

Building on these insights, researchers have proposed various approaches, including a hybrid framework combining Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and Gated Recurrent Units (GRU) to enhance prediction accuracy for both SOH and Remaining Useful Life (RUL) [10]. Other studies have focused on GRU-based models, with some incorporating attention mechanisms [3] or optimizing for online prediction [9]. The integration of GRU with CNN has also been explored, leveraging charging curve data to estimate SOH [4]. These approaches have demonstrated improved accuracy compared to conventional methods, with error rates generally below 5%. While these studies have made significant strides in SOH prediction, they primarily focus on developing predictive models rather than integrating refinement techniques without synthetic data generation. This work fills this gap by proposing a deep learning framework that not only predicts SOH with high accuracy using GRU but also refines these predictions using GAN-based adversarial learning, thereby improving prediction reliability and robustness for practical applications.

Given these advancements, an important research question arises: How do GRU and GAN improve State of Health estimation in Lithium-ion batteries?

This study aims to investigate how the combination of GRU's sequential modeling capabilities and GAN's adversarial learning can enhance prediction accuracy, reduce errors, and provide a more robust estimation of battery health.

3 SCIENTIFIC RESEARCH METHODOLOGY

This study employs an experimental study approach to develop and evaluate a GRU-GAN-based model for State of Health (SOH) estimation in lithium-ion batteries. The process is organized into the following stages:

3.1 Data Collection

This study utilizes the Battery Health - NASA dataset [6], focusing on Batteries 05 and 18 under charging, discharging, and impedance measurement conditions. The dataset captures key performance metrics across multiple cycles, enabling an in-depth analysis of battery degradation. Recorded attributes include:

- Charging Data: Voltage, current, temperature, and charge duration.
- Discharging Data: Voltage, current, temperature, discharge capacity, and time.
- Impedance Data: Battery impedance, current ratios, and estimated resistance values.

Data collection continues until the batteries reach their end-of-life (EOL) threshold, defined as a 30% reduction in rated capacity (from 2Ah to 1.4Ah).

3.2 Data Preprocessing

In data preprocessing, the discharge data is first loaded, and the capacity values are extracted from the dataset. This capacity data represents the battery's available charge at any given time during the discharge cycle. To prepare the data for model training, the capacity values are normalized using a MinMaxScaler to scale them between 0 and 1, ensuring that the input data is within a suitable range for training deep learning models. Next, sequences of data points of length 10 are generated. These sequences are used as input features for the model, with the following data point (the next capacity value) serving as the target label. The sequences are created by sliding a window over the data and pairing each sequence of 10 data points with the next single data point.

To prepare the dataset for training, the data is split into training and testing sets. The training set consists of 70% of the data, used to train both the GRU model and the GAN. The remaining 30% of the data is used as the testing set, providing an unseen set of battery cycle data to evaluate the performance and generalization of the trained model. This chronological split ensures that the model is trained on earlier data and tested on future data, simulating real-world battery predictions where future data is unknown during training.

3.3 Ethics

This study utilizes the Battery Health - NASA dataset [6], which is publicly available on Kaggle. Since the dataset does not contain any personally identifiable information or sensitive data, ethical concerns related to privacy and data protection are minimal. However, care has been taken to ensure responsible data usage. Potential biases in the dataset, such as imbalances in battery usage conditions or inconsistencies in measurements, have been considered during preprocessing to enhance model fairness. Additionally, as this research involves predictive modeling for battery health estimation, ethical considerations include responsible AI practices to avoid overfitting or misleading predictions, which could impact real-world battery management decisions. By following transparent and reproducible research practices, this study aligns with ethical standards in data-driven research and machine learning applications.

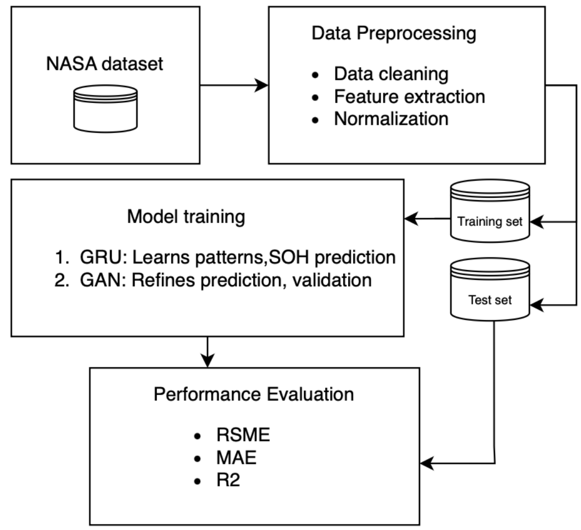

Figure 1: Overall process flow of the proposed GRU-GAN based SOH estimation model

