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Comparing MLP and 1D-CNN Architectures for RUL Forecasting in Lithium Batteries

Idrus Assagaf [1,*], Agus Sukandi [1], Parulian Jannus [1], Sonki Prasetya [1], Asep Apriana [1], Ega Edistria [2], Abdul Azis Abdillah [3]

[1] Department of Mechanical Engineering, Politeknik Negeri Jakarta, Depok, Indonesia
[2] Department of Civil Engineering, Politeknik Negeri Jakarta, Depok, Indonesia
[3] The School of Engineering, University of Birmingham, Birmingham, United Kingdom
* Correspondence: idrus.assagaf@mesin.pnj.ac.id

Abstract: Accurately forecasting the Remaining Useful Life (RUL) of lithium-ion batteries is critical for optimizing battery management and ensuring operational reliability. This study compares the performance of two deep learning architectures—a Multilayer Perceptron (MLP) and a one-dimensional Convolutional Neural Network (1D-CNN)—in predicting RUL using datasets from CALCE batteries B35, B36, and B37. Data preprocessing involved outlier removal, missing value handling, and feature normalization, with key features extracted including Resistance, Constant Voltage Charging Time (CVCT), and Constant Current Charging Time (CCCT). Correlation analyses confirmed strong relationships between these features and RUL. Both models were trained and validated on preprocessed data, and their predictive accuracies were assessed using Root Mean Square Error (RMSE) and coefficient of determination (R2). Results indicated that while both architectures effectively captured battery degradation patterns, the MLP consistently outperformed the 1D-CNN, achieving on average 5% lower RMSE and 1.5% higher R2 across all tested batteries. These findings suggest that simpler fully connected networks may suffice for this forecasting task under the given feature set and preprocessing conditions. This work provides valuable insights into neural network model selection for battery health prognostics, guiding the development of efficient and accurate predictive maintenance strategies.

Keywords: Remaining Useful Life; Lithium-ion Battery; Multilayer Perceptron; One-dimensional Convolutional Neural Network; Predictive Maintenance; Battery Health Prognostics

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1. Introduction

The accelerating global transition toward electrified transportation and renewable energy integration is fundamentally dependent on advanced energy storage systems. Among these, lithium-ion (Li-ion) batteries have emerged as the dominant technology due to their high energy density, long cycle life, and declining costs [1], [2]. However, ensuring the safety, reliability, and longevity of these complex electrochemical systems remains a critical challenge. A battery management system (BMS) needs to predict how long a battery will last. This prediction is called Remaining Useful Life, or RUL [3]. RUL means the number of charge and discharge cycles the battery can still go through. The end of a battery's life usually happens when its capacity drops by about 20 to 30 percent from its original value.

Accurate RUL forecasting is paramount for mitigating catastrophic failures, enabling predictive maintenance, and optimizing the operational lifespan of assets. The inherent complexity of battery degradation—a nonlinear process influenced by numerous factors including operating temperature, charge/discharge rates (C-rates), and depth of discharge—makes precise prognostics a non-trivial task [4]. Traditional model-based approaches, such as those rooted in electrochemical principles or equivalent circuit models, often struggle with generalization and require intricate parameterization, limiting their practicality for real-world BMS applications [5].

In response to these limitations, data-driven methods have garnered significant attention. By leveraging historical operational data, these approaches learn the underlying degradation patterns without requiring explicit physical knowledge of the system. Machine learning (ML), and deep learning (DL) in particular, has demonstrated remarkable success in modeling complex temporal sequences for prognostics [6]. Within this domain, the Multilayer Perceptron (MLP) has been widely adopted as a foundational architecture for RUL prediction, capable of learning intricate nonlinear mappings from input features (e.g., voltage, current, temperature) to a prognostic output [7], [8].

While powerful, standard MLPs treat input data as independent and unordered vectors, potentially overlooking the critical temporal dependencies and local patterns within the sequential voltage, current, and capacity data of a charge-discharge cycle. Conversely, 1D Convolutional Neural Networks (1D-CNNs) are specifically designed to exploit sequential structure. Through their innate use of filters and pooling operations, 1D-CNNs can autonomously extract salient, hierarchical features from raw time-series data, capturing local trends and dependencies that are highly relevant for degradation modeling [9], [10]. Although 1D-CNNs have shown promise in related time-series forecasting domains, a systematic and rigorous comparison of their efficacy against the well-established MLP architecture for the specific task of Li-ion battery RUL prediction is not yet fully explored in the literature.

