Machine learning-based lithium-ion battery life prediction for electric vehicle applications

Vo Thanh Ha[1], Vo Quang Vinh[2], Le Ngoc Truc[3]
[1]Department of Cyberntics, Faculty of Electrical and Electronic Engineering, University of Transport and Communications, Hanoi City, Vietnam
[2]Faculty of Control and Automation, Electric Power University, Hanoi City, Vietnam
[3]Department of Electromechanics-Refrigeration and Air-Conditioning Technology, Faculty of Automobile Engineering, Hung Yen University of Technology and Education, Hung Yen, Vietnam

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ABSTRACT

The actual and anticipated battlefield creates a model capable of accurately estimating the lifetime of lithium-ion batteries used in electric cars. This inquiry uses a technique known as supervised machine learning, more particularly linear regression. In lithium-ion batteries, modeling temperature-dependent per-cells is the basis for capacity calculation. When a sufficient quantity of test data is accessible, a linear regression learning method will be utilized to train this model, ensuring a positive outcome in forecasting battery capacity. The conclusions drawn in the article are derived from the attributes of the initial one hundred charging and discharging cycles of the battery, enabling the determination of its remaining power. This determination facilitates the swift identification of battery manufacturing procedures and empowers consumers to detect flawed batteries when signs of performance degradation and reduced longevity are observed. MATLAB simulations have demonstrated the accuracy of the projected results, exhibiting a margin of error of approximately 9.98%. With its capacity to provide a reliable and precise means of estimating battery lifespan, the developed model holds the potential to revolutionize the electric vehicle industry.

Corresponding Author:

Vo Thanh Ha
Department of Cyberntics, Faculty of Electrical and Electronic Engineering,
University of Transport and Communications
N02, Cau Giay District, Hanoi City, Vietnam
Email: vothanhha.ktd@utc.edu.vn

1. INTRODUCTION

Lithium-ion batteries (LIBs) have recently garnered significant interest in research and practical application due to their numerous advantages. These benefits encompass high energy density, low self-discharge, rapid charging, large capacity, minimal pollution, and extended lifespan. As a result, the market dominance of lithium-ion batteries continues to expand [1]–[3]. In recent years, there has been a notable increase in scientific focus on battery power management research [4]–[6], primarily driven by these distinctive attributes. For a comprehensive analysis, it is essential to consider the state of health (SOH) as a significant metric for evaluating battery degradation. This study encompasses the analysis of battery deterioration and predicts the duration of both charging and discharging cycles. The model's findings are valuable for predicting and accelerating the development of new electrode materials with enhanced capacity and durability through materials research and assessing the value of battery life [7]. Physical modeling and data collection are the primary techniques used to forecast standard batteries' ability and capacity degradation [8]. Mathematical methods are employed to accurately depict performance decline, using models derived from batteries' physical or experimental degradation. The coulomb (CC) approach quantifies the energy remaining in the storm by measuring power over a specific duration of time. This technique incorporates the flow of electric current during discharge or charge and is often used for basic computations [9]. A real-time filtering technique was used to adjust the model parameters, while the literature included theoretical polynomial and exponential regression models [10]–[13] for progress monitoring.

Battery cells experience progressive degradation with increasing age, achieved through examining and interpreting experimental data. The authors in [14]–[16] developed a non-linear battery model using a modified Randle circuit model. This model incorporates circuit elements such as resistors, capacitors, and inductors to forecast capacity degradation accurately. However, interference from other integrated components within the system might affect the measurement accuracy. Multiple discrete battery capacity models use a multi-model interactive modeling technique to represent a set of state equations. These model-based strategies have made significant progress in achieving high performance. The results of this experiment have been disclosed. The accuracy and flexibility of physical models depend on the precision of battery deterioration predictions [17]–[22]. Integrating advanced materials and modeling techniques has led to significant advancements in understanding battery degradation. By incorporating physical and experimental degradation models, researchers have accurately predicted capacity decline over time. Using techniques such as the coulomb counting approach and real-time parameter adjustment has further improved the precision of these predictions. Developing non-linear battery models using circuit elements has also provided a more comprehensive understanding of capacity degradation. However, challenges related to measurement accuracy and interference from integrated components within the system remain areas of focus for future research. The ongoing refinement of physical models and utilizing multi-model interactive modeling techniques are expected to enhance the accuracy and flexibility of battery deterioration predictions.