3.4 Model Design

The first model in our architecture is a Gated Recurrent Unit (GRU) network, which is particularly well-suited for time-series prediction tasks, such as predicting battery capacity based on discharge cycles. The GRU model consists of several layers that work together to capture the temporal dependencies in the sequential data, all processed at a time lag of 250. The input layer accepts sequences of length 10, each containing one feature: the battery capacity. The first GRU layer contains 100 units and is configured to return sequences, enabling the model to process data over multiple time steps. The second GRU layer, also with 100 units, outputs a single predicted value, representing the battery capacity for the next time step. To prevent overfitting, dropout layers are added after both GRU layers, randomly dropping units during training. Finally, a dense output layer produces a single value, the predicted battery capacity. The GRU model is compiled using the Adam optimizer, with mean squared error (MSE) as the loss function, which is ideal for regression tasks like capacity prediction.

To enhance the predictions generated by the GRU model, we incorporate a Generative Adversarial Network (GAN). The GAN consists of two main components: the generator and the discriminator. The generator takes the output from the GRU model and refines it to improve the prediction. It is a simple feedforward neural network with dense layers and Leaky ReLU activation functions, which allow small negative values to improve learning of complex data relationships. The final layer of the generator produces a single refined prediction for the battery capacity. The discriminator's role is to differentiate between "real" data (actual State of Health (SOH) values) and "fake" data (predictions made by the generator). This binary classifier consists of two dense layers, followed by Leaky ReLU activations and a sigmoid output layer. It is trained using binary cross-entropy loss and the Adam optimizer. The GAN model integrates the generator and the discriminator, with the discriminator's weights frozen during training. The generator's weights are updated based on the feedback from the discriminator, which attempts to classify the generator's predictions as either real or fake.

3.5 Model Training Procedure

The training procedure begins with training the GRU model for 100 epochs using the training data at a time lag of 250. Early stopping is employed to avoid overfitting, while a model checkpoint is used to save the best-performing model. The GRU model uses mean squared error (MSE) as the loss function, and Adam optimizer for training. Once the GRU model is trained, its predictions are used as input for the generator in the GAN. The GAN training proceeds over 100 epochs and involves alternating between training the discriminator and the generator. The discriminator is first trained on both real SOH values from the training data and fake SOH values predicted by the GRU model. The goal is for the discriminator to accurately classify the data as real or fake. In parallel, the generator is trained to refine the GRU's predictions so that they closely resemble the true SOH values, as judged by the discriminator. Throughout this process, the generator improves its ability to produce more realistic predictions, while the discriminator becomes better at distinguishing between real and fake data.

4 RESULTS

In this section, we present the experiments conducted to evaluate the performance of the prediction models. To assess the accuracy of the predictions, we employed several key metrics commonly used in State of Health (SOH) estimation: i) Root Mean Square Error (RMSE), which measures the discrepancies between the predicted and actual values; ii) Mean Absolute Error (MAE), which calculates the average absolute difference between the observed and predicted values, providing a clear indication of the accuracy of the SOH estimates; iii) the Coefficient of Determination (R^2), which evaluates how well the model's predictions align with the true regression line, indicating the overall fit of the model.

The GRU model [2], trained with a time lag of 250, serves as the initial predictive framework. Its performance metrics indicate its effectiveness in capturing temporal dependencies in battery capacity data. However, to further enhance prediction accuracy, we incorporated a Generative Adversarial Network (GAN) to refine the GRU model's outputs.

The comparative performance of both models is summarized in Table 1.

Table 1: Performance Comparison of GRU and GRU-GAN Models

Model	RMSE	MAE	R^2
GRU	0.046	0.037	0.921
GRU-GAN (Proposed)	0.038	0.029	0.953

5 DISCUSSION

The results show that the GRU-GAN model performs better than the GRU model[2]. The lower RMSE and MAE, along with the higher R^2, indicate that the GRU-GAN model produces more accurate predictions of battery capacity.

One reason for this improvement could be the adversarial training process in GANs, which helps refine predictions by continuously adjusting the generator and discriminator. This process may reduce prediction errors and improve how well the model captures patterns in battery degradation. GANs are also useful for learning complex dependencies in sequential data, which may help in modeling the nonlinear behavior of battery capacity decline.

Another possible explanation is that GANs improve the way the model learns from data. While a GRU model relies only on past observations, the GRU-GAN model benefits from the generative approach, which may reduce biases and improve generalization. This likely contributes to lower error values and more consistent State of Health (SOH) estimations.

