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Original Article

Experimental Study on Lithium-Ion Batteries Remaining Useful Life Prediction by Developing a Feedforward and a Long-Short-Time-Memory (LSTM) Neural Network for Electric Vehicles Application

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Abstract - *This paper proposes a model to predict Lithium-ion battery life for electric cars based on a supervised machine-learning linear regression algorithm. The capacity prediction of Lithium-ion batteries is based on voltage-dependent per-cell modeling. When sufficient test data is available, a linear regression learning algorithm will train this model to give a promising battery capacity prediction result. The paper's results are based on the voltage value for battery Lithium-ion to measure a battery's voltage. Thus, the battery's remaining life is predicted. Expected results are proven by an experiment table system with NVIDIA Jetson Nano 4GB Developer Kit B01, battery, and voltage sensor. This result allows rapid identification of battery manufacturing processes and will enable users to decide to replace defective batteries when deterioration in battery performance and lifespan are identified.*

Keywords - *Lithium-ion, Machine Learning, Electric car, Linear regression, Electric vehicle battery.*

1. Introduction

In recent years, lithium-ion battery (LIB) has attracted wide attention in research and application due to the advantages of high energy density, low self-discharge characteristics, Fast charging, high capacity, low pollution, and long life, so the market share of lithium-ion batteries in the market is increasing continuously [1-3]. Because of these outstanding features have attracted many scientists to study battery power management in recent years [4]. In particular, the state of health (SOH) is an indicator used to assess the battery's aging, including its ability to degrade and predict the life of the charge and discharge cycle of the storm. This model provides valuable information for prediction, such as accelerating the development of new electrode materials with higher capacity and life by designing materials and assessing battery life [5].

Currently, methods to predict universal batteries' capacity and capacity loss are based on physical modeling and data collection [6]. Model-based methods use mathematics. The model is determined according to the battery's physical or experimental degradation mechanism to capture the decay law of the battery [7]. The literature [8] used fuzzy logic mathematics to analyze the data obtained by impedance. The coulomb (CC) method of counting capacity over time uses the integral of the discharge or charge current to calculate the remaining power in the battery. This CC method performs simple calculations, which is widely used [9]. The authors of [10] developed a nonlinear model of the battery using circuit parameters such as resistors, capacitors, and inductors based on a modified Randle circuit model to predict the depletion of battery capacity. However, the accuracy of measurements is affected by the interference caused by other integrated components in the system [11]. Besides, according to the literature [27], the lifetime prediction model combined with advanced filtering technology will predict the battery capacity decline for equivalent circuit models with many complex parameters. Complex, diverse and unknown of the battery cell.

Moreover, in the document [13], an empirical exponential and polynomial regression model was proposed to monitor the trend of deterioration of the battery cell over the life of the battery cell based on the analysis of experimental data and use a filtering method to tune the model parameters online. In reference [14], a new model was developed using a Kalman filter with a regression vector and applied to the battery's cycle life and short-term capacity prediction. Furthermore, the literature [15] has developed a new predictive method based on filter multiple interaction models to determine battery cycle life. The multi-model interaction modeling method for different equations of state is used for many battery capacity models. It is found here that these model-based methods have achieved significant progress in high performance. This result is experimentally proven. However, the accuracy and robustness of these models are limited by the battery degradation accuracy of the physical model [16-19].

Today, artificial intelligence (AI) methods have been widely applied in image processing, speech recognition, natural language processing, and state prediction. The machine learning method (ML) is a classic neural network, but algorithms follow the system. In addition, the scientists combined the efficiency of ML with training programs and intelligent modifications to predict the SOH of Li-ion battery packs. Therefore, in this paper, the proposed method is combined with the Gaussian Network Process (NGP) model [20-25], which considers the deterioration of the battery under different operating conditions. First, based on the correlation analysis, the paper predicts that the average power loss in the early cycles of the battery is related to the life of the charge and discharge cycles. Then, the cycle life of the Li-ion battery is predicted using the established model (ML). Finally, the papers are based on the characteristics of the first 100 charging and discharging cycles to indicate the battery's capacity. This result allows rapid identification of battery manufacturing processes and will enable users to decide to replace defective batteries when deterioration in battery performance and lifespan are identified.

