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Research Article

Prediction of the Remaining Useful Life of Lithium-Ion Battery Using Multilayer Perceptron

Basanta Pancha[1], Sushil Paudel[2, *], Basanta Thapaliya[3], Tomasz Siewerski[4], Dayasagar Niraula[5]

[1]Department of Electrical and Electronics Engineering, Nepal Engineering College, Changunarayan, Bhaktapur, Nepal
[2]Research Training and Consultancy Division, Kantipur Engineering College, Dhapakhel, Lalitpur, Nepal
[3]Department of Electrical Engineering, Khwopa College of Engineering, Libali, Bhaktapur, Nepal
[4]Institute of Electrical Power Engineering, Lodz University of Technology, Lodz, Poland
[5]Department of Electrical and Computer Engineering, Iowa State University, Ames, United States

Abstract

Cogitating the reliability of the supply and ensuring continuous delivery of power to the loads, especially in the growing demand for Lithium-Ion batteries in electric vehicle applications, prediction of the remaining useful life of Lithium-Ion batteries is crucial for the timely replacement. For prediction of non-linear and chaotic relationship, experience-based approach, physics-based approach and data driven approach are used among which data driven approach is a model free, accurate and reliable approach. Therefore, a driven approach in predicting remaining useful life can be implemented in the battery management system. This research uses a multilayer perceptron to predict the remaining useful life of the battery. The NASA Ames Prognostics Center of Excellence (PCoE) battery dataset is used to test the proposed methodology. The use of multilayer perceptron for remaining life prediction seems promising despite the significant number of jump points, gaps in data and a small quantity of experimental data in the National Aeronautics and Space Administration (NASA) dataset. The predicted result was obtained with 8.52 % mean absolute error and 9.59 % root mean square error. When compared with the predicted results of different literatures, proposed multilayer perceptron with sliding window approach outperforms most of the existing approach. Incorporation of optimization techniques and hybrid algorithm in proposed approach can further enhance the accuracy of the model.

Keywords

Lithium-Ion Battery, Multilayer Perceptron (MLP), Charge-Discharge Cycle, Remaining Useful Life (RUL), Depth of Discharge (DOD)

1. Introduction

Use of Lithium-ion battery has outnumbered the usage of lead-acid batteries due to the numerous merits in terms of technical aspects such as fast rate of charging, wide operating temperature range, lightweight, high-energy density, high galvanic potential, longer service life, emission-free, high efficiency, less maintenance costs and high Depth of

*Corresponding author: sushilpaudel@kec.edu.np (Sushil Paudel), erpaudelsushil@gmail.com (Sushil Paudel)

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Dis-charge (DoD) [1-4]. Almost all the industrial energy supply areas extensively use this storage technology [5]. The major demerit of Lithium-ion batteries, when compared with Lead-acid batteries, underlies the high investment cost. However, due to the degradation and deterioration of pole materials, electrolyte changes, and ageing factors, the dis-charge capacity gradually deteriorates over time in the long run [6]. The application areas of Lithium-ion batteries are not limited to and range from cell phones, laptops, mobile electronics, and other electronic goods, communications, electric vehicles, transportation, power backup like Uninterruptible Power Supply (UPS), energy storage systems, military, to aerospace applications [7-11]. Lithium-ion battery applications range from mobile electronics, electric vehicles, and military to aerospace applications [12]. Considering various energy storage technologies, one of the typical energy storage components in life is a lithium-ion battery [13]. Lithium-ion batteries are the primary energy sources for major complex electrical and electronic systems [14]. Estimating the remaining useful life of the battery is one of the significant counterparts of the battery management system and is used for the efficient working of all associated systems [15-17]. It is one of the crucial factors for managing the health and predicting the state of the battery [6, 18]. Hence, for an effective battery management system, the two critical parameters are the estimation of the state of health of the battery and the prediction of its remaining useful life [19, 20]. Predicting the battery's remaining useful life is vital to prevent possible accidental damages and limit the risks in Electric Vehicles [21].

Out of the numerous research studies being carried out on the prediction of the remaining useful life of the battery, cur-rent research mainly elucidates three techniques for predicting the remaining useful life of the battery: model-based, da-ta-driven and hybrid methodology. The mechanism-based and empirical-based methods are subdivisions of the model-based method, which is based on the prediction of the remaining useful life of the battery, which is mainly used in conjunction with the Kalman filter and particle filter. The model is primarily based on the life prediction of the battery's various parameters, such as a change in impedance, electrochemical reaction, and the material's properties [6, 22]. The data-based model utilizes the prediction of the battery's life mainly by reference to the charge-discharge characteristics of the battery. Multilayer Perceptron (MLP) is a tool based on a data-based model. The hybrid method is also widely used to predict the remaining functional life of the battery. It is more accurate since it combines model-based and data-driven methodology [6].

The battery's good health ensures continuous power delivery to the required devices. Thus, regulating the battery performance is crucial for getting maximum output power from the required loads. If we can predict the precise life of the battery, we can make a replacement strategy. Hence, the battery can be replaced in advance, ensuring proper appliance operation.

The battery's remaining useful life can be predicted using a data-based Multilayer Perceptron (MLP) model. Instead of using analytical and mathematical formulations, MLP has the peculiar feature of learning from past experiences and instances and is suitable for variable atmospheres [23]. MLP has a wide range of applications and day-by-day growing demand in forecasting problems due to its superiority and reliability compared to the other forecasting techniques. The available data on the battery is used to model the trend of the deterioration of the battery over time. With the data available and the modelling, the remaining useful life of the battery can be predicted so that it can be replaced in time, thereby ensuring the reliable supply to the appliances as per the requirements. In controlling the health and determining the status of the health of a battery, it is critical to accurately anticipate the Remaining Useful Life (RUL) of a battery.

In this study, the authors aim to predict the remaining useful life of the Lithium-Ion battery using MLP. The context of this study is:

i. Lithium ions batteries are mostly used in various applications and industries due to its high-power density compared to other commercially available batteries.
ii. The capacity of lithium-ion battery degrades over time after each charging and discharging cycle.
iii. For timely replacement and maintenance of batteries, in order to improve system reliability prediction of remaining useful life of the battery is active research area.

Therefore, in this context identified research problems are explained below:

i. For prediction of remaining useful life experience-based method, physics (model) based method and data driven methods are used.
ii. Previous problem is applied in solving similar or new problem with expert knowledge and engineering experience in experience-based approach.
iii. Physics based models are not suitable for complex system due to cumbersome mathematical modelling and lack of understanding of battery failure modes.
iv. Data driven approach are solely dependent on historical data and does not require detail mathematical model of battery degradation mechanism.
v. However, in data driven approach for there is need reliable and accurate model that provides best estimate of remaining useful life of battery.

The contribution of this paper in addressing aforementioned research problems are:

i. Proposes multilayer perceptron model with sliding window approach in preparing the data for training.
ii. Utilizes capacity degradation data of all battery sets for training the model in order to obtain overall nature of capacity degradation curve.
iii. Validates the proposed model on NASA Ames Prognostics Center of Excellence (PCoE) battery dataset.
iv. Compares the performance of proposed model with

other data driven model applied on same battery data set.

v. Identifies future research direction for the proposed model.

This section introduces the Lithium-Ion battery and its features when compared with other types of batteries, the need for prediction of the remaining useful life of the battery for continuous and reliable delivery of power to the loads, methods of predicting the life of the batteries and merits, uses and applications of MLP in the prediction of the life of the battery. Section II presents the literature study on the prediction of the remaining useful life of the batteries to date through various techniques. Section III focuses on the methodology followed in this study for the prediction of the remaining life of the battery. Section IV illustrates the modelling and analysis for the research work. Section V elucidates the results obtained and validation/discussion of the results with a similar type of study. Section VI shows the study's conclusion and recommendations. Section VII presents the bibliography of the research.

2. Literature Review

Reference [24] elucidated that monitoring of the state of health of battery is very mandatory. The prediction of the remaining useful life of the battery was performed using a novel approach. The method proposes a new health indicator of the battery, changing rate of temperature (TR) for the estimation of state of health of the battery. This technique utilized a binary linear regress model for the analysis of the remaining useful life of the battery.

The research paper [6] employed hybrid methodology combining broad learning system with relevance vector ma-chine for predicting the remaining useful life of the battery. Both the data-based, and model-based technique was implied for the estimation. The study also compared the accuracy with the other algorithms.

The reference paper [25] combined two computational models, SVR and MLP, to predict the accuracy elevation. The NASA Lithium-ion battery dataset was employed to verify the proposed methodology's superiority. The NASA real-lifecycle dataset helps evaluate the proposed method with high accu-racy compared with traditional approaches and methodologies [26].

Traditional approaches for the prediction of remaining useful life of the battery by traditional unscented Kalman Filtering (UKF) method had some problems due to which an improved UKF method is used to predict the remaining useful life of the battery [27]. Reference conference proceeding [28] utilizes a modified extend Kalman filter to predict the re-maining useful life of the battery. A data-driven method was deployed to predict the battery's remaining useful life using the Frisch Scheme-based Bias Compensating Recursive Least Squares (FBCRLS) algorithm [29].