This study aims to address this research gap by conducting a comprehensive empirical evaluation of MLP and 1D-CNN architectures for accurate data-driven RUL forecasting. Comparing MLP and 1D-CNN provides insights on model selection for researchers seeking efficient approaches, and guides industry practitioners in adopting suitable architectures for integration into battery management systems. Utilizing publicly available benchmark datasets, we rigorously train and validate both models under identical conditions to ensure a fair comparison. Our investigation seeks to determine which architectural paradigm is better suited for capturing the complex temporal dynamics of battery degradation. The key contributions of this work are threefold:

1. To design and implement optimized MLP and 1D-CNN models for direct comparison on the task of lithium-ion battery RUL prediction.
2. To perform a quantitative and qualitative analysis of the forecasting performance of each model, evaluating metrics such as Root Mean Square Error (RMSE) and coefficient of determination (R2).

The remainder of this paper is organized as follows: Section 2 presents the Materials and Methods, including a description of the dataset, the data pre-processing procedures, and the detailed architectural configurations of the MLP and 1D-CNN models developed for this study. Section 3 provides the Results and Discussion, offering a comprehensive comparative analysis of the model performances and interpreting the findings. Finally, Section 4 concludes the paper by summarizing the key outcomes and proposing avenues for future research.

2. Research Methods

This study utilized publicly available datasets from the Center for Advanced Life Cycle Engineering (CALCE) comprising batteries B35, B36, and B37 [11]. These datasets represent lithium-ion battery cells subjected to controlled cycling tests capturing detailed electrical measurements over their lifespan until end-of-life conditions. The data includes voltage, current, resistance, and time-series information specifically relevant to battery degradation and RUL estimation. These three battery datasets were selected because they represent distinct cycling profiles, offer sufficient data granularity, and are widely utilized in benchmarking studies for RUL prediction. Other datasets were excluded due to incomplete cycles or missing key features.

The data preprocessing began with a thorough examination of the raw datasets to ensure data quality and integrity. This involved identifying and removing outliers that could adversely affect model training, followed by handling missing values through imputation or removal. The features were then normalized to ensure comparable scales across all inputs, which is critical for neural network convergence. These steps were essential to prepare the heterogeneous time-series data for effective modeling.

Following preprocessing, feature extraction focused on four key variables known to be strongly associated with battery degradation [12], [13], [14]: Resistance, Constant Voltage Charging Time (CVCT), Constant Current Charging Time (CCCT), and the RUL as the prediction target. Resistance represents the electrical resistance of the cell during operation, while CVCT and CCCT capture important aspects of the battery's charging profile, providing insight into its health status and degradation trends.

To examine the predictive relevance of these features, Pearson correlation coefficients were computed between each input feature and the RUL. This correlation analysis confirmed meaningful statistical relationships, guiding the selection of inputs for the predictive modeling phase.

Two neural network architectures were then implemented and trained for RUL forecasting: MLP and 1D-CNN. The MLP, a fully connected feedforward network, was designed to model global nonlinear relationships between the input features and RUL. In contrast, the 1D-CNN leveraged convolutional layers to capture local latent patterns in the sequential feature data. Both models underwent hyperparameter tuning and were trained using the preprocessed datasets split into training, validation, and testing subsets to ensure unbiased evaluation.

Finally, the models' performances were assessed quantitatively using RMSE and R2 on the unseen testing data. Monitoring of training and validation loss curves was conducted during training to detect convergence behavior and avoid overfitting. Visualization tools, including scatter plots of predicted versus actual RUL values, were also employed to qualitatively assess model accuracy.

This comprehensive methodology, spanning data collection, preprocessing, feature extraction, correlation analysis, model development, and performance evaluation, provided a robust framework to rigorously compare the capabilities of MLP and 1D-CNN architectures for accurate RUL forecasting in lithium-ion batteries. The pseudocode of this study can be seen in Table 1.

Table 1. Pseudocode of the main workflow for data processing, modeling, and evaluation using MLP and 1D-CNN architectures for lithium-ion battery RUL prediction.