The article is arranged into six sections as follows. First, the extraction of the physical features of the battery is shown in section 2. In section 3, the physical characteristics of the battery. The method of learning-ML linear regression method is introduced and is expressed in section 4. Experiment and evaluation results are presented in section 5—finally, conclusions in section 6.

2. Electric Car Battery Key Parameters

2.1. Internal Power Supply DC

According to the document [13], the DC internal resistor is determined by the formula (1). The procedure assumes that the battery capacity drops over a short-specified period, so the internal DC resistance causes the voltage drop.

$$R_{DC} = \frac{V_{t1}-V_{t2}}{I_{t2}} \tag{1}$$

In which V_{t1}; V_{t2} is the battery voltage terminal at t_1 and t_2; I_{t2} is the discharge current at time t_2.

2.2. Variance of Temperature

The surface temperature increases during heat generation, remain constant and vary during the discharge phase. I2R and the chemical reaction create this temperature; as the battery capacity declines, the temperature increases, leading to a large thermal variance. The temperature variance in each cycle is calculated by the formula (2).

$$T = E(T_t - \mu)^2 \tag{2}$$

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

2.3. Discharge Voltage Variance

As the voltage discharges faster as the battery capacity declines. Discharge voltage variance in each cycle is written as formula (3).

$$V = E(V_t - \mu)^2 \tag{3}$$

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

2.4. Voltage Difference

The voltage difference between the first and subsequent cycles is the discharge energy difference between the first and next cycles. This energy difference has a nonlinear relationship with battery capacity degradation.

$$\varDelta Q_{n-1} = Q_1 - Q_n \tag{4}$$

3. Physical Characteristics of Battery

The observed discharge capacity curves, including the color of the angles, change along the spectrum over the battery life cycle shown in Figure 1.

Figure 1 shows the relationship between the estimated discharge capacity and the number of cycles over the entire battery life. The battery's capacity decreases slowly during the early cycles, and in the later stages of the process, the ability discharges rapidly. In addition, it is found that the power characteristics are both alternating, which means that the model between capacity and battery life is nonlinear. Therefore, to accurately determine the battery's life, the paper proposes a model built on fundamental physical parameters with the premature discharge of the storm.

Based on the initial data in part 2 (voltage, current, temperature ...), predict the battery life based on the battery capacity formula at each cycle (5). The recipe shows the relationship between discharge at first cycles and battery life.

$$P_{jk} = \sum_{i=2}^{n} U(t_i)(Q(t_i) - Q(t_{i-1}))/(t_n - t_1) \tag{5}$$

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.

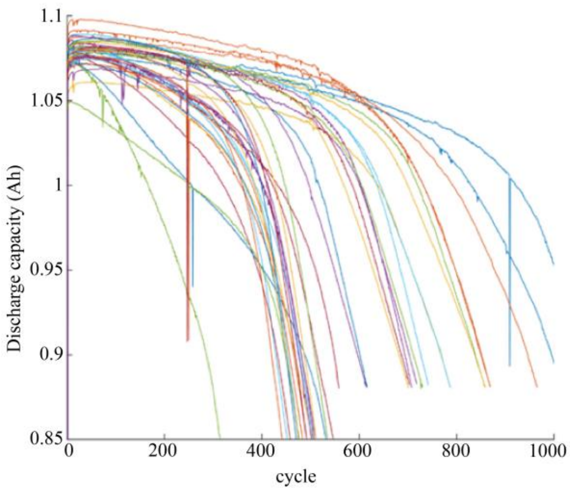

Fig. 1 Observable discharge power curve and the curve's colour changes along the spectrum over the life cycle

Based on Figure 1, it can be seen that the capacity curves of the battery cells decline in the early cycles because of the slight increase in capacity during the early discharge phase. Therefore, to study the relationship between the characteristics and the subsequent period related to the battery cycle life, the paper uses data from 10 to 100 cycles. In Figure 1, the curve is shown. Power P indicates that the attenuation of the battery is minimal during the whole cycle. The paper uses variance statistics to convert the attenuation fluctuation of the average power P_j of each battery from 10 to 110 cycles into energy P_{Dj} to establish the related corresponding to the period L_j. The relationship between P_{Dj} and L_j is determined through Eq. (6).

$$\rho_{p_D,L} = \frac{E(P_D L)-E(P_D)E(L)}{\sqrt{E(P^2{}_D)-(E(P_D))^2}\sqrt{E(L^2)-(E(L))^2}} \quad (6)$$

Each voltage-discharge power relationship is different from the 100th and 10th cycles, $\Delta Q_{100-10}(V)$ as shown in Figure 2. The small relationship coefficient between P_{Dj} and L_j is shown in Figure 3.

