Cycle life prediction method of lithium ion batteries for new energy electric vehicles

Runze Gao*, Xiao Li, Haitao Yu
Research Institute of Highway Ministry of Transport, Beijing 100088, China
E-mail address: rz.gao@rioh.cn, x.li@rioh.cn, ht.yu@rioh.cn

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Abstract: In order to solve the problems of high battery capacity detection error and low life prediction accuracy existing in traditional lithium-ion battery cycle life prediction methods, based on the battery capacity detection results, the cycle life prediction of lithium-ion batteries for new energy electric vehicles was carried out. Firstly, the principle of charge and discharge of lithium-ion battery is analyzed. Based on this, the idea of differential equation is introduced to detect the capacity of lithium-ion battery in real time. Secondly, according to the battery capacity test results, the exponential function of lithium-ion battery cycle life decline is constructed, and the calculation result of life influence factor is obtained. Finally, the lithium-ion battery cycle life prediction model is constructed, and the final prediction results are obtained. The experimental results show that the proposed method can always keep a low battery capacity detection error in multiple charging and discharging cycles, and the battery cycle life prediction accuracy can reach 97%.

Key words: New energy electric vehicles; Lithium ion battery; Recycling; Life prediction

I. INTRODUCTION

In order to protect the environment and reduce energy consumption, the development of new energy electric vehicles has become the only way for the transformation and development of automobile enterprises. For new energy electric vehicles, the most important thing is the performance of power battery, which is the key factor affecting the driving performance of new energy electric vehicles. The most widely used battery is lithium-ion battery [1-3]. Different charging methods will also affect the service life of lithium-ion batteries. Therefore, detecting the state of lithium-ion batteries and accurately predicting the cycle life of batteries can effectively improve the reliability of new energy electric vehicle battery system [4].

The paper presents a method for predicting the life of lithium-ion battery cycle based on the equal pressure difference charging time. The Gauss process regression model is used to simulate the charging and discharging process of lithium-ion battery, and the kernel function and particle swarm optimization algorithm are combined to calculate the health factors of lithium-ion batteries. Finally, the cycle life of lithium-ion battery is predicted by the method of equal pressure difference charging time. However, it is difficult to monitor the real-time capacity of the battery, which leads to inaccurate life prediction results. A method for predicting the cycle life of lithium-ion batteries based on wavelet packet energy entropy is proposed in reference [6]. The fractional grey degradation model is constructed by using wavelet packet energy entropy to directly measure the discharge voltage of lithium-ion batteries. According to the measurement results of discharge voltage, a model of life prediction of lithium-ion battery cycle is built by using the non trace particle filter algorithm. However, the method has the problem of low prediction accuracy. In reference [7], a method of lithium-ion battery cycle life prediction based on fusion method is proposed. In this method, unscented Kalman filter algorithm is used to screen the factors affecting the life of lithium-ion battery, and genetic algorithm is used to optimize the factors. According to the optimized output results, the lithium-ion battery cycle life prediction is completed. However, this method is difficult to detect the battery capacity state, resulting in the final prediction result is not ideal.

In order to improve the accuracy of lithium-ion battery cycle life prediction, based on the detection of battery capacity, the cycle life prediction of lithium-ion battery in new energy point EMU is carried out.

II. CYCLE LIFE PREDICTION METHOD OF LITHIUM ION BATTERIES FOR NEW ENERGY ELECTRIC VEHICLES

Lithium ion battery is a kind of rechargeable battery which can be recycled. Its main structure is composed of positive and negative electrodes, electrolyte and separator. Among them, the cathode material is composed of layered oxide, spinel or anion, the anode material is generally graphite, and the electrolyte is organic carbonate [8-10].

The power supply principle of lithium-ion battery is that lithium ion moves between positive and negative poles of the battery to complete the charge and discharge function [11]. The working principle of lithium-ion battery is shown in Figure 1.