Artificial intelligence (AI) methods have seen a significant increase in prevalence in recent years. Machine learning (ML) is a neural network where the system executes algorithms. In addition, researchers have used machine learning, training programs, and intelligent changes to accurately forecast the state of health (SOH) of Li-ion battery packs. This paper includes the recommended approach to the gaussian network process (NGP) model [23]–[25]. This model considers the battery's deterioration under different operational circumstances. According to the results of the correlation analysis, the research suggests a connection between the average power loss in the first cycles of the battery and the duration of the charge and discharge cycles. This forecast is derived from the correlation between the two variables. Then, the constructed machine learning model is used to forecast the cycle life of the li-ion battery. The attributes shown throughout the first one hundred cycles of charging and discharging the storm determine the battery's capacity.

The article is divided into five distinct parts. In the first place, the data gathering for the battery is provided in section 2. In the next part, section 3, the extraction of the physical characteristics of the battery is shown. This part presents the learning-ML linear regression approach, which is given in the fourth section. Section 5 presents the outcomes of the simulation and assessment.

2. BATTERY KEY PARAMETERS

2.1. Battery temperature parameter

Managing these temperature fluctuations is crucial for optimizing battery performance and ensuring safety in various applications. Closely monitoring and controlling temperature changes can prolong battery life and improve overall efficiency. The chemical process and I^2R contribute to this temperature. Reduced battery capacity leads to a temperature rise, causing significant thermal variation. The formula can be used to calculate temperature changes throughout each cycle as shown in (1).

$$T = E(T_t - \mu)^2 \quad (1)$$

Where: E is the electromotive force; T_t is the i^{th} temperature sample in n cycles.

2.2. Variation in the electrode voltage

The variation in electrode voltage is directly related to how quickly the battery's capacity decreases. The (2) is used to symbolize the change in discharge voltage for each cycle.

$$V = E(V_t - \mu)^2 \quad (2)$$

Where: E is the electromotive force; V_i is the i^{th} voltage sample in n cycles.

2.3. Voltage disparity

The discharge energy difference between the initial and subsequent cycles equals the voltage change between the first and following cycles. This energy variance has a nonlinear relationship with battery capacity degradation. The difference in voltage is expressed by (3).

$$\Delta Q_{n-1} = Q_1 - Q_n \tag{3}$$

3. BATTERY DATA

The research papers [18] utilized 124 lithium-ion (Li-ion) batteries. These batteries had a rated capacity of 1.1 ampere-hours (Ah), with a damaged capacity of 0.88 Ah, and operated at a rated voltage of 3.3 V. The batteries underwent cycles within a chamber throughout the testing process, maintaining a consistent temperature of 30 degrees Celsius. Continuous measurements of various parameters such as voltage, power, current, temperature, and internal resistance were taken during the discharge and charge cycles. The data set was produced through online testing using three batches: the first batch comprised 41 batteries, the second contained 43 batteries, and the third with 4 consisted. Notably, this dataset encompasses all cells charged using the rapid charging method, making it the most comprehensive public collection of definitions for several similar commercial lithium-ion battery (LIB) pins. The primary objective of this article is to examine the degradation of LIB battery performance in diverse scenarios, encompassing those occurring during the manufacturing process and the operational configurations of the data set. Furthermore, the article delves into the potential of a fast-charging state to estimate a battery's remaining life and enhance its performance under intense pressure.

A structure that contains the following information comprises the data that is kept for each cell: i) Data consists of the mobile barcode, the charging policy, and the life cycle characteristics; ii) The data per cycle includes the number of processes, the ability to discharge, the internal resistance, and the amount of time it takes to charge; and iii) Time, temperature, discharge capacity, and linearly interpolated voltage are the variables gathered during a cycle.