The remaining useful life of lithium-ion batteries can also be predicted through the deployment of a novel method, that combines Kalman filter and PSO based particle filtering. This technique improves the accuracy over standard particle fil-tering and also mitigates the degradation of particles because of particle resampling [20]. The article [7] used a new ap-proach to predicting the remaining useful life (RUL) of Lithium-ion batteries with Li(NiMnCo)O2 cathode. The proposed method used an improved unscented particle filter (UPF) to account for capacity diving in the later stages of the capacity degradation curve. Key aspects of the paper include presenting a new empirical model that outperforms commonly used UPF models; incorporating Gamma distribution noise in the state space equations to avoid potential curve shifting during the prediction process; preprocessing the training data to reduce residual error and improve the quality of predictions. The proposed method was validated through experiments that demonstrate improved prediction performance under various working conditions.

The conference article [30] employs Time Window and Gradient Boosting Decision Trees for the prediction of remaining useful life of lithium-ion battery. A new data-driven approach was introduced for system prognostics and health management (PHM) using deep convolutional neural net-works (DCNN) [18]. The traditional PHM method required prior knowledge of component degradation, but this new approach eliminated the need for expertise by using raw, normalized data as inputs to the network. The proposed method was tested on the popular C-MAPSS dataset and achieved high accuracy in RUL estimation. The results were compared with other popular approaches and demonstrated the superiority of the proposed data-driven prognostic method. This study suggested a new and promising approach for PHM.

The battery's remaining useful life can also be predicted using the XBoost algorithm based on a CART classification and regression tree [31]. This is an alternative approach to empirical selection. To maximise estimation accuracy, XGBoost integrates CART-driven methods by merging sup-port vector regression and long short-term memory, which was proposed in reference [31].

The research article [24] combined an improved particle filter with sliding window gray model to predict the remaining useful life of the lithium-ion battery. The battery test setup was designed, and various experiments at different temperatures, such as accurate capacity measurement and dynamic loading profiles test, were also conducted. The resampling method of the standard particle filter was improved through the linear optimisation of resampling technology. This technique produced higher accuracy when compared with the standard particle filter. Two types of batteries were employed for the study to demonstrate the effectiveness of the proposed methodology.

ANN was deployed to predict battery performance by investigating charge-discharge characteristics for 50 cycles. The battery consisted of a single input layer corresponding to a single input and a hidden layer with three neurons that pro-duced their outputs with two neurons [23]. It was clearly shown that ANN could estimate the life cycle of a Li-ion cell using a CoO anode.

A new RUL estimation method was presented using a hy-brid CNN-RNN model [32]. Unlike traditional methods, the proposed approach did not require setting thresholds and accurately predicted RUL. The hybrid model extracted local features and captured degradation processes, leading to im-proved results compared to MLP, SVR, and CNN on the NASA C-MAPSS turbofan engine dataset.

The assessment of the remaining useful life of the battery is a prime concern as it assists in the timely replacement of the battery without causing any disturbances in the power delivery to the required appliances. For this purpose, MLP is one of the accurate tools that helps in the projection of life with high accuracy. The model-based method of the remaining useful life projection involves fitting the degradation curve of the battery and modelling it mathematically for the elaboration of the physical properties. The data-driven method analyses the historical data. Various deep-learning techniques have been used to predict the remaining useful life of the batteries.

3. Methodology

The modelling through the application of MLP can be visualised as one of the black boxes that links the input with that of the output data. LPs are trained through various input data corresponding to the output data. Multiple factors, such as architecture, training algorithm, and transfer function, affect and influence the ANN'. The number of layers (input layer, hidden layer, and output layer) in MLP and the number of neurons in each layer are also crucial factors. The input and output parameters directly reflect the number of neurons in the input and output layer. Sliding window approach is used for preparation of training data in this work. The detail architecture of the MLP network used in this work is presented in Figure 1(a). The detailed methodology of the study work using this MLP architecture presented in Figure 1(b).

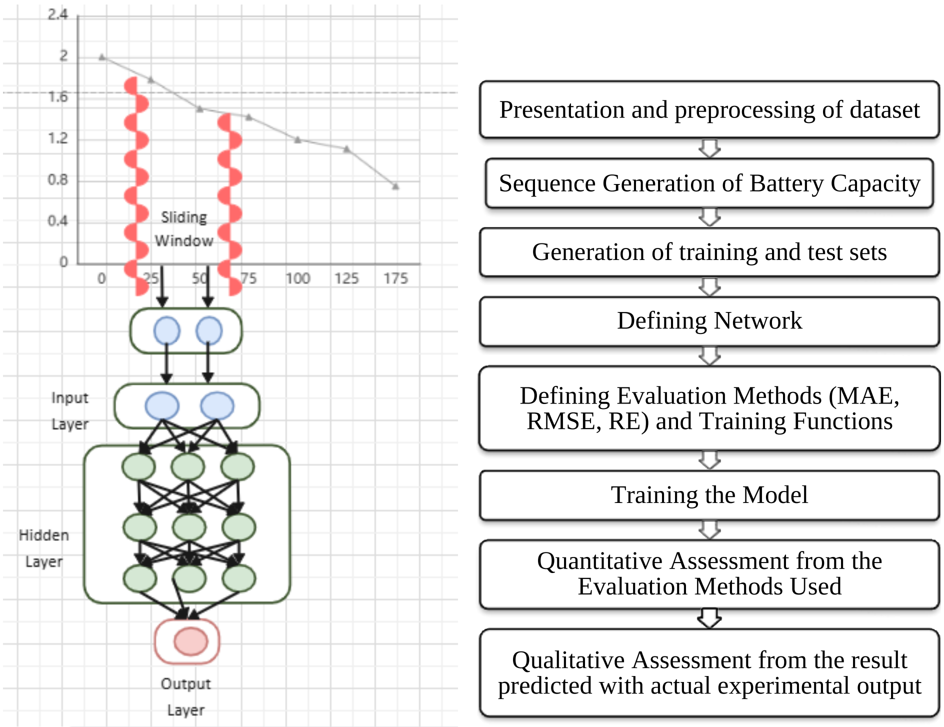

Figure 1. *(a). Architecture of MLP model; (b). Flowchart showing the methodology of the study.*

3.1. Sequence Generation

In battery capacity prediction, sequence generation is a pre-processing step that helps prepare the data for training the model. The capacity of a lithium battery can be represented as a time series, which typically has an overall decreasing trend. To use this data for training a model, it must be transformed into a format that can be fed into the model.

The sliding window technique is used to convert the sequence of battery capacity into training data. A specific size window (defined by the window size parameter) is created and moved along the sequence from the start to the end. For each window position, the values within the window are used as input features (x), and the value immediately following the window is used as the label (y).

For example, consider the sequence (1, 2, 3, 4, 5) and a window size of 3. The training data and labels generated using the sliding window method would be (1, 2, 3, 4) and (2, 3, 4, 5). These pairs of input features and labels can be used to train the model to predict the next value in the sequence based on the previous values.

This sequence generation method enables the model to learn the dependencies between the values in the sequence and make predictions based on these dependencies. It is commonly used in time series prediction problems, such as battery capacity prediction.

3.2. Generate Training Set and Test Set

Once the sequence has been generated using the sliding window method, the next step is to split the data into training and test sets. The goal of this split is to evaluate the model's performance on unseen data. The model is trained on the training data and tested on the test data. In this case, the data from three sets of Lithium-Ion batteries is used to create the training set and the remaining data set is used as the test set. This approach is called leave-one-out evaluation, as one set of data is left out and used as the test set, while all other data is used for training. Splitting the data into training and test sets is relatively simple and provides an essential evaluation of the model's performance. However, it is important to remember that the evaluation results may be sensitive to the specific chosen test set. In some cases, it may be beneficial to use a more sophisticated method of splitting the data, such as k-fold cross-validation, to evaluate the model's performance more robustly.

3.3. Definition of Network

This work defines a neural network using the PyTorch ‘nn’ module. The network is called "Net". The Net class has two constructor arguments: feature size and hidden size. Feature size is the size of the input layer, and hidden size is a list of integers representing the size of each hidden layer. A linear transformation is applied for each layer, followed by ReLU activation. In this network, the forward method implements the forward pass of the network, taking an input vector as input. It passes the input through the initial layer and then through the other hidden layers using a ‘for’ loop. Finally, the output of the final hidden layer is passed through the last linear layer to produce the final prediction. The prediction is then returned as the output of the forward pass.

3.4. Training and Evaluation

The machine learning model is repetitively trained, each time with a different random seed, and its performance is evaluated using three metrics: *RE* (relative error), *MAE* (mean absolute error), and *RMSE* (root mean squared error).

The parameters such as window size, Epoch, learning rate, feature size, hidden size, and weight decay are used as hyper-parameters to control the model. The provided hyper-parameters can train the model using a suitable training function. The function returns lists of evaluation metrics for each epoch. These lists of metrics are then aggregated to obtain the mean values across all epochs and seeds. Finally, the mean and standard deviation of the aggregated metric values can be obtained.