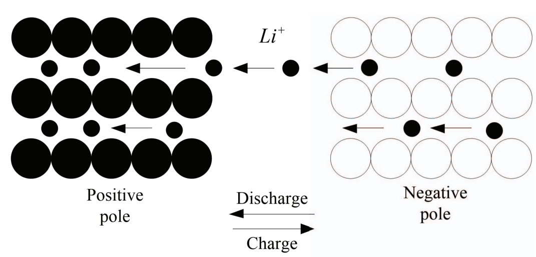

Figure 1 Charging and discharging principle of lithium-ion battery

2.1 Capacity test of lithium ion battery

In the continuous driving process of electric vehicles, lithium-ion batteries are required to cycle charge and discharge to provide power energy. However, with the increase of charge and discharge times, the performance of lithium-ion batteries will gradually decline, leading to the same reduction in capacity, and the capacity of lithium-ion batteries is the key factor to determine their cycle life [12]. Therefore, the effectiveness of battery cycle life prediction can be improved by detecting the attenuation transformation of battery capacity.

In order to describe the change of battery capacity accurately, the idea of differential equation is introduced to detect the battery capacity in real time. The calculation formula of battery capacity degradation rate is as follows:

$$\frac{dq}{dC} = f(q,C) \tag{1}$$

In the formula, q represents the nominal capacity of the lithium-ion battery, and C represents the actual cycle life of the lithium-ion battery. Carry out Taylor series expansion on the nonlinear function $f(q,C)$, and get the following calculation formula:

$$\frac{dq}{dC} = a_1 q + a_2 C \tag{2}$$

In the formula, a_1 is the degradation factor of battery capacity and a_2 is the fatigue factor of the battery.

As the number of cycles increases, the capacity of lithium-ion batteries continues to decrease, and there are:

$$\begin{aligned} & a_1 q + a_2 C < 0 \\ & q > 0, C > 0 \end{aligned} \tag{3}$$

Order:

$$u = a_1 q + a_2 C \tag{4}$$

The results are as follows:

$$u < 0 \tag{5}$$

Differential calculation is carried out at both ends of formula (4):

$$du = a_1 dq + a_2 dC \tag{6}$$

Taking formula (6) into formula (2), the following formula is obtained:

$$\frac{du}{dC} = a_1 u + a_2 \tag{7}$$

By solving the calculation result of formula (7), the real-time detection result of lithium-ion battery capacity can be obtained:

$$Q = k_1 C + k_2 e^{\alpha C} + k_3 u \tag{8}$$

In the formula, Q represents the real-time capacity of the lithium-ion battery, and α and k_1, k_2, and k_3 represent the battery capacity change parameters.

In the actual working environment, the capacity of lithium-ion battery is affected by temperature, charging current and discharge voltage. However, due to the complexity of simulating the actual working environment, in this detection and calculation process, the real-time detection of lithium-ion battery capacity is realized by calculating the influencing parameters of lithium-ion battery [13-15].

2.2 Cycle life prediction model of lithium ion battery

According to the test results of lithium-ion battery capacity, the lithium-ion battery cycle life prediction model is constructed to complete the battery cycle life prediction.

The exponential function of the life decline of lithium-ion battery is as follows:

$$D = R_1 \exp(\lambda_{R_1} k) + R_2 \exp(\lambda_{R_2} k) \tag{9}$$

In the formula, k is the charge and discharge cycle of Li ion battery, and R_1, R_2, λ_{R_1} and λ_{R_2} are the decay factors.

According to the above-mentioned relevant parameters, the expression of the state space model for the cyclic service life decline of lithium-ion batteries can be obtained:

$$\begin{cases} R_{1,k+1} = R_{1,k} + v_{1,k} \\ \lambda_{R_{1,k+1}} = \lambda_{R_{1,k}} + v_{2,k} \\ R_{2,k+1} = R_{2,k} + v_{3,k} \\ \lambda_{R_{2,k+1}} = \lambda_{R_{2,k}} + v_{4,k} \end{cases} \tag{10}$$

$$C_k = R_{1,k} \exp\left(\lambda_{R_{1,k}} k\right) + R_{2,k} \exp\left(\lambda_{R_{2,k}} k\right)$$

In the formula, v_k is the system noise of lithium ion battery and n_k is the result output noise.