4. Linear RegressionModel

Linear regression is a method to predict the dependent variable (y) based on the value of the independent variable (x). This means that linear regression should have a linear relationship between the independent and non-independent variables, and the effect of a change in the values of the independent variables should further affect the dependent variables. Belong. Some properties of linear regression are that the regression line always passes through the mean of the independent variable (x) and the standard of the dependent variable (y). The regression line minimizes the sum of the "area of errors." The sum of areas measures the response/dependent variable (y) ratio variation. The amount of variation inherent in the reaction can be considered before regression is performed [19,20,28].

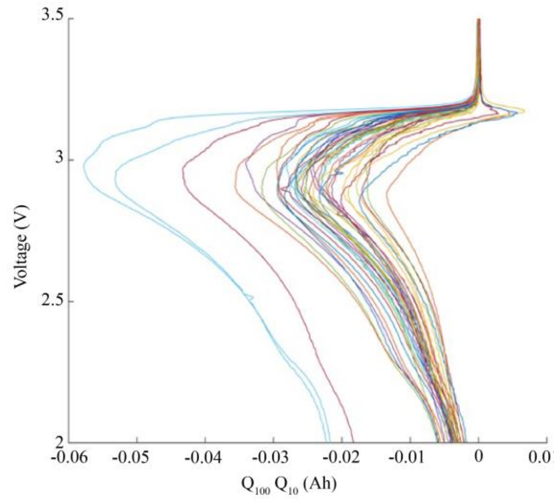

Fig. 2 Each voltage-discharge power relationship is different from the 100th and 10th cycles $\Delta Q_{100-10}(V)$

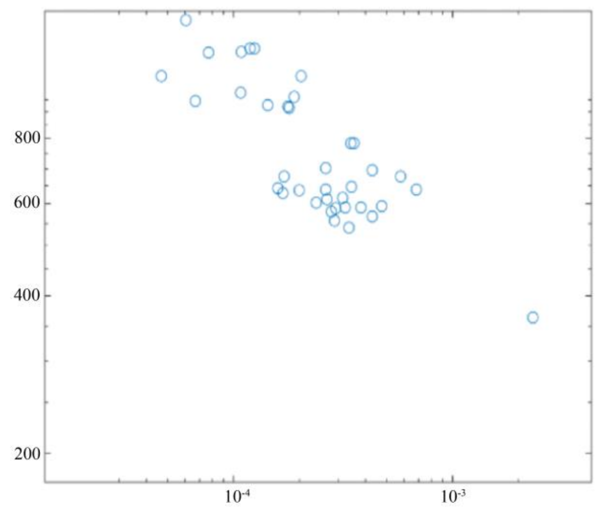

Fig. 3 Relationship coefficient between P_{Dj} and L_j

The linear regression model is shown in Figure 4, and the steps are as follows:

Step 1: Define input data characteristics
Step 2: Analyze the correlation of the data
Step 3: Estimating the model
Step 4: Determine the fitting line
Step 5: Analyze the model
Step 6: Test the model with tested data
Step 7: Calculation with metric types of sampled data.

The paper uses a simple linear regression model to predict the remaining life of the battery cell. This model calculates but gives accurate results. The linear model has the form of a formula (7).

$$\hat{y}_i = \hat{w}^T x_i + \beta \quad (7)$$

Where: $\hat{y}_i$ is the period forecast of the i^{th} battery cell, the feedback variable; 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;$\beta$is the regression coefficient.

A penalty function is added to the least squares optimization formula when applying regression techniques to avoid overfitting. Linear regression uses an elastic network to fit and select the model by finding the sparse coefficient vectors. The linear regression formula using an elastic network has the following form:

$$\widehat{w} = min_w \|y - Xw - \beta\|_2^2 + \lambda P(w) \qquad (8)$$

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.

$$P(w) = \frac{1-\alpha}{2}\|w\|_2^2 + \alpha\|w\|_1 \qquad (9)$$

Where:$\alpha$is the scalar coefficient between 0 and 1.