The evaluation parameters are obtained as follows:

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} * \sum_{i=1}^{N}(actual_i - predicted_i) \tag{1}$$

Root Mean Square Error (RMSE)

$$RMS = \sqrt{\frac{1}{N} * \sum_{i=1}^{N}(actual_i - predicted_i)^2} \tag{2}$$

where N is the number of samples, $actual_i$ is the actual value of the i^{th} sample, and $predicted_i$ is the predicted value of the i^{th} sample.

Relative Error (RE)

$$RE = \frac{|RUL_{pred} - RUL_{true}|}{RUL_{true}} \tag{3}$$

3.5. Quantitative and Qualitative Analysis

Finally, after completing the model's training, the program outputs the value of the evaluation parameters, from which the quantitative relationship between the actual and predicted parameters can be evaluated. The plot of the actual and predicted data elucidates the quality of the neural network model.

3.6. Algorithm for Prediction of RUL from NASA Dataset

The algorithm for the prediction of RUL from the NASA Dataset is enumerated below:

1. Define a function that takes in a MATLAB file and loads its data into Python as a list of dictionaries.
2. Define a function that takes in the loaded data and returns the discharge cycles and capacities of the batteries.
3. Define a function that takes in the loaded data and the type of battery data (charge or discharge) and returns the relevant data.
4. Load the data for the batteries B0005, B0006, B0007, and B0018 and store it in a dictionary Battery.
5. Define a function that builds a sequence, takes in a list of values and a window size, and returns sequences and targets for training an MLP.
6. Define a function that takes in the data, battery name, window size, and train ratio and returns the training and testing data for the MLP.
7. Define a battery model class inherited from PyTorch, ‘nn.Module’ class. This class contains the definition of the MLP.
8. Create instances of the ‘nn.Linear’ layer to define the

MLP's architecture and the forward method in the battery model class.

9. Define a loss function, an optimiser, and a metric for evaluation.
10. Train the model on the training data by looping through the data and using the optimiser to update the model weights.
11. Evaluate the trained model on the testing data and compute the mean absolute and root mean square errors.
12. Plot the capacity degradation of the batteries and display the results.

4. Modelling and Analysis

4.1. Data Set Introduction and Features of Battery Dataset

In this article, the NASA Ames Prognostics Center of Excellence (PCoE) battery datasets B0005, B0006, B007 and B0018 are taken for training and testing the MLP model to predict RUL. Four lithium-ion batteries are operated in the charge, discharge, and impedance modes at room temperature (24 ℃). The charging process occurs for each battery where a constant 1.5 A current is applied until the voltage reaches 4.2 V. Then, constant voltage charging mode commences till the charging current reaches 20 mA. The second step involves discharging each battery, until its voltage reaches 2.7 V, 2.5 V, 2.2 V and 2.5 V, respectively, under a constant current of 2 A. Finally, the impedance process uses electrochemical impedance spectra scanned from 0.1 to 5 kHz. All four batteries are subjected to charge and discharge cycles, and the end-of-life (EOL) point is obtained for each battery when the capacity of each battery has been decreased by 30% of its nominal capacity, i.e. from 2 Ah to 1.4 Ah.

The RUL prediction model was trained using this research study's charge and discharge test data. In this dataset, various types of data are included in addition to the charge and discharge voltage and current throughout the battery cycle testing. Although the reported impedance can indicate battery degradation or ageing, it is not consistently recorded throughout the data collection. However, the battery must be isolated from its host system, and the electrochemical impedance spectrometer required for the studies is expensive. To accomplish RUL prediction, only data obtained during charging and discharging are used from all the battery data that could be gathered during the operation of an electric vehicle. This study attempts to eliminate the use of expensive equipment to determine battery degradation.

Features must be extracted following the appropriate test conditions to predict the capacity at any battery cycle. Over time, with the growing number of battery cycles, the differences between charging curves became negligible. However, ageing has caused distinct alterations in the curves. For instance, with the increase in the internal resistance, the constant-voltage portion is gradually reduced during the discharging period. As a result, the useable time has steadily declined. Figures 2-5 illustrates the current curve of batteries for 1, 75, and 125 charge cycles, respectively. Figures 6-9 elucidates the voltage curve of the same batteries for 1, 75 and 125 discharge cycles, respectively. The constant-voltage region has increased while the constant-current segment has shrunk with the number of cycles. Figure 10 depicts the capacity degradation of the four batteries over the numerous charging and discharging cycles.