During the battery's life cycle, as seen in Figure 1, the discharge capacity curves are recorded and change in color and shape over the spectrum. Figure 1 displays the association between the projected discharge capacity and the cumulative number of cycles the battery has undergone. In the first phases of the process, the battery's capacity gradually declines, but as the process advances, the total drops considerably quickly. Another discovery is that the power characteristics exhibit alternation, suggesting that the correlation between ability and battery life is non-linear. This is because the power characteristics exhibit alternating behavior. The research proposes a model that considers crucial physical elements and includes the storm's premature discharge to accurately calculate the battery's lifespan.

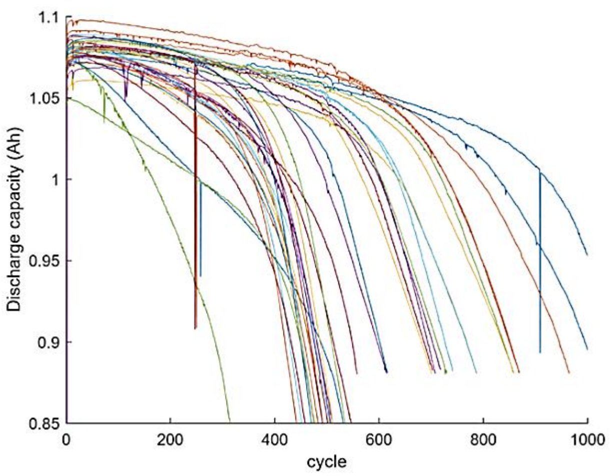

Figure 1. The discharge power curve is visible, and its color changes across the spectrum during its lifespan

4. THE PHYSICAL CHARACTERISTICS OF THE BATTERY

Battery life can be predicted using the capacity formula at each cycle (4) and the initial data from part 2. The model considers the impact of temperature variations on performance. Understanding these factors helps refine predictions and optimize usage, enhancing overall performance and durability.

$$P_{jk} = \sum_{i=2}^{n} U(t_i)(Q(t_i) - Q(t_{i-1}))/(t_n - t_1) \quad (4)$$

Where: P_{jk} is the battery capacity at each cycle; $U_{(t)}$ is the discharge voltage; $Q_{(t)}$ is discharged power; t is the discharge time at each cycle to determine the average power, j is the j^th battery and k number of discharge cycles.

The battery cells' capacity curves show a decrease in the early cycles, as illustrated in Figure 1. This is due to a slight capacity increase during the battery's early discharge phase. The study utilizes data from ten to one hundred cycles to explore the relationship between the features and the subsequent period associated with the battery capacity. Figure 1 represents the curve, indicating a small amount of attenuation over the entire cycle as the power P parameter. To determine the corresponding period L_j, the research employs variance statistics to transform the attenuation variation of the average power P_j of each battery, ranging from 10 to 110 cycles, into energy P_{Dj}. The (5) establishes the relationship between P_{Dj} and L_j to identify the connection between the two variables.

$$\rho_{p_D,L} = \frac{E(P_D L) - E(P_D)E(L)}{\sqrt{E(P^2{}_D) - (E(P_D))^2}\sqrt{E(L^2) - (E(L))^2}} \quad (5)$$

There is a difference between the 100th and 10th cycles in each voltage-discharge power connection $\Delta Q_{100-10}(V)$ represents what is shown in Figure 2. Figure 3 illustrates the relatively low connection coefficient that exists between P_{Di} and L_j.