One way to gauge how "good" a model fits a given data set is to calculate the square root mean square error (RMSE). RMES is a known metric that averages predicted values far from observed values. RMSE and mean percent error was chosen to evaluate the model's performance. RMSE is calculated as formula (10) as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (10)$$

Where y is the observed lifetime, $\hat{y}$ is the predicted period, and n is the total number of samples. The average percentage error is determined by the formula (11):

$$\%erro = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)}{y_i} \; x100 \qquad (11)$$

5. Experiment Results and Discussion

The experimental table is built as shown in Figures 5 & 6:

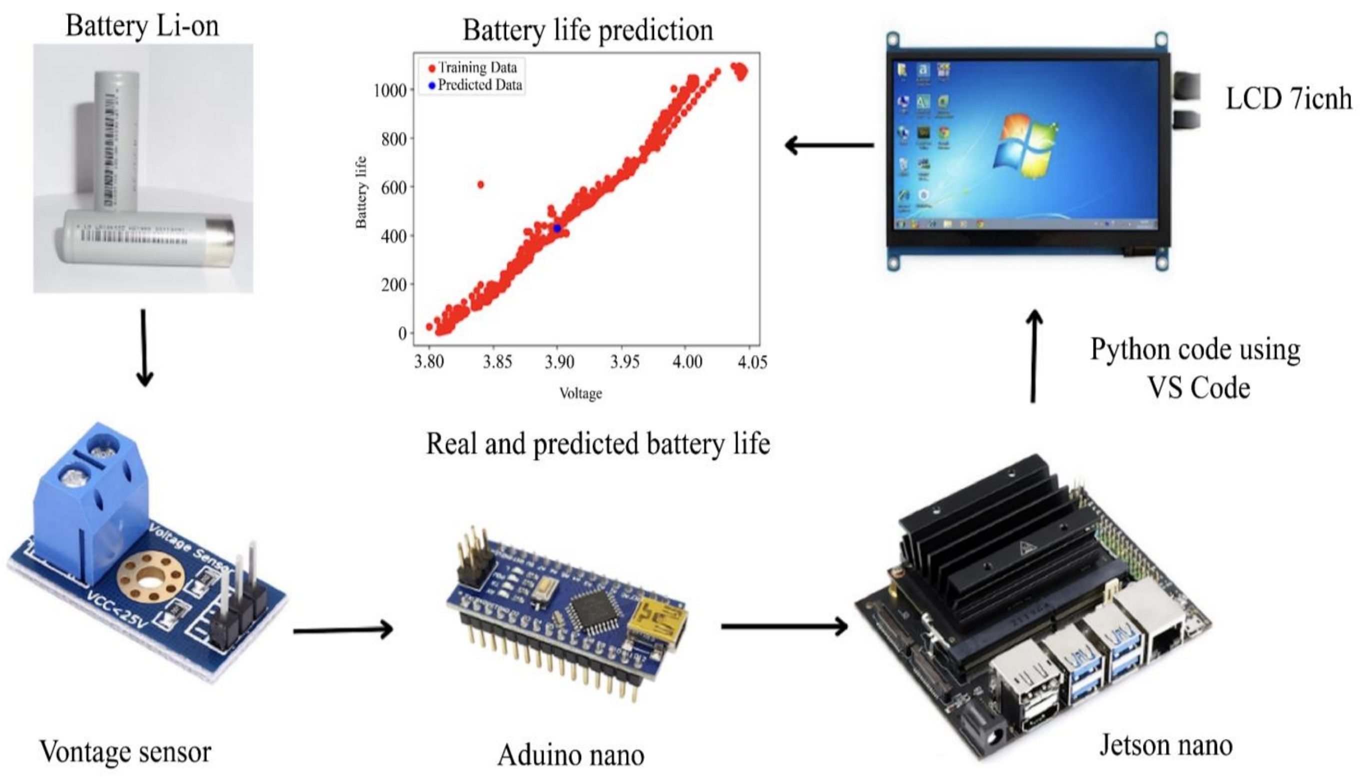

Fig. 5 Experiment model to predict the life of Lithium-Ion battery

Fig. 6 Experimental model predicts battery life

The parameter of the battery to estimate the life is as follows:

- Cycle Index: number of cycles
- Decrement 3.8-4.05V(s)
- Max. Voltage Discharge (V): 4.05V
- Min. Voltage Charge (V): 3.8V
- Time Constant Current (s)After being tested, the model could accurately calculate the battery's voltage in one hour. This data could be further extrapolated to estimate the entire life cycle. Power management can become more approachable and more effective by adding machine learning to clever battery technology.