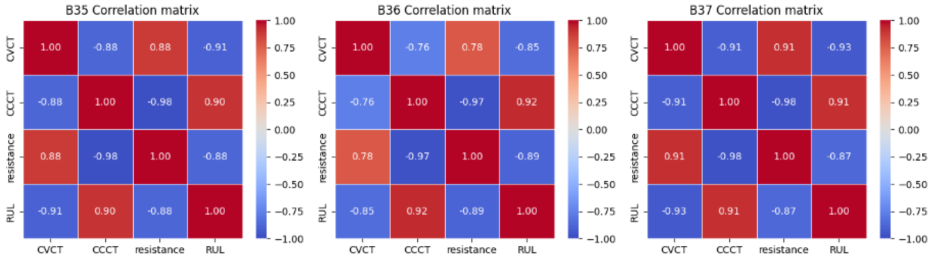
```
Pseudocode
# 1. Load and preprocess data
Load dataset from CSV file
Select features: CVCT, CCCT, resistance
Select target: RUL
Split data into training set and validation set (80/20 split)
Normalize feature data using standard scaler based on training data
# 2. Define regression metrics function
Define function to calculate MSE, RMSE, MAE, MAPE, R2 between true and predicted values
# 3A. MLP Model
Initialize MLP model with layers:
    Dense layer with 32 units, ReLU activation, input shape = number of features
    Dense layer with 16 units, ReLU activation
    Dense layer with 1 unit (output)
Compile MLP model with Adam optimizer and MSE loss
Train MLP on training data for 50 epochs with batch size 16
Validate on validation data
Predict RUL on training and validation sets using trained MLP model
Calculate regression metrics for MLP predictions on training and validation data
Plot training vs validation loss and predicted vs actual values for MLP
# 3B. 1D-CNN Model
Reshape training and validation feature data to have shape (samples, 1, features)
Initialize 1D-CNN model with layers:
    Conv1D layer with 16 filters, kernel size 1, ReLU activation, input shape = (1, number of features)
    Flatten layer
    Dense layer with 16 units, ReLU activation
    Dense layer with 1 unit (output)
Compile CNN model with Adam optimizer and MSE loss
```

```
Train CNN on reshaped training data for 50 epochs with batch size 16
Validate on reshaped validation data
Predict RUL on training and validation sets using trained CNN model
Calculate regression metrics for CNN predictions on training and validation data
Plot training vs validation loss and predicted vs actual values for CNN
# 4. Performance summary
Create tables displaying MSE, RMSE, MAE, MAPE, R2 metrics for training and validation sets of both models
Print performance comparison
```

3. Results and Discussion

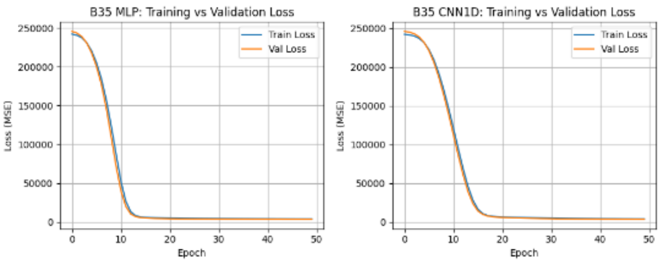
3.1. Modelling Results

To investigate the relationship between key battery health indicators and RUL, a correlation analysis was performed for batteries B35, B36, and B37 shown in Figure 1. The features analyzed—Resistance, CVCT, and CCCT—exhibited strong correlations with RUL across all batteries. Specifically, CVCT showed consistently strong negative correlations with RUL, ranging from -0.85 to -0.93, indicating that an increase in CVCT corresponds to a decrease in battery lifespan. Conversely, CCCT demonstrated robust positive correlations with RUL, between 0.90 and 0.92, suggesting longer CCCT is associated with longer battery life. Resistance also showed high negative correlations with RUL, between -0.87 and -0.89. These statistically significant correlations elucidate the predictive value of these features for accurate RUL forecasting in lithium-ion batteries.