Additionally, the adversarial component of the GAN may help prevent overfitting. Standard recurrent models like GRU can sometimes rely too much on specific training data, but the GAN structure may act as a form of regularization, allowing the model to perform better on new data.

Overall, these results suggest that combining GANs with recurrent models can improve SOH estimation. The GRU-GAN model provides more accurate and reliable predictions, making it a useful approach for battery health forecasting. Future research could explore different GAN structures or training methods to further improve results.

5.1 Threats to Validity

This study acknowledges several validity threats that may impact the reliability and generalizability of the results. These threats are categorized into internal validity, external validity, and construct validity. Internal validity concerns factors that may introduce bias in model training or data quality. The Battery Health - NASA dataset was collected under controlled laboratory conditions, which may not fully capture all real-world variations in battery usage. Additionally, preprocessing techniques such as MinMax scaling and sequence generation could introduce biases if not carefully handled. Efforts were made to mitigate these risks by ensuring consistent preprocessing and using a chronological split for training and testing.

External validity refers to the generalizability of the findings beyond the dataset used. Since the dataset contains battery cycles collected under predefined conditions, the trained models may not perform equally well in real-world electric vehicle (EV) applications, where factors such as temperature fluctuations, varying charging patterns, and load variations influence battery health. Future studies should incorporate diverse datasets covering multiple battery types and real-world driving conditions to improve model robustness.

Construct validity assesses whether the chosen evaluation metrics (RMSE, MAE, and R^2) accurately measure the model's effectiveness in predicting battery health. While these metrics provide a solid statistical basis for evaluating model performance, they do not fully capture the impact of prediction errors in practical applications. For instance, small prediction errors may be acceptable in some cases but critical in others, such as battery safety monitoring. Future work could explore additional domain-specific evaluation criteria to enhance result interpretation.

5.2 Social Impact

Improving battery SOH estimation models, such as the GRU-GAN, has significant social benefits. Accurate predictions enhance electric vehicle (EV) reliability, reduce battery waste, and promote sustainability by extending battery life and minimizing premature replacements. This leads to a more eco-friendly approach to battery production and disposal. Furthermore, better SOH models boost consumer confidence, encouraging wider EV adoption and contributing to reduced greenhouse gas emissions. Additionally, optimizing battery health can lower maintenance costs, improve energy efficiency, and support the growth of renewable energy systems, benefiting both society and the environment.

6 CONCLUSION

This study demonstrates the effectiveness of a GRU-GAN framework for battery capacity prediction, achieving significant improvements in SoH estimation over the baseline GRU model. The model was trained using a dataset chronologically split into 70% for training and 30% for testing, with time-series sequences of length 10 and a time lag of 250. The GRU model was optimized using mean squared error (MSE) loss and the Adam optimizer. To enhance prediction accuracy, we incorporated a GAN, where the generator refines the GRU's predictions, and the discriminator differentiates between real and predicted State of Health (SoH) values. Over 100 training epochs, the generator progressively improved the accuracy of capacity predictions.

Our experimental results demonstrated that the GRU-GAN model significantly outperforms the baseline GRU model in terms of multiple evaluation metrics, including RMSE, MAE, and R^2. This enhanced model effectively captures battery degradation patterns, showcasing its potential to advance predictive maintenance strategies, optimize battery life cycles, and improve the reliability of electric vehicle applications and energy storage systems.

While the integration of GANs led to notable improvements in prediction accuracy, it also increased the model's computational complexity. This trade-off between improved performance and efficiency highlights the need for further optimization in future work. Nonetheless, the proposed approach provides a promising direction for battery health monitoring and management.

7 FUTURE WORKS

While this study demonstrates the effectiveness of the GRU-GAN model in battery SOH estimation, there are several avenues for future research to further enhance its performance and applicability:

- Incorporating Real-World Data: Future work should involve testing the model on more diverse datasets, including those from real-world electric vehicle usage, to account for environmental variables and unpredictable charging/discharging patterns.
- Model Generalization: To improve the model's ability to generalize across different battery types and conditions, research should explore transfer learning techniques and multi-source learning approaches.
- Hybrid Models: Further exploration of hybrid models, combining GRU-GAN with other advanced techniques (e.g., reinforcement learning or attention mechanisms), could further refine the predictions and enhance SOH estimation.
- Real-Time Application: Implementing the model in real-time battery health monitoring systems for electric vehicles would be a critical next step in demonstrating its practical value and improving battery management.

These areas will help improve the accuracy, robustness, and real-world applicability of battery SOH prediction models, advancing the field of energy storage and electric mobility.

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