The cycle life decline process of lithium-ion battery is a linear process. According to formula (10), the parameters affecting the life of lithium-ion battery can be calculated. The capacity decline is the key factor affecting the life of lithium-ion battery. When the battery capacity declines to the point where it cannot work normally, the life of lithium-ion battery reaches the end point. Therefore, it is necessary to calculate the effect of capacity life decline of lithium-ion battery:

$$R_{a,n} = R_{1,N} \exp(\lambda_{R_{1,N}} n), n = 1,2,...,M; M \geq N_{EOL} \tag{11}$$

$$R_{a,n} = R_{1,N} \exp(\lambda_{R_{1,N}} n), n = 1,2,...,M; M \geq N_{EOL} \tag{12}$$

In the formula, N_{EOL} is the final cycle of battery recycling. Taking the results of formula (11) and formula (12) as the parameters of the prediction model of lithium-ion battery cycle life, the prediction model of lithium-ion battery cycle life is obtained:

$$\begin{cases} \lambda^*_{R_{1,k+1}} = \lambda^*_{R_{1,k}} + v^*_{1,k} \\ R^*_{1,k+1} = R^*_{1,k} \exp(\lambda^*_{R_{1,k}}) + v^*_{2,k} \\ \lambda^*_{R_{2,k+1}} = \lambda^*_{R_{2,k}} + v^*_{3,k} \\ R^*_{2,k+1} = R^*_{2,k} \exp(\lambda^*_{R_{2,k}}) + v^*_{4,k} \\ C^*_{N+k+1} = R^*_{1,k+1} \exp\left(\lambda^*_{R_{1,k+1}}\right) + R^*_{2,k+1} \exp\left(\lambda^*_{R_{2,k+1}}\right) + v^*_{5,k} \end{cases} \tag{13}$$

Among them:

$$\begin{cases} R_{a,k} = R^*_{1,k} + n^*_{1,k} \\ R_{b,k} = R^*_{2,k} + n^*_{2,k} \end{cases} \tag{14}$$

In the prediction model shown in formula (14), v^*_k

and n_k^* points represent the noise of the prediction variable. When the capacity of lithium-ion battery reaches the end of life, the final prediction result of lithium-ion battery cycle life can be obtained by solving the prediction model shown in formula (13):

$$RUL^* = N_{EOL}^* - N \qquad (15)$$

According to the calculation results of formula (15), the results of the cycle life of lithium-ion batteries of new energy electric vehicles can be predicted accurately.

III. EXPERIMENTAL VERIFICATION

In order to verify the application performance of the proposed prediction method, this paper uses this method to predict the cycle life of lithium-ion batteries for new energy electric vehicles, and verifies the prediction performance of this method.

This experiment uses a CFC11AH0400076 lithium-ion battery, and the tested environment temperature is 23(±1)℃. One cycle of the battery is defined as: charge the lithium-ion battery in 1C current mode, adjust to constant voltage charging when the voltage reaches 3.65V, and stop charging the lithium-ion battery when the charging current drops to 0.05C. Charge and place the battery for 1 hour. After one hour, discharge the battery with 1C current. When the voltage reaches 2.5V, stop discharging and measure the capacity of the battery at this time. After the capacitance measurement is completed, leave it for 0.5 hours.

3.1 Experimental scheme

Setting the overall experimental scheme: Taking the battery capacity detection error and service life prediction accuracy as experimental comparison indexes, the method in this paper is compared with reference [6] and reference [7].

Battery capacity detection error: battery capacity detection error refers to the error value between the battery capacity detection results of different methods and the actual battery capacity results. The lower the battery capacity detection error is, the higher the effectiveness of the method is.

Service life prediction accuracy: service life prediction accuracy refers to the degree of similarity between the prediction results of different methods and the actual service life results. The higher the service life prediction accuracy is, the better the prediction performance of the method is.