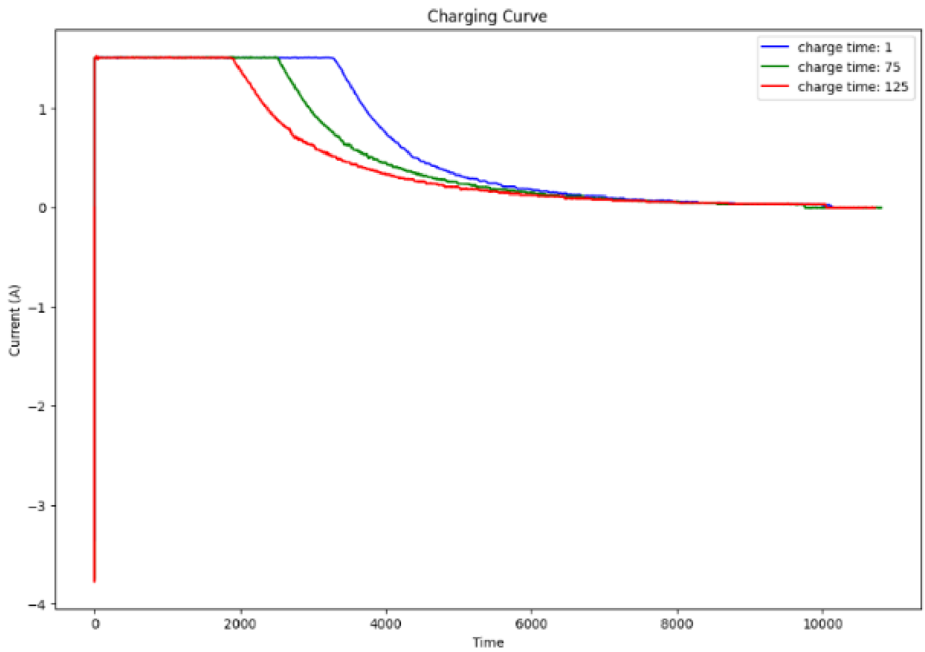

Figure 2. *Charging curve of B0005 battery.*

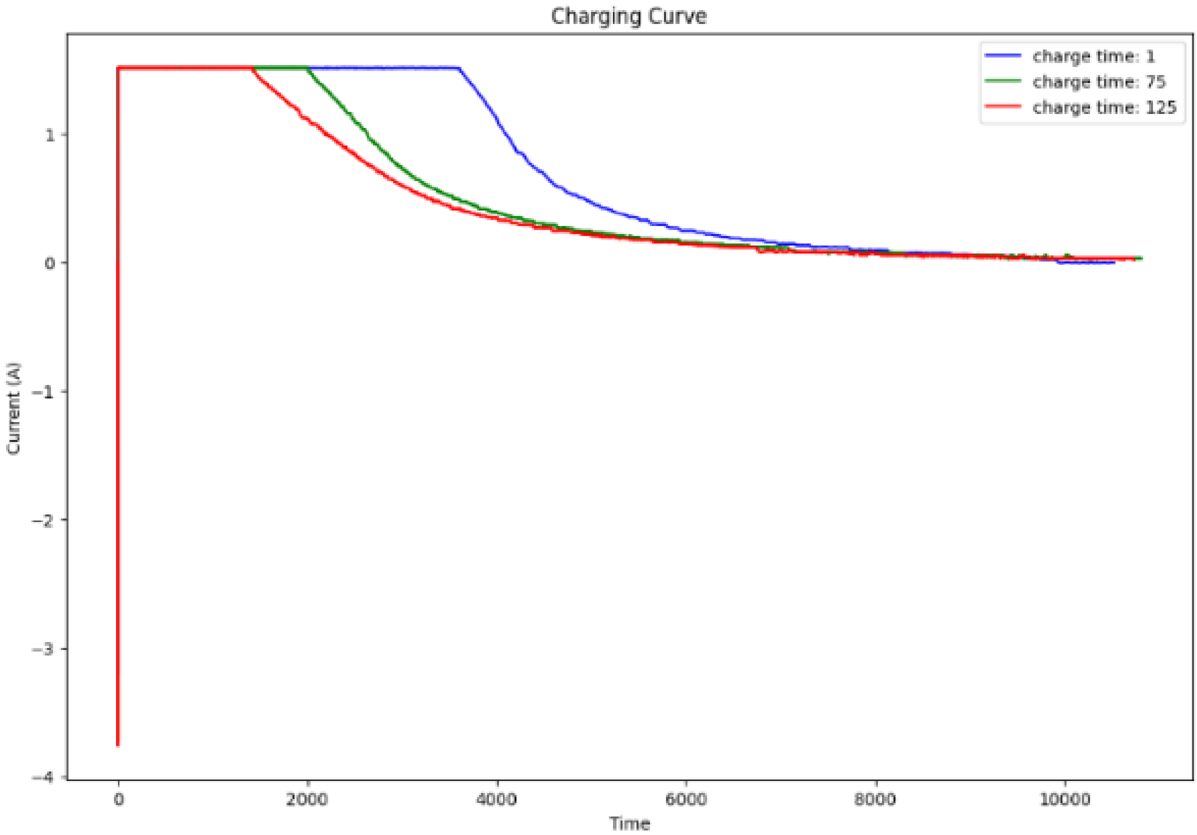

Figure 3. *Charging curve of B0006 battery.*

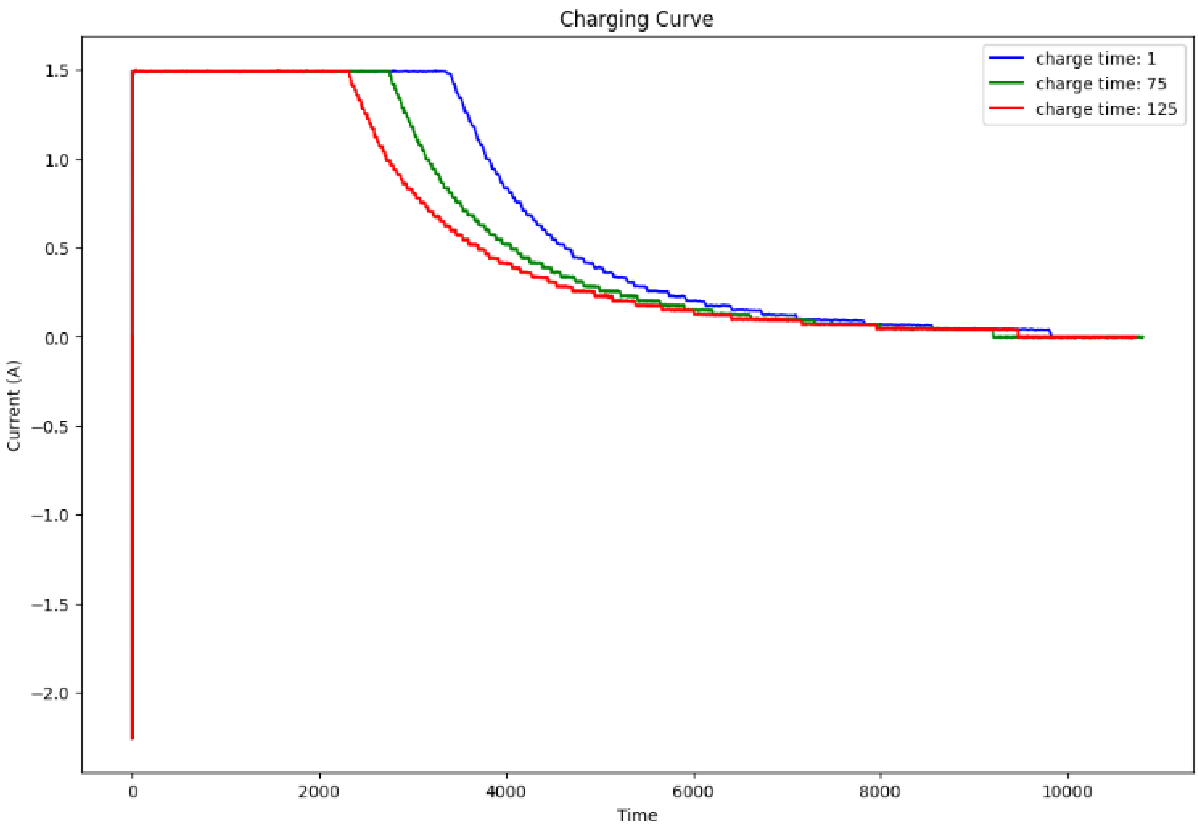

Figure 4. *Charging curve of B0007 battery.*

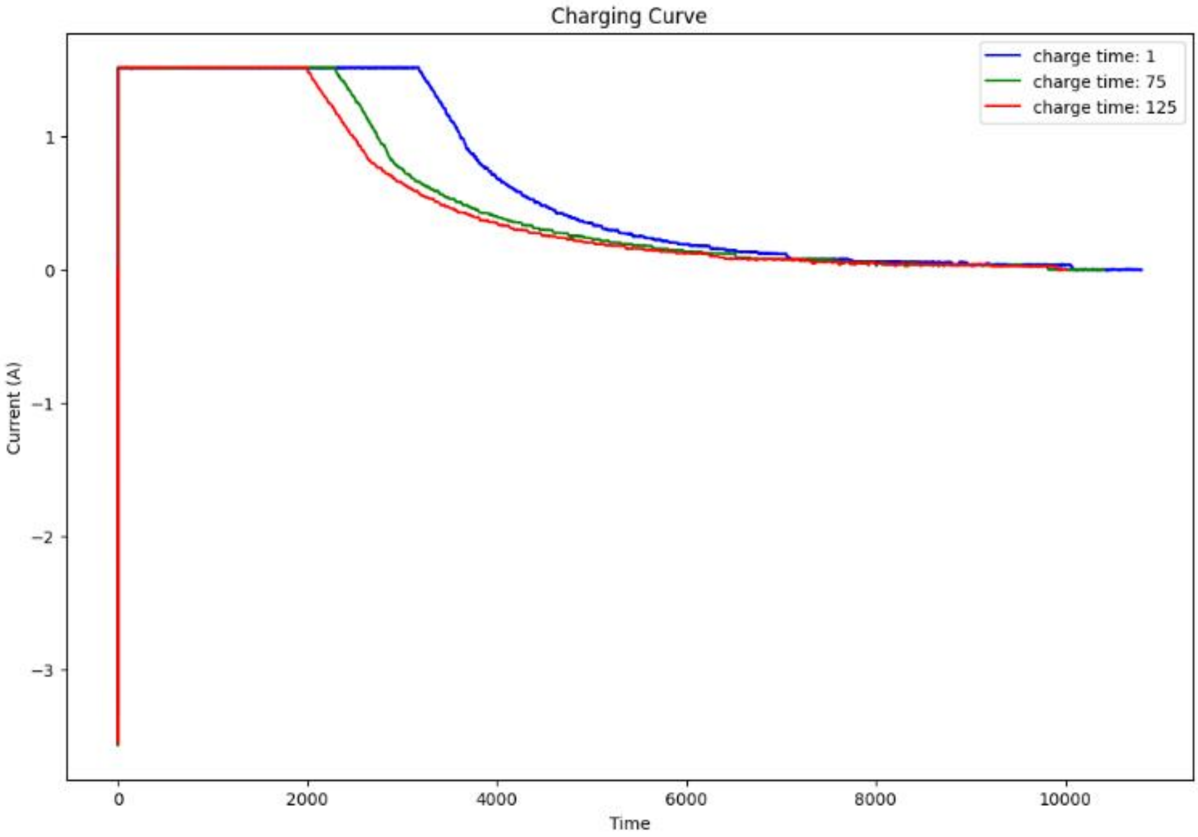

Figure 5. *Charging curve of B0018 battery.*

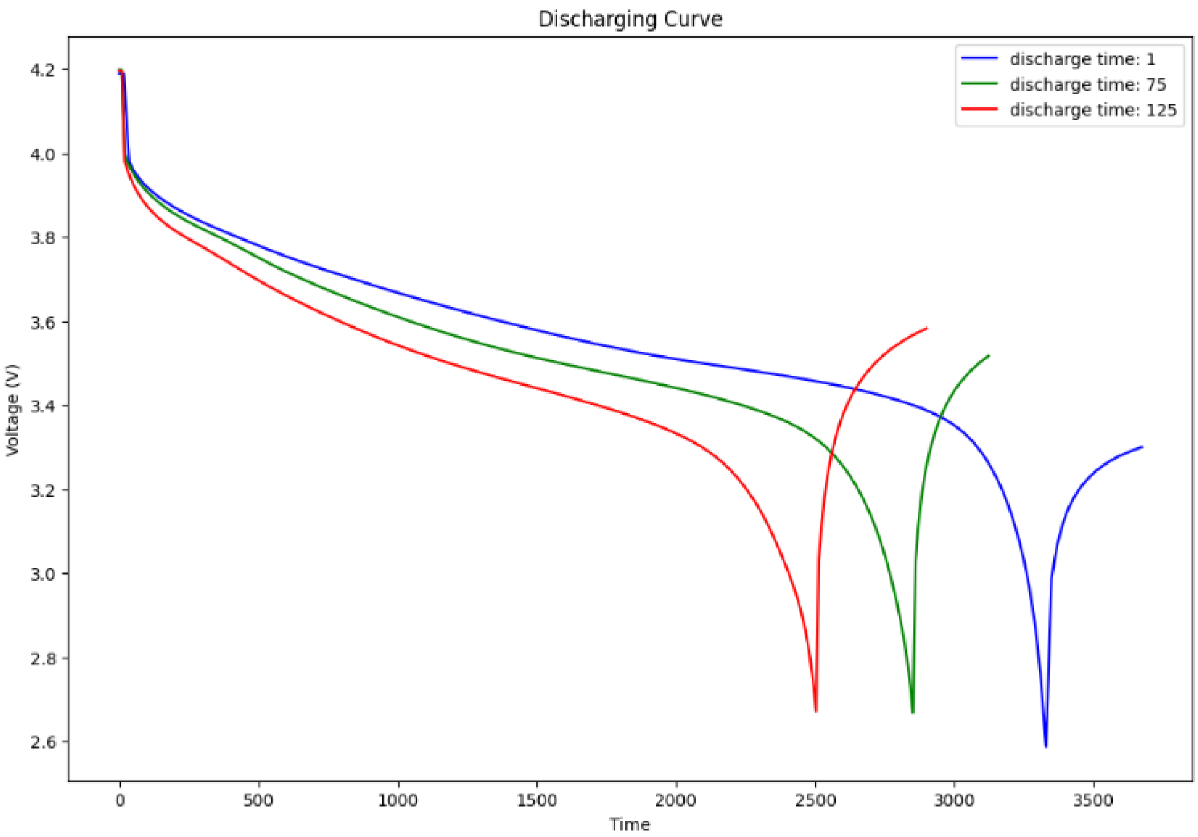

Figure 6. *Discharging curve of B0005 battery for 1,75, and 125 discharge cycles.*