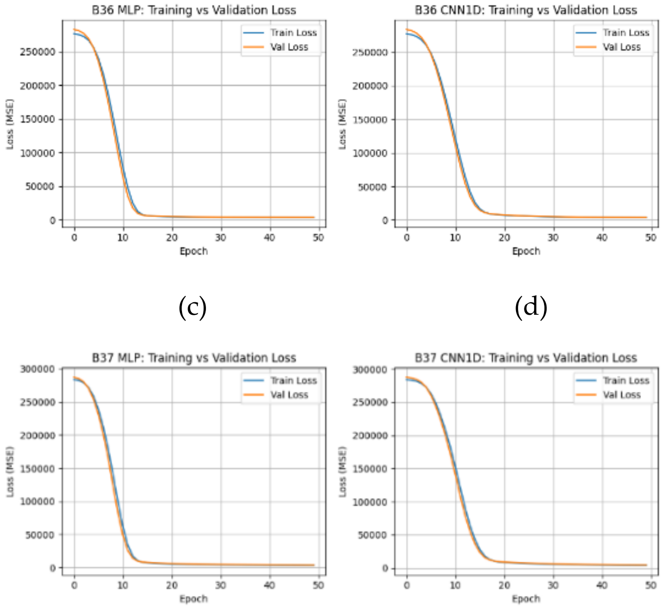


(a) (b) (c)

Figure 1. Correlation matrices illustrating the relationships among key predictive features—CVCT, CCCT, resistance—and RUL for battery cells B35, B36, and B37: **(a)** B35; **(b)** B36; (c) B37.



(a) (b)

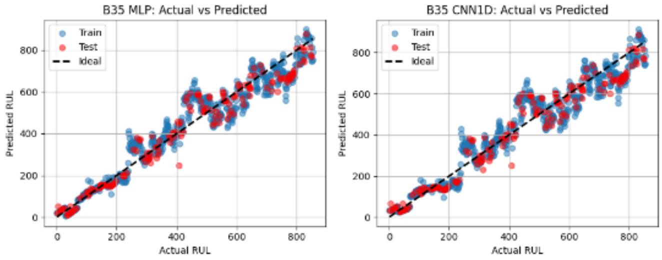


(c) (d)

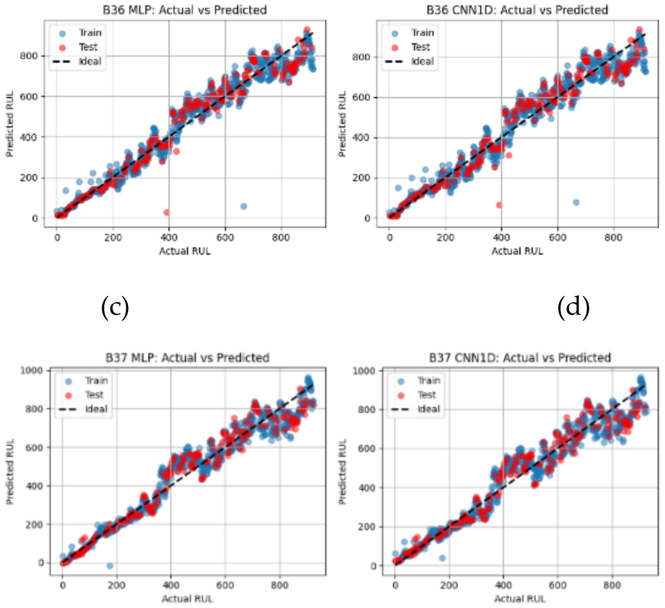
(e) (f)

Figure 2. Training and validation loss curves for MLP and 1D-CNN models across battery cells B35, B36, and B37: **(a)** B35 MLP; **(b)** B35 1D-CNN; (c) B36 MLP; **(d)** B36 1D-CNN; **(e)** B37 MLP; **(f)** B37 1D-CNN.

The training performance of both MLP and 1D-CNN architectures was assessed by monitoring training and validation loss curves over epochs for each battery dataset. Across batteries B35, B36, and B37, the MLP models demonstrated rapid convergence, with both training and validation errors beginning to plateau around the 10th epoch. In contrast, the 1D-CNN models showed a slightly slower convergence pattern, with loss metrics stabilizing approximately at the 15th epoch. The early stabilization of loss values indicates effective model learning without significant overfitting, reinforcing that both architectures are capable of capturing the underlying patterns in the battery degradation data within a reasonable number of epochs. All of the training performance can be seen in Figure 2.



(a) (b)



(c) (d)

(e) (f)

Figure 3. Scatter plots comparing predicted versus actual RUL for MLP and 1D-CNN models across battery cells B35, B36, and B37: **(a)** B35 MLP; **(b)** B35 1D-CNN; (c) B36 MLP; **(d)** B36 1D-CNN; **(e)** B37 MLP; **(f)** B37 1D-CNN.