5.1. Evaluate the Performance of the Trained Model

To make the model sustainable, in the paper, the scalar and regression coefficients are selected as follows:

Case 1:

Select coefficientα: 0.01: 0.1:1

Select coefficientβ: 0:0.01:1

The results of Figure 7 show that all the points in the above graph are close to the diagonal. Thus, the trained model is similar to the theory of linear regression. Based on the above training model, it is found that the larger the rated voltage, the larger the battery life. For example, if the measured voltage is 4V, the battery will still be discharged for 1000 cycles. While the battery voltage is 3.85V, the battery is still discharged for 100 cycles. The square root means that the squared error (RMSE) is 211.61, and the average percentage error is 9.98%.

Case 2:

Select coefficientα: 0.1: 0.1:1

Select coefficientβ: 0:0.1:1

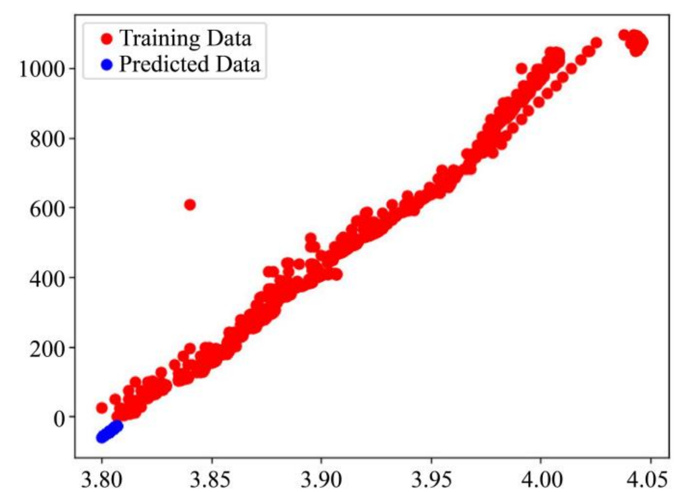

Fig. 7 Case 1 for real and forecasted battery life

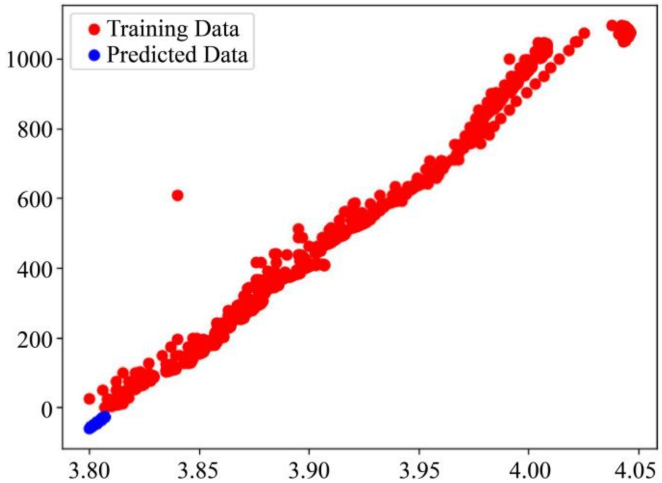

Fig. 8 Case 2 of real and forecasted battery life

According to Figure 8, every point in the graph above is quite near the diagonal, like in Fig.5. The trained model, therefore, resembles linear regression theory. According to the training model, the higher the rated voltage, the longer the battery life. For instance, the battery will still undergo 1000 drain cycles even if the reported voltage is 4V. Therefore, the battery is still depleted 100 times despite its voltage of 3.85V. According to the square root, the average percentage error is 9.98%, and the squared error (RMSE) is 210.41%.

6. Conclusion

The paper employed a straightforward linear regression model to forecast battery cycle life. First, calibration characteristics were derived from the underlying physical data, and then training data were used to fit a straightforward linear regression model. The validation dataset was then used to choose the hyperparameters. The performance of this model was then assessed using test data. The remaining life cycle prediction of the cells in the test dataset had an RMSE of 211.61 (210.41%) and an average percentage error of 9.98% when only the first 100 cycles were measured. The user can therefore determine when to replace the battery using this mining model. However, an experimental study is required to validate the suggested battery cycle life prediction model.

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