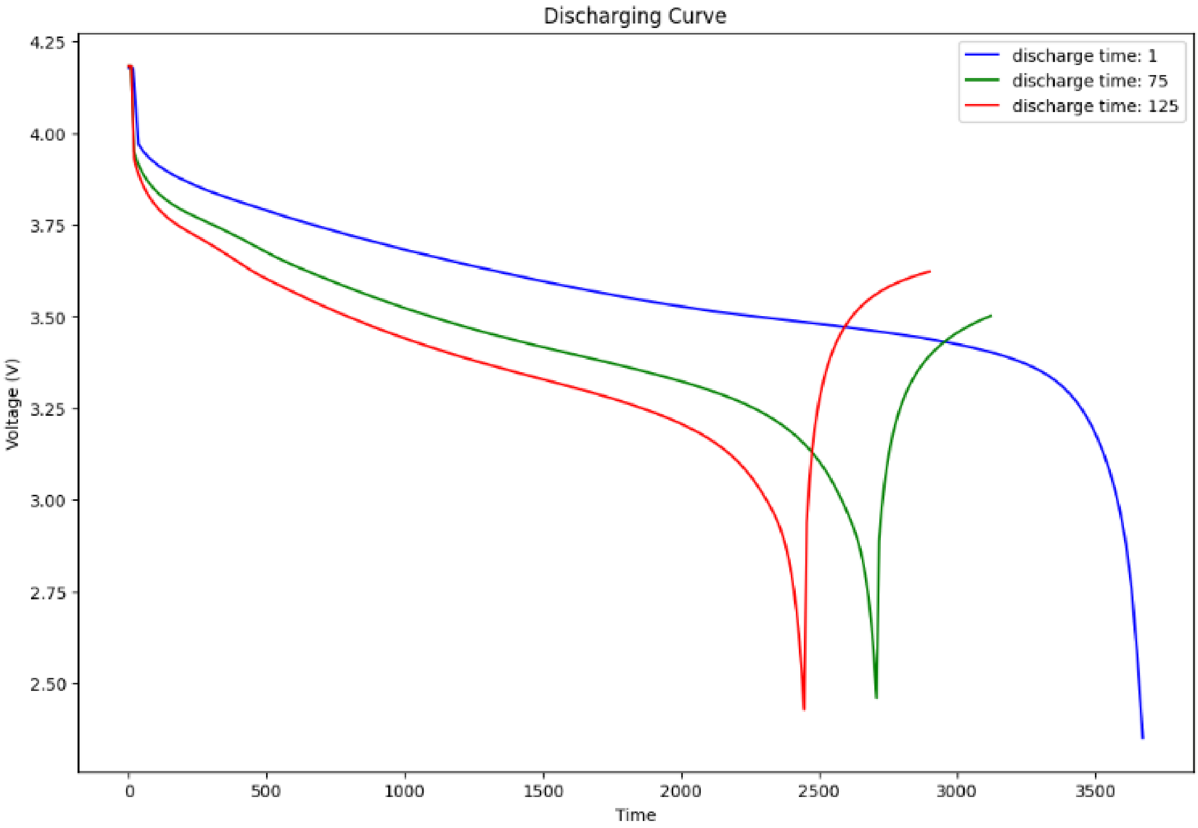

***Figure 7**. Discharging curve of B0006 battery for 1,75, and 125 discharge cycles.*

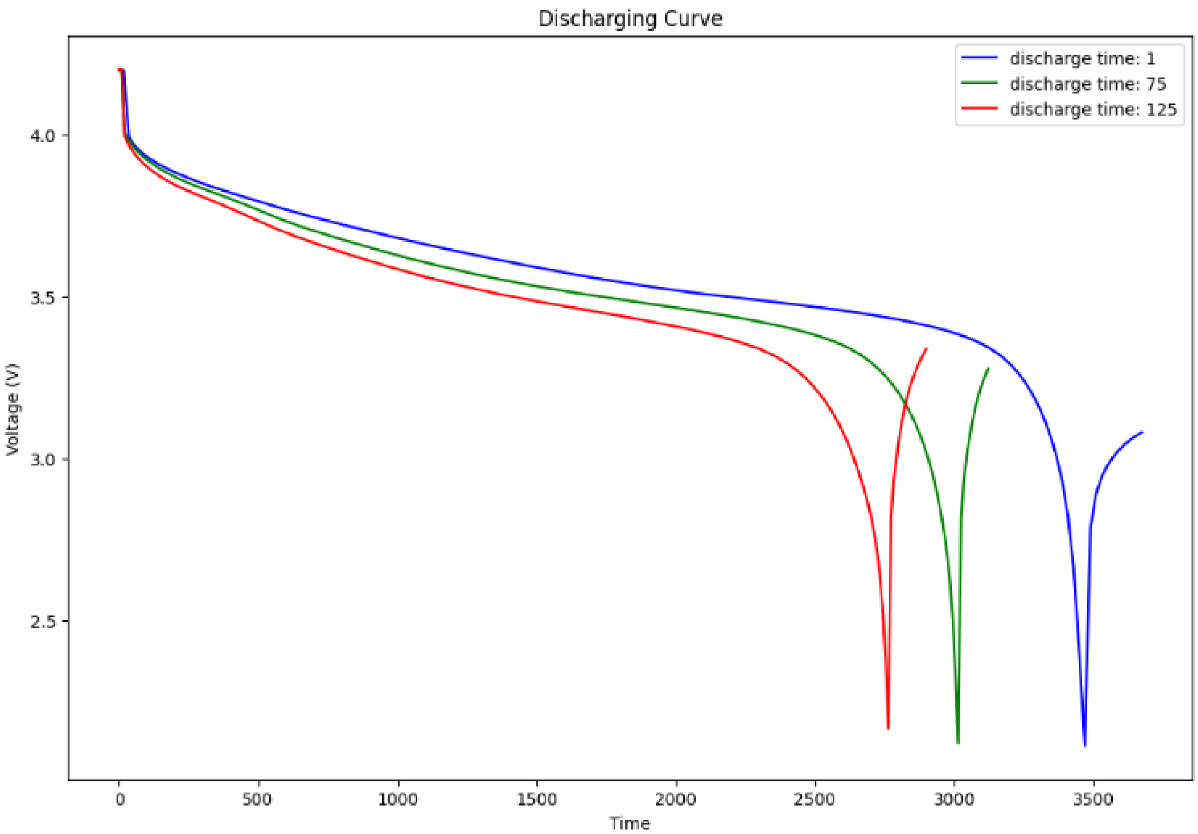

***Figure 8**. Discharging curve of B0007 battery for 1,75, and 125 discharge cycles.*

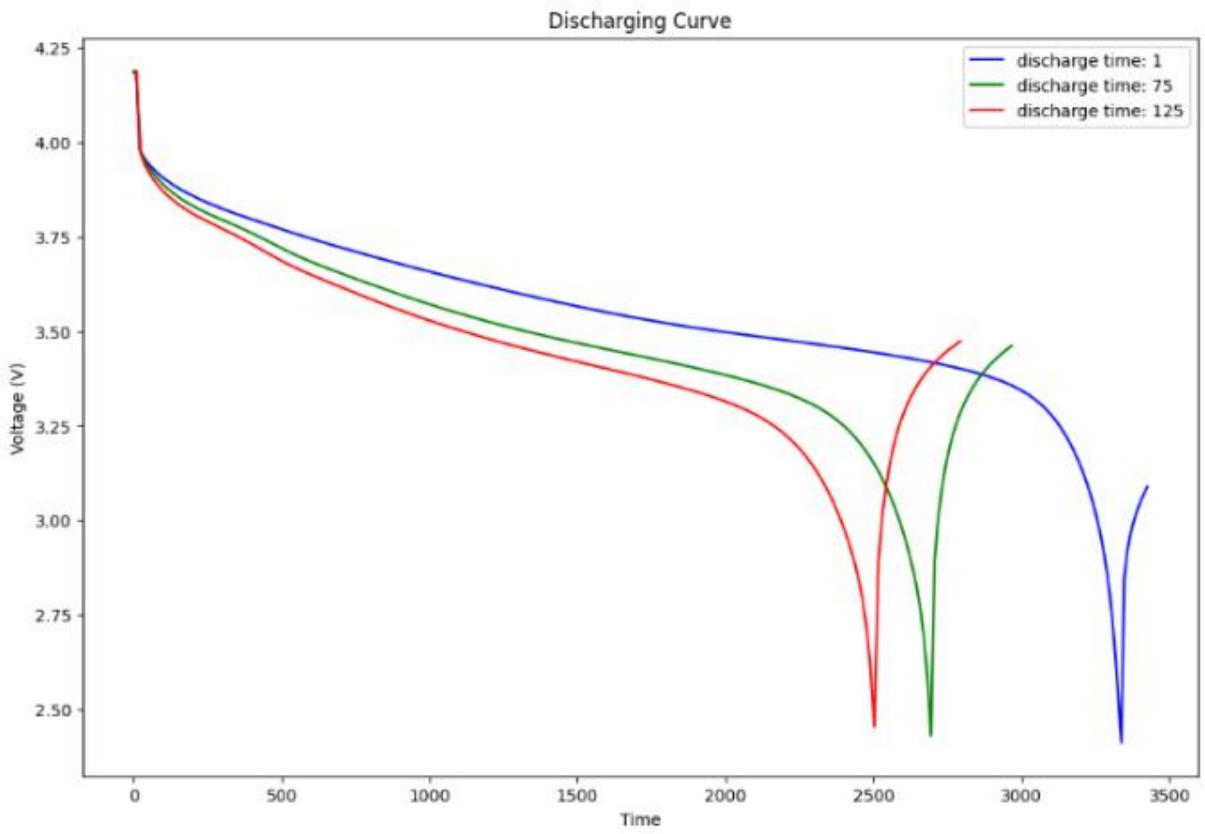

Figure 9. *Discharging curve of B0018 battery for 1,75 and 125 discharge cycles.*

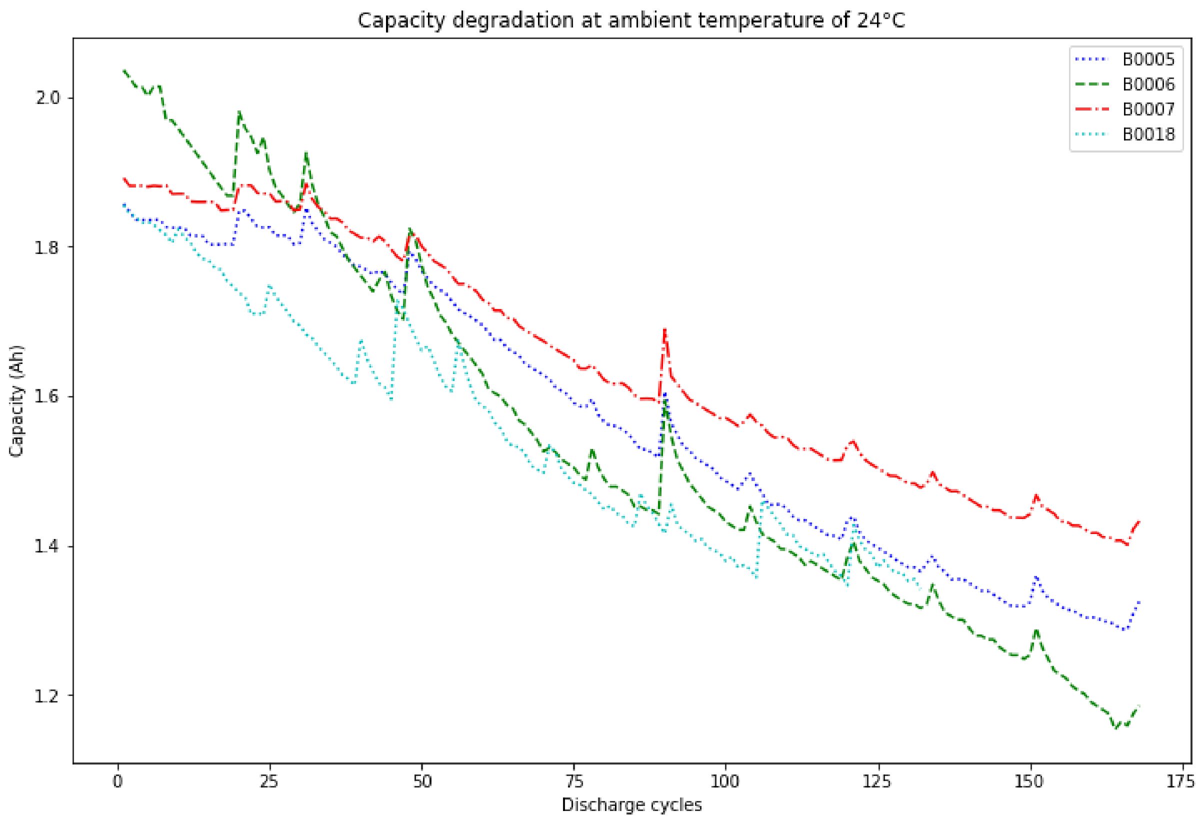

Figure 10. *Comparison of Capacity Degradation Curves of Lithium-Ion Batteries.*

4.2. Modality of Training a Multilayer Perceptron (MLP) Network

The proposed technique trains the MLP network of the battery usage prediction for four different batteries. The network uses PyTorch, a Mean Squared Error (MSE) as a loss function, and the Adam Optimizer to minimise the loss. The program takes several parameters as input:

1. LR: the learning rate for the Adam Optimizer.
2. Feature size: the number of input features to the network.
3. Hidden size: a list representing the number of nodes in each hidden layer of the network.
4. Weight decay: the weight decay term to be used in the Adam optimiser.
5. Window size: the number of steps taken in the past that are used as input features.
6. Epoch: the maximum number of training iterations to perform.
7. Seed: the seed for the random number generator to ensure reproducibility.

The program trains the network for each of the four batteries and returns the following results:

1. RE list: a list of the relative errors for each battery.
2. MAE list: a list of the mean absolute errors for each battery.
3. RMSE list: a list of each battery's root mean squared errors.
4. Result list: a list of the final predicted values for each battery.

The network training is performed in a loop for each of the four batteries. The names of the batteries are obtained from the battery list. The function is called for each battery to get the training and test data. The training data is then used to train the network using the MSE loss and the Adam optimiser. The script performs training for a specified number of epochs or until the change in loss between two consecutive epochs is within the converging criteria.

This program consists of a training function for an MLP network for a time series prediction problem. It has hyper-parameters such as learning rate (LR), feature size, hidden size, weight decay, window size, and number of epochs.