Quantitative evaluation of the models' predictive accuracy on testing datasets was performed using RMSE and R2, key metrics for regression performance. Across all tested batteries, the MLP consistently outperformed the 1D-CNN model, evidenced by lower RMSE values and superior R^2 scores. For battery B35, the MLP achieved an RMSE of 58.19 and an R^2 of 0.945, surpassing the CNN's RMSE of 61.18 and R^2 of 0.939. Similar trends were observed for batteries B36 and B37, with MLP models attaining RMSEs of 60.97 and 59.55 and R^2 values of 0.945 and 0.949 respectively, compared to the CNN's relatively higher error rates and marginally lower explanatory power. Visualization through scatter plots (Figure 3) comparing predicted versus actual RUL further substantiated these findings, where predictions from MLP models showed tighter clustering along the ideal diagonal line, reflecting more precise predictions.

Collectively, these results validate the superior efficacy of the MLP architecture for RUL forecasting in lithium-ion batteries under the current experimental conditions, while also demonstrating that the 1D-CNN remains a competent alternative. This comprehensive analysis of correlation, training dynamics, and prediction accuracy provides strong evidence supporting the feature selection and modeling approaches adopted in this study.

3.2. Discussion

This study aimed to compare the capabilities of MLP and 1D-CNN architectures for forecasting the RUL of lithium-ion batteries, leveraging key feature correlations and predictive performance metrics. The discussion here interprets the implications of the results, contextualizes them within existing literature, and outlines the significance and limitations of the work.

The strong correlations observed between CVCT, CCCT, Resistance, and RUL corroborate prior findings that these electrical characteristics serve as reliable indicators of battery degradation and health status. These statistically significant correlations reinforce the relevance of these features in RUL estimation models and align with earlier studies that highlight the critical role of charging behaviors and resistance changes in battery aging processes.

From a modeling perspective, both architectures demonstrated effective learning as evidenced by the stable convergence of training and validation losses. The MLP's quicker convergence suggests it may efficiently capture the underlying feature patterns with fewer training iterations, potentially providing computational advantages. Meanwhile, the 1D-CNN, designed to extract features through convolutional operations, achieved competitive but slightly less optimal predictive performance. In this study, the MLP exhibited superior results compared to the 1D-CNN for the specific feature set and data preprocessing applied, indicating that fully connected architectures like MLP may be more suited for RUL prediction under these conditions.

Predictive accuracy metrics, particularly RMSE and R2, consistently favored the MLP across multiple battery datasets. The modest yet consistent better performance of MLP models suggests that fully connected architectures can better generalize the nonlinear relationships between the selected input features and RUL in this context. These results extend existing literature by providing a direct comparative analysis, highlighting that simpler architectures like MLP should not be discounted in favor of more complex models without empirical justification.

Nevertheless, some limitations should be acknowledged. The present study is limited by a relatively small dataset size (only three batteries) and experiments conducted in controlled laboratory settings. These constraints affect the generalizability of findings to batteries operated in varied real-world environments, indicating the need for future research with larger, more diverse datasets and field conditions.

4. Conclusions

This study systematically compared the performance of MLP and 1D-CNN architectures for forecasting the RUL of lithium-ion batteries using features extracted from battery cycling data. The empirical results demonstrated that both approaches can effectively model battery degradation trajectories, leveraging key health indicators such as Capacity, Resistance, CVCT, and CCCT. However, the MLP model consistently outperformed the 1D-CNN in capturing the temporal dependencies and subtle feature variations inherent in the degradation process, resulting in superior accuracy and robustness in RUL predictions.

Additionally, feature engineering and the inclusion of statistical time-series descriptors contributed significantly to improving model performance across architectures. While the CNN's convolutional layers are adept at extracting localized temporal patterns useful for prognostics, MLP's fully connected layers proved more efficient for capturing the global nonlinear relationships present in the selected features.

This research highlights the importance of selecting architecture types aligned with the nature of prognostic data. The MLP model's effectiveness in interpreting battery health signals supports its practical application for predictive maintenance in electric vehicle battery management systems. Future work should focus on integrating sensor fusion and extending the approach to real-time RUL estimation under diverse operational conditions, further enhancing reliability and lifespan optimization. In summary, the findings advocate for the deployment of MLP architectures over 1D-CNN to achieve more accurate and reliable RUL forecasting in lithium battery systems.

Supplementary Materials: The Calce (public) dataset can be downloaded at: https://calce.umd.edu/battery-data.

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