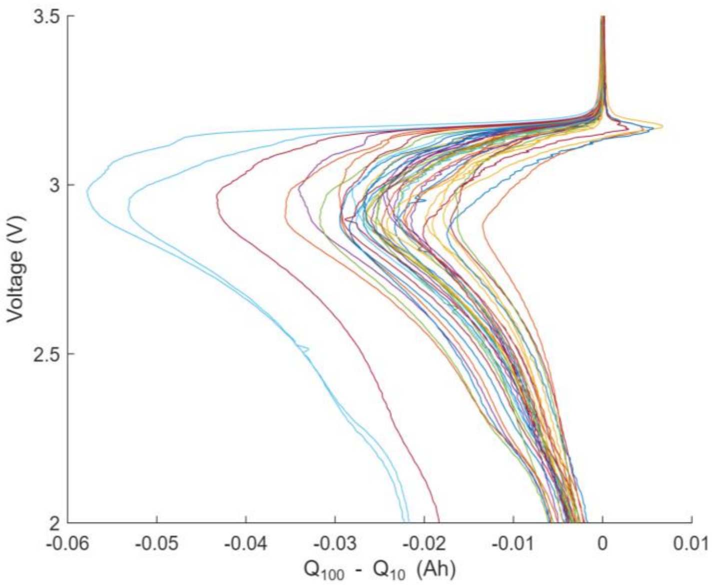

Figure 2. Each voltage-discharge power relationship is different from the 100th and 10th cycles $\Delta Q_{100-10}(V)$

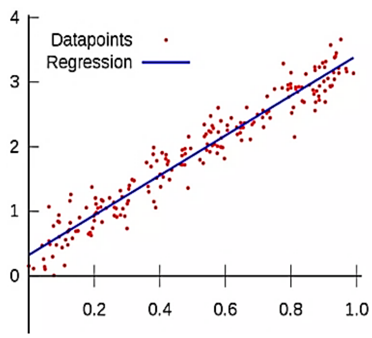

Figure 3. Cyclic behavior of linear regression models $\Delta Q_{100-10}(V)$

5. LINEAR REGRESSION MODEL (LG) AND TRAINED MODEL ASSESSMENT RESULTS
5.1. The LG models
Linear regression is a statistical method used to predict the dependent variable (y) based on the value of the independent variable (x). It relies on the assumption of a linear relationship between the variables, where changes in the independent variable impact the dependent variable. The regression line in linear regression always aligns with the mean of the independent variable (x) and the standard of the dependent variable (y), minimizing the overall "area of errors." To evaluate the variance in the dependent variable (y), the sum of squares is utilized. Before conducting regression analysis, it's important to consider the inherent variance in the response [19]–[21].

A depiction of the linear regression model is illustrated in Figure 3, with the following steps: step 1 defines the data's features. Data correlation analysis is performed in the second step. The model is estimated in the third step. Determining the fitting line is the fourth step. The model is analyzed as the fifth step. Step 6 involves validating the model using pre-validated data. Calculating various metrics of sampled data is the seventh step.

The study predicts the remaining battery cell life using a simple linear regression model, which reliably produces results. The (6) represents the linear model formally.

$$\hat{y}_i = \hat{w}^T x_i + \beta \tag{6}$$

Where: $\hat{y}_i$ is the period predict of the i^{th} battery cell; x_i is the feature vector p for the i^{th} battery cell, the predictor variable; $\hat{w}$ is a vector *of p*-dimensional model coefficients; β is the regression coefficient.

To prevent overfitting, the least squares optimization algorithm is adjusted to incorporate a penalty function when using regression procedures. The model is fitted and selected using an elastic network in linear regression, which is achieved by identifying sparse coefficient vectors. With an elastic network, the formula for linear regression can be expressed as in (7).

$$\hat{w} = min_w \|y - Xw - \beta\|_2^2 + \lambda P(w) \tag{7}$$

Where the *min* function represents finding the value of w that minimizes the argument, y is the n-dimensional vector of the observed battery life, X is the $n \times p$ matrix of objects, and λ is a quantity non-negative directional. Inside $\|y - Xw\|_2^2$ found in the smallest regular squares. *P(w)* depends on the elastic network regression technique.

$$P(w) = \frac{1-\alpha}{2}\|w\|_2^2 + \alpha\|w\|_1 \tag{8}$$

Where: α is the coefficient between 0 and 1.