The function takes the input hyper-parameters, then loops through four different time series data stored in the Battery list and trains the MLP network for each time series data. For each time series data, the function calls the following function to get the train and test data and sets up the seed for reproducibility. After that, the MLP network is initialised and optimised using the Adam Optimiser, which uses the mean squared error (MSE) loss function.

The program then trains the network over the specified number of epochs. The input train data is normalised in each epoch and converted to PyTorch tensors. The network's output is compared with the actual output values, and the gradients are computed using the backpropagation algorithm. The optimiser is then applied to update the network parameters.

After every 100 epochs, the program tests the test data by generating new time series points using the trained network. The evaluation metrics, such as mean absolute error (MAE), root mean squared error (RMSE), and relative error (RE), are computed. The training is stopped if the difference between consecutive losses is less than $1e^{-5}$.

5. Validation, Results, and Discussions

As leave-one-out evaluation is a technique used to measure the accuracy of a model, one data point is removed from the training set and used as the validation set. The model is then trained on the remaining data points and tested on the validation set. This process is repeated for each data point in the dataset so that each data point is used as the validation set once. By averaging the accuracy scores of each iteration, a more reliable evaluation of the model's accuracy is obtained. The model's stability is tested by running the evaluation with different seeds. The random seed is used to initialise the generator of a random number, which is used to shuffle the data and divide the data into folds. By changing the seed, different random partitions of the data are generated, and the model is trained and evaluated on different data each time. By averaging the results of other runs, the variability of the model's performance is reduced, and a more robust evaluation is obtained. This evaluation function obtains the list of relative errors, mean absolute errors, root mean squared errors and final predictions for each time series data.

After training the neural network using one-out evaluation, i.e., taking three battery datasets as a training set and the remaining as a test set, the mean along with the standard deviation of Relative Error, Mean Absolute Error, and Root Mean Square Error of the predicted capacity degradation data is presented in Table 1 and Table 2.