3.2 Battery capacity detection error

The battery capacity can reflect the attenuation characteristics of lithium-ion batteries. Therefore, the detection results of battery capacity have an important influence on the prediction accuracy of service life. Therefore, the error of battery capacity detection is taken as the experimental comparison index, and the method in this paper is compared with two traditional literature methods. The comparison results of the method in this paper with the battery capacity test error of reference [6] and reference [7] are shown in Figure 2.

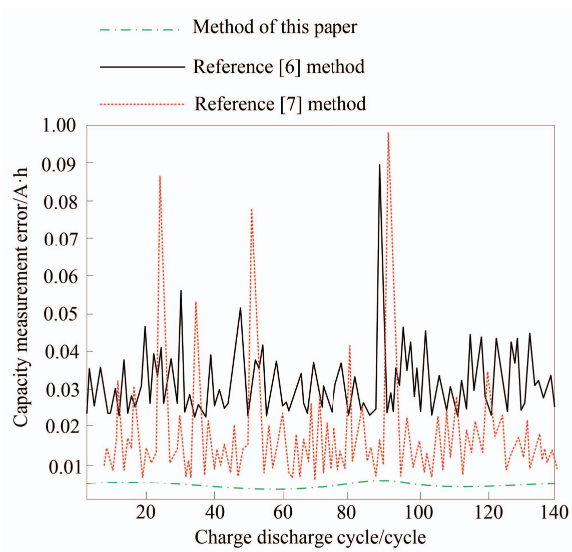

Figure 2 Comparison results of battery capacity test error

From the comparison results of battery capacity detection error shown in Figure 2, it can be found that the maximum error value of battery capacity detection of this method is not more than 0.01A·h in multiple charging and discharging cycles, and the error change of this method is not obvious, which indicates that the reliability of battery capacity detection of this method is high. However, it can also be seen that the battery capacity detection error of the two literature comparison methods is higher, and the maximum detection error of reference [6] and reference [7] methods is 0.09A·h and 0.098A·h respectively.

3.3 Service life prediction accuracy

The accuracy of lithium-ion battery cycle life prediction can directly reflect the prediction performance of different methods, so the accuracy of life prediction is directly taken as the experimental comparison index, and the method in this paper is compared with reference [6] and reference [7] to reflect the prediction performance of this method. The comparison results of service life prediction accuracy of the three methods are shown in Figure 3.

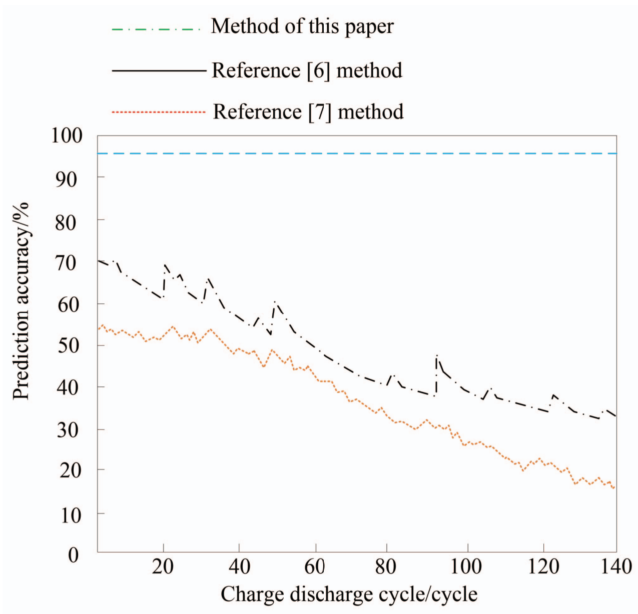

Figure 3 Service life prediction accuracy results

By analyzing the comparison results of service life prediction accuracy shown in Fig. 3, it can be seen that the prediction accuracy of this method can always be maintained at 97%, while the service life prediction accuracy of reference [6] and reference [7] shows a continuous downward trend, and the final prediction accuracy of the two traditional literature comparison methods is more than 50%.