The root mean square error (RMSE) is a method that can be used to assess how well a model fits a particular dataset. RMSE is a widely recognized statistic that calculates the average of the differences between expected and observed values. We chose to use RMSE and mean percent error to evaluate the model's performance. RMSE is calculated using (9).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

Where y is the observed lifetime, $\hat{y}$ is the predicted period, and n is the total number of samples. Using (10), one can calculate the average percentage of mistake:

$$\%error = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)}{y_i} x100 \tag{10}$$

5.2. Evaluate the performance of the trained model
5.2.1. Case 1 (choose the coefficient. $\boldsymbol{\alpha}$: 0.011: 0.11:1 and choose the coefficient. $\boldsymbol{\beta}$: 0:0.011:1)
Figure 4 reveals that all the points in the plot shown before are located close. At the point in time when the remaining lifespan is between 500 and 1200 cycles, the trained model is functioning normally. Once the model has completed 1200 cycles, its performance will begin to deteriorate. The model consistently exaggerates the amount of life that is still present in this region. One of the primary reasons for this is because the test and validation datasets include a substantially greater number of cells, with a total lifespan of around one thousand cycles. It was determined that the square root means square error (RMSE) was 211.61, and the mean percentage error reached 9.98%.

5.2.2. Case 2 (adjust the coefficient. α: 0.12: 0.12:1 and adjust the coefficient. β: 0:0.12:1)

All locations in the top plot are very near diagonal, as shown by the findings gained in Figure 5. At the point in time when the remaining lifespan is between 500 and 1200 cycles, the trained model is functioning normally. Once the model has completed 1200 cycles, its performance will deteriorate. The RMSE was found to be 218.4, while the mean percentage error was found to be 10.35%.

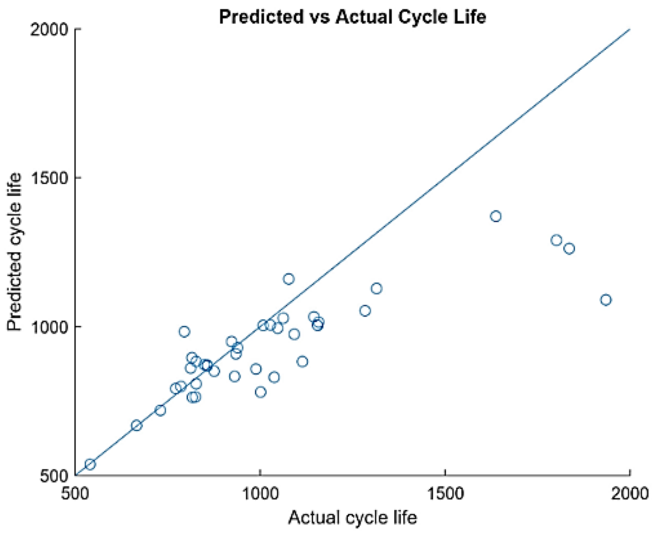

Figure 4. Estimated and actual battery life measurements

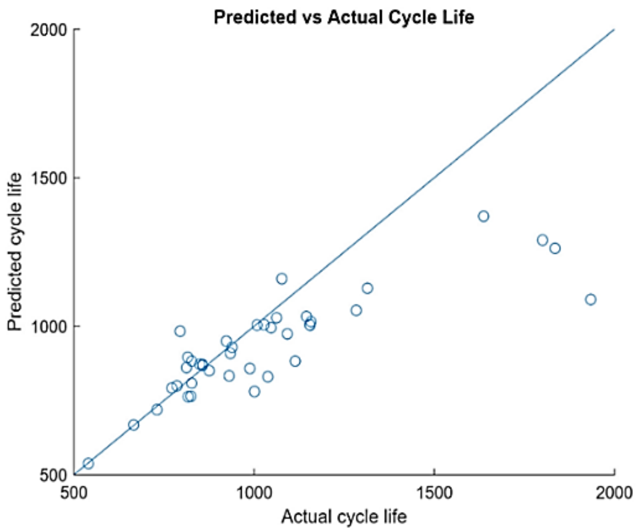

Figure 5. Estimated and actual battery life measurements

5.2.3. Case 3 (determine the coefficient. α: 0.21: 0.11:1 and determine the coefficient. β: 0:0.21:1)

According to the findings shown in Figure 6, every single point in the top plot is located in close proximity to the diagonal. When there are between 500 and 1200 cycles left in the lifespan, the trained model should function without any problems. Once the model has completed 1200 cycles, its performance will deteriorate. The mean percentage error reached 11.09%, and the square root means square error (RMSE) was 229.49. If lifetime is more than 1200 cycles, the performance of model's performance worsens, with the root mean square error (RMSE) reaching 229.49 and the mean percentage error increasing to 11.09%. The fact that this is the case suggests that the model's prediction accuracy decreases as the equipment gets closer to the end of its functional life. To resolve this problem, more investigation and model revision may be required.