Table 1. *Performance Metrics for Individual Battery.*

Battery	Relative Error (RE)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
B0005	0.0614	0.0608	0.0771
B0006	0.9813	0.1217	0.1378

Battery	Relative Error (RE)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
B0007	0.3522	0.1253	0.1286
B0018	0.2791	0.0033	0.0401

***Table 2**. Overall Performance Metrics.*

Parameters	Relative Error (RE)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
Mean	0.4185	0.0852	0.0959
Standard Deviation	0.0028	0.0034	0.0026

It is observed that relatively more accurate predication is obtained for battery B0005 and battery B0018. By training the model with varying seeds, the prediction of RUL of the model has average RMSE of 0.0959 with standard deviation of 0.0026 and average MAE of 0.0852 with standard deviation of 0.0034.

The comparison between actual degradation curve extracted from experimental data of batteries B0005, B0006, B0007 and B0018 with the degradation curve predicted by the MLP model is presented in Figure 11 to Figure 14. Like-wise, Table 3 compares and contrasts the accuracy of the proposed model with other models.

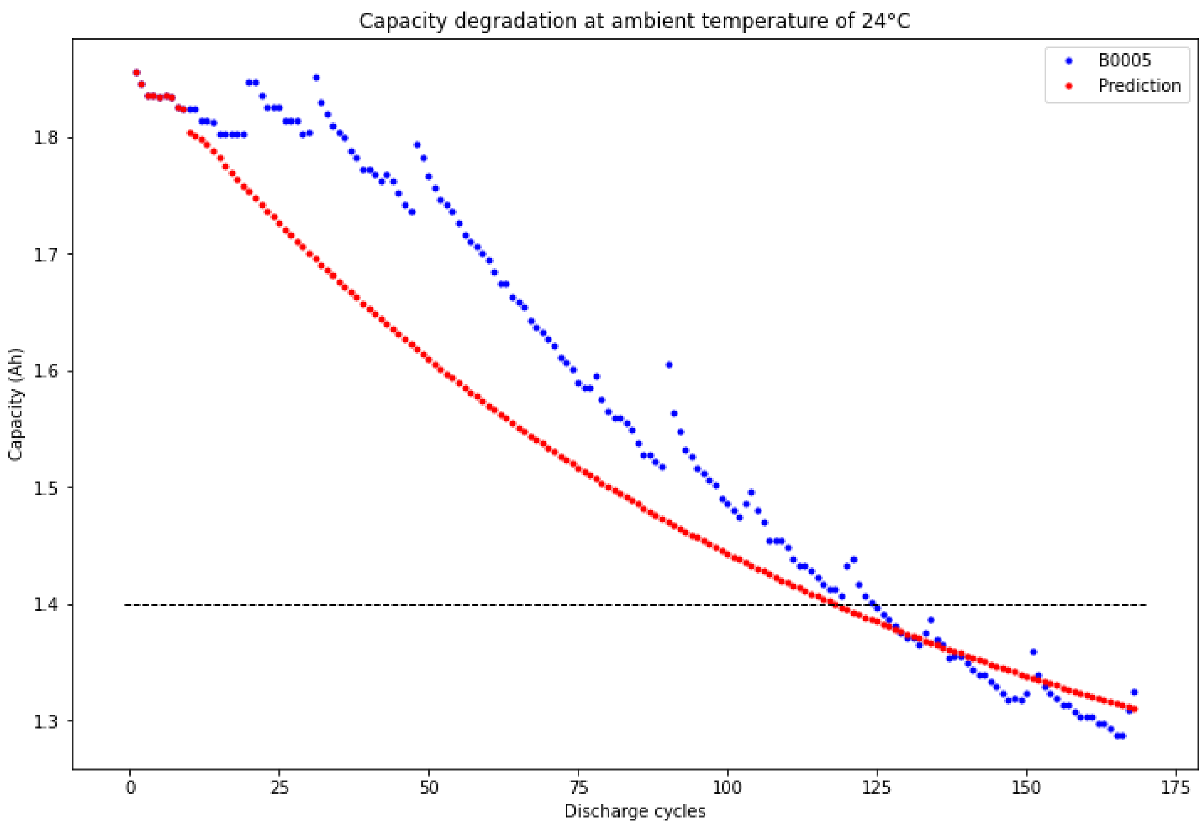

***Figure 11**. Prediction results for B0005 battery.*

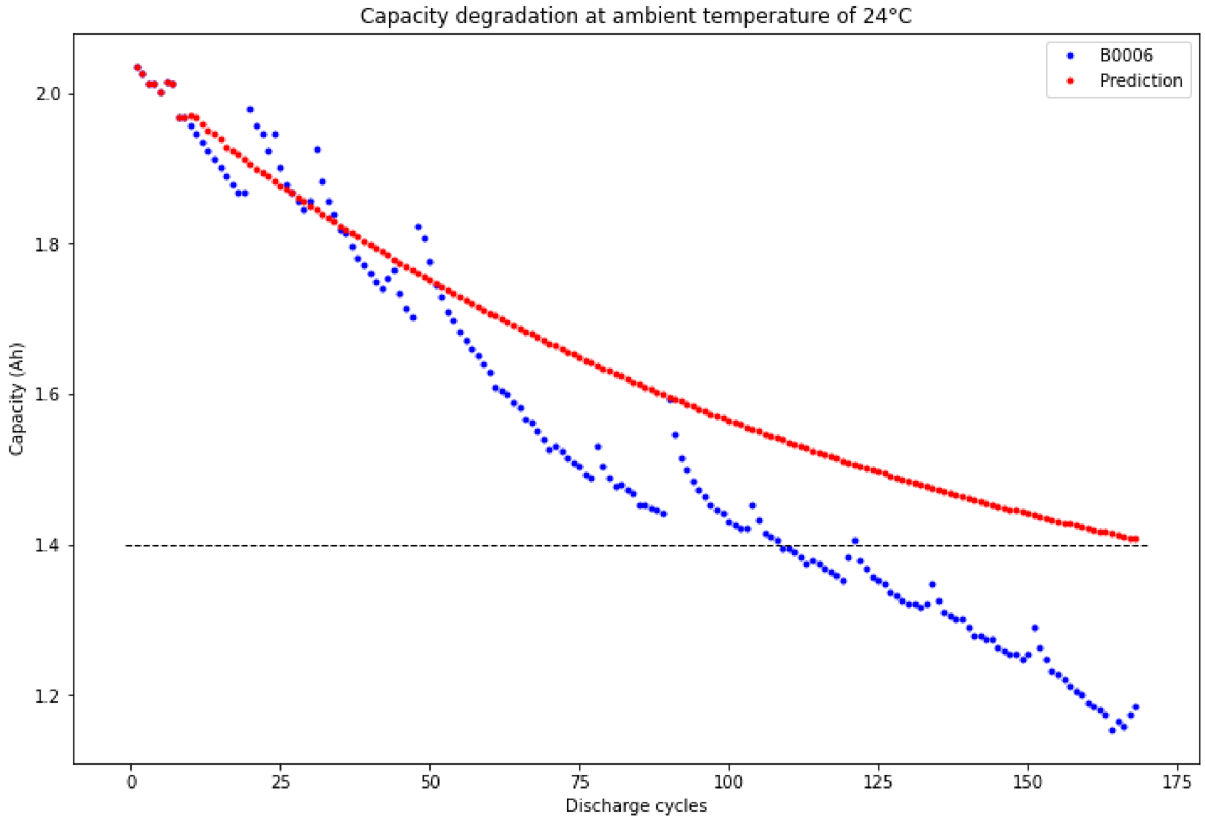

Figure 12. Prediction results for B0006 battery.