IV. CONCLUSION

In order to improve the prediction accuracy of the cycle life of lithium-ion batteries for new energy electric vehicles, the battery capacity detection was studied, and the performance of the proposed prediction method was verified theoretically and experimentally. This method has lower battery capacity detection error and higher prediction accuracy in the cycle life prediction of lithium-ion batteries for new energy electric vehicles. Specifically, compared with the method based on wavelet packet energy entropy, the battery capacity detection error is significantly reduced, and the maximum detection error is only 0.005a · H; Compared with the fusion method, the prediction accuracy is greatly improved, and the highest prediction accuracy is 97%. Therefore, the research method can effectively improve the reliability of lithium-ion battery cycle life prediction.

REFERENCES

[1]Ding YangZheng, Jia Jianfang. Improved PSO optimized extreme learning machine predicts remaining useful life of lithium-ion battery[J]. Journal of Electronic Measurement and Instrumentation, 2019, 33(02):77-84.

[2]Liu Yuefeng, Zhao Guangquan, Peng Xiyuan. A Lithium-Ion Battery Remaining Using Life Prediction Method Based on Multi-kernel Relevance Vector Machine Optimized Model[J]. Acta Electronica Sinica , 2019, 47(06):1285-1292.

[3]Tian Jun, Gao Hongbo, Zhang Yueqiang, et al. Research of life prediction methods for power Li-ion battery in electric vehicles[J]. Chinese Journal of Power Sources, 2020, 44(05):767-770.

[4]Ding Jintao, Luo Meijun, Luo Xiaobing, et al. Available capacity and RUL prediction model for aviation Li-ion battery[J]. Battery Bimonthly, 2019, 49(04):329-333.

[5]Liu Jian, Chen Ziqiang, Huang Deyang, et al. Remaining Useful Life Prediction for Lithium-Ion Batteries Based on Time Interval of Equal Charging Voltage Difference[J]. Journal of Shanghai Jiaotong University, 2019, 53(09):1058-1065.

[6]Chen Lin, Chen Jing, Wang Huimin, et al. Prediction of Battery Remaining Useful Life Based on Wavelet Packet Energy Entropy[J]. Transactions of China Electrotechnical Society, 2020, 35(08):229-237.

[7]Lin Na, Zhu Wu, Deng Baoan. Remaining Useful Life Prediction of the Lithium-ion Battery Based on Fusion Method[J]. Science Technology and Engineering, 2020, 20(05):1928-1933.

[8]Li Yabin, Lin Shuo, Yuan Xueqing, et al. Research on RUL Prediction of Lithium-Ion Batteries Based on a New Capacity Degradation Model[J]. Computer Simulation, 2020, 37(02):125-129.

[9]Wang Zhuqing, Guo Yangming, Xu Cong. An HI Extraction Framework for Lithium-Ion Battery Prognostics Based on SAE-VMD[J]. Journal of Northwestern Polytechnical University, 2020, 38(04):137-144.

[10]Liu Guixing, Mu Dongxu. Remaining useful life prediction for B787 plane battery based on DEPSO-RVM[J]. Modern Electronics Technique, 2019, 42(20):94-98+102.

[11]Sun Daoming, Yu Xiaoli. Capacity Prediction Method of Lithium-ion Battery Under Random Discharge Condition[J]. Automotive Engineering, 2020, 42(09):1189-1196.

[12]Shi Yongsheng, Ma Mingyuan, Ding ensong, et al. Capacity estimation of lithium ion battery based on support vector regression[J]. Chinese Journal of Power Sources, 2019, 43(12):1996-2000.

[13]Liu Xintian, Zhang Heng, He Yao, et al. Prognostics of Lithium-ion Batteries Based on IMM-UPF[J]. Journal of Hunan University(Natural Sciences), 2020, 47(02):102-109.

[14]Wu Zhongqiang, Shang Mengyao, Shen Dandan, et al. Estimation of SOC of Li-ion Battery in Pure Electric Vehicle by BSA-RELM[J]. Acta Metrologica Sinica, 2019, 40(04):693-699.

[15]Ma Xiangping, Jin Haoqing, Zhu Qixian, et al. An online fusion

estimation method for state of charge of lithium ion batteries[J]. Journal of Lanzhou University of Technology, 2020, 46(05):84-90.