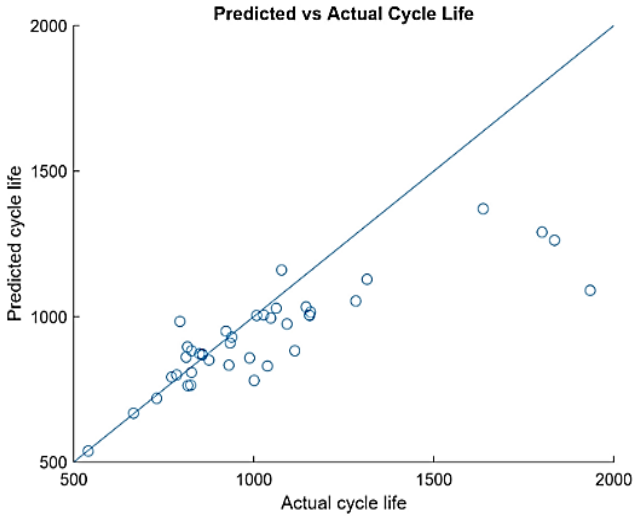

Figure 6. Estimated and actual battery life measurements

6. CONCLUSION

In the paper, a simple linear regression model was used to predict the battery's cycle life by depending on information from the first one hundred cycles. The first step was obtaining the calibration properties from the physical data lying under the surface. After that, a straightforward linear regression model was constructed using the training data. The validation dataset served as the data source for selecting the hyperparameters. In conclusion, the performance of this model was evaluated based on test data. A root-mean-square-error (RMSE) value of 211.61 was obtained for the remaining life cycle prediction of the cells in the test dataset. Additionally, an average percentage error of 9.98% was attained. The measurement of the first one hundred cycles was all used to arrive at this conclusion. The approach that has been offered for forecasting the cycle life of a battery, on the other hand, has to be confirmed by testing. During the process of experimental validation, the model was put through its paces on a unique set of battery cells that had cycle life data that was previously known. This was done to ensure that the model was accurate. The results of the comparison between the predictions generated by the model and the actual cycle life measurements indicated the exceptional degree of accuracy and dependability that the model has. During this experimental validation, the utility of the proposed model for predicting the life of a battery cycle was shown. This validation instilled confidence in the model's ability to accurately estimate the life of a battery cycle based on data collected from the first one hundred cycles.

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BIOGRAPHIES OF AUTHORS

Vo Thanh Ha is a lecturer in the Faculty of Electrical and Electrical Engineering, University of Transport and Communications. She received her B.S degree in control, and automation engineering from the Thai Nguyen University of Technology, Vietnam, in 2002. She received her master's degree from the Hanoi University of Science and Technology, Vietnam, in 2004. She received a Ph.D. degree from the Hanoi University of Science and Technology, Vietnam, in 2020, both in control and automation engineering. Her research interests include the field of electrical drive systems, power electronics, and electric vehicles. She can be contacted at email: vothanhha.ktd@utc.edu.vn.

Vo Quang Vinh graduated from Thai Nguyen University of Technology and received a master's degree from Hanoi University of Science and Technology in 1997. In 2004, he received a Ph.D. in control engineering from Hanoi University of Science and Technology. Currently, he works at the University of Electricity. His main research includes directions control and automation as well as power electronics. He can be contacted at email: vinhvq@epu.edu.vn.

Le Ngoc Truc majored in control engineering and automation. He received his B.Sc., M.Sc., and Ph.D. degrees from Hanoi University of Science and Technology (HUST), Vietnam, in 2006, 2010, and 2021, respectively. He has been working as a lecturer in Hung Yen University of Technology and Education since 2007. His researches are in fields of control engineering, robotics, system dynamics, and modeling. He can be contacted at email: lengoc.truc@utehy.edu.vn.