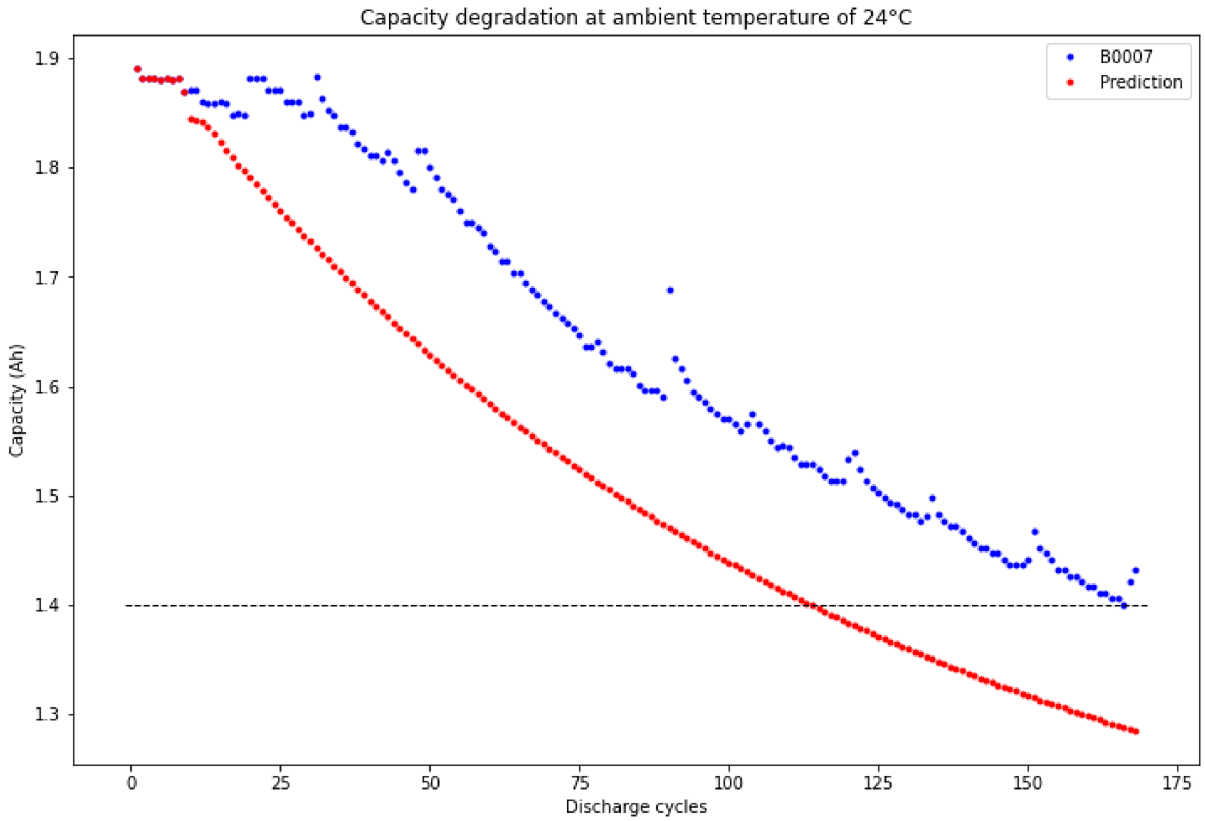

Figure 13. Prediction results for B0007 battery.

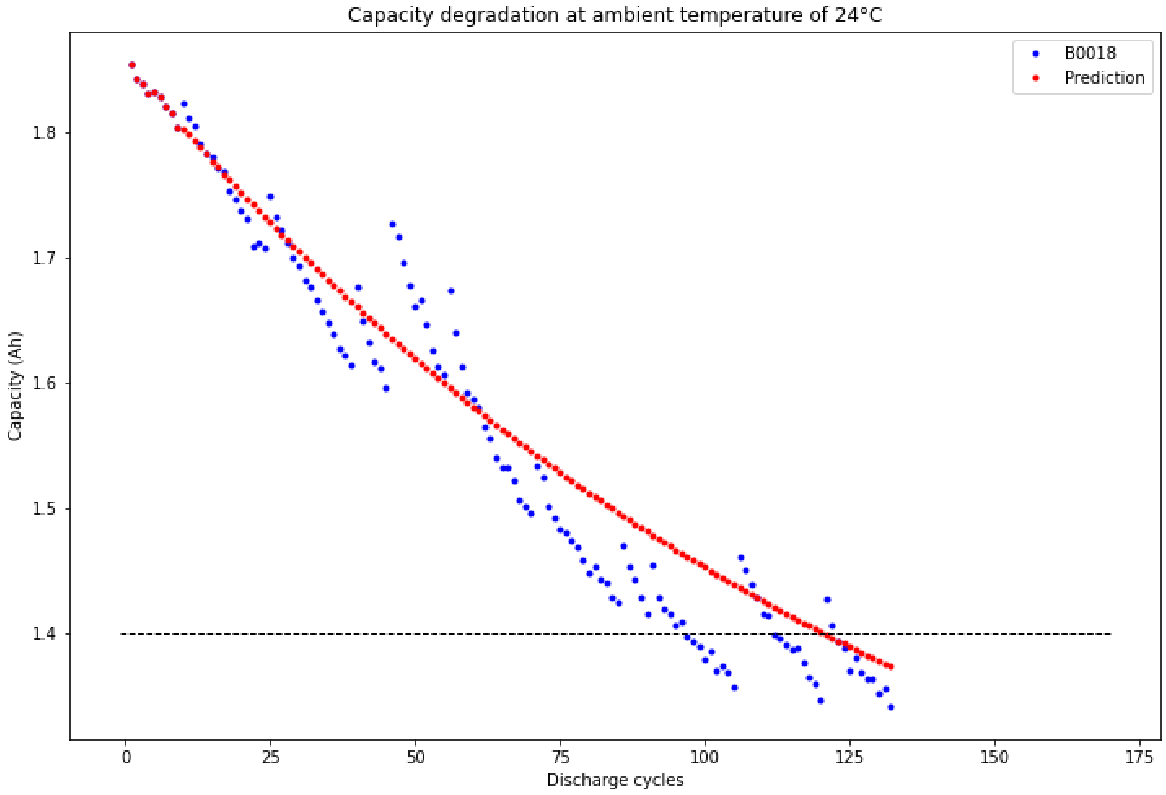

Figure 14. *Prediction results for B0018 battery.*

Table 3. *Comparative Performance Analysis.*

References	Algorithm	Validation	Features and Output	Performance Metrics
[33]	FFNN	NASA PCoE battery dataset	Input- Voltage, capacity Output- RUL	MAE- 29.4218
[34]	SVM	NASA PCoE battery dataset	Input- Voltage, current temperature, capacity and time Output- RUL	RMSE- 0.2159 MAE- 0.3108
[35]	EEMD and RVM	NASA PCoE battery dataset	Input- Capacity Output- RUL	MSE- $4.497*10^{-5}$ and $1.644*10^{-5}$ (for battery 5 and 18)
[36]	Hybrid PSO and SVM	NASA PCoE battery dataset	Input- Discharge Cycle Output- RUL	MSE- 0.0213
[37]	Linear Particle Filter	NASA PCoE battery dataset	Input- Impedance, charging cycle number, aging Output- RUL	RMSE- 0.2902
[38]	Single Channel Profile based ANN	NASA PCoE battery dataset	Input- Voltage, current, capacity, temperautre Output- RUL	RMSE- 1.5018 MAE- 0.4884
[38]	Multi Channel Profile Based ANN	NASA PCoE battery dataset	Input- Voltage, current, capacity, temperautre Output- RUL	RMSE- 0.2917 MAE- 0.1679
[39]	Deep Neural Network	NASA PCoE battery dataset	Input- voltage, current, capacity, temeperature Output- RUL	RMSE- 3.427
Proposed Method	MLP	NASA PCoE battery dataset	Input- Discharge cycle date, capacity Output- RUL	RMSE- 0.0959 MAE- 0.0852

The proposed method demonstrates superior performance compared to other RUL prediction algorithms, such as feed-forward neural networks, support vector machines, linear particle filters, single-channel profile-based ANNs, multichannel profile-based ANNs, and deep neural networks. However, hybrid algorithms have shown better results than the proposed method. This suggests that predicting RUL using proposed method is competitive and often surpasses most neural network algorithms. The integration of optimization techniques and hybrid approaches can further enhance the accuracy of this model.

6. Conclusions and Recommendations

The implementation of MLP seems promising when one-out evaluation is used from the experimental results on the NASA data set. However, the result does not entirely meet the expectations due to the following two factors:

The battery capacity sequence contains many jump points (capacity regeneration phenomenon), particularly at the beginning of the curve, making it challenging for the model to infer a reliable trend from the battery history to estimate the battery life.

These data sequence deviations are significant. For instance, B0007 contains no data after 1.4 Ah, while B0018's data is relatively short and subject to extreme fluctuations, which makes it challenging for the model to identify commonalities.

MLP can produce decent results if the data gap between the capacity curves is minimal, the variations are gradual, and there are enough experimental data points.

For future work, it is recommended that MLP be tested on another available dataset with enough experimental results to train the MLP. Moreover, laboratory experiments can be done to produce enough datasets for the lithium-ion battery, which can be later incorporated into the battery management system. Alternates to MLP, hybrid or novel prediction approach can be explored to predict the RUL of Lithium-ion batteries with limited and chaotic data.

Abbreviations

ANN	Artificial Neural Network
EEMD	Ensemble Empirical Mode Decomposition
EV	Electric Vehicle
FFNN	Feed Forward Neural Network
MAE	Mean Average Error
SVM	Support Vector Machine
SCI	Single Channel Input
MCI	Multi-Channel Input
MLP	Multi-Layer Perceptron
MSE	Mean Square error
PF	Particle Filtering
PSO	Particle Swarm Optimization
RE	Relative Error
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
RVM	Relevance Vector Machine

Author Contributions

Basanta Pancha: Conceptualization, Writing – original draft

Sushil Paudel: Methodology, Visualization, Writing – review & editing

Basanta Thapaliya: Conceptualization, Data curation, Methodology, Software, Visualization, Writing – original draft

Tomasz Siewerski: Writing – review & editing

Dayasagar Niraula: Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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