The theoretical Algorithm Analysis of LOC for LiFePO4 Batteries

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Abstract. LOC represents the usage time of a single battery, which is different from the battery capacity calibrated by SOC and the remaining battery capacity of RUL. It uses the usable time of a single battery as a scale, which can clearly reflect the remaining life of the battery under specific cycle times, current, voltage, temperature, discharge depth, and other conditions. Based on LOC (Life of Charge), using AI algorithm to accurately establish a single battery model, taking this as the starting point to establish a BMS system.

Keywords: LOC, LiFePO4 batteries, SOC,RUL.

1. Introduciton

The internal electrochemical reaction of lithium batteries is complex, and there are many interference factors during operation. At the same time, considering the limited computing power of the vehicle battery management system, the vehicle power battery model must have the characteristics of simple structure, fast calculation speed, and high prediction accuracy, in order to lay a solid foundation for subsequent state estimation work. For electric vehicles, the state of charge of a power battery is used to describe the remaining capacity of the power battery, equivalent to the fuel gauge of a traditional engine vehicle. At the same time, as the most important decision-making factor in electric vehicle energy management, state of charge (SOC) estimation also has important significance in optimizing vehicle energy distribution, improving battery energy utilization, preventing overcharging and discharging, and ensuring the stability and safety of the entire vehicle and battery system. Like all products, electric vehicles and their battery systems also have a certain service life. Reasonable estimation of the health status of the battery, accurate prediction of the battery service life, and timely provision of decision-making basis to the vehicle fault diagnosis system and the driver before the power battery failure, as well as timely elimination of hidden dangers, are of great significance for ensuring the safe driving of electric vehicles and the safety of the driver's life and property.

The traditional lithium battery model is based on SOC algorithm, without comprehensive consideration of the battery availability time in working state. Therefore, battery modeling must fully consider the actual application environment. Developing an accurate and reliable battery model in an actual vehicle environment is still the focus and difficulty of battery management systems. LOC represents the usage time of a single battery, which is different from the battery capacity calibrated by SOC and the remaining battery capacity of RUL. It uses the usable time of a single battery as a scale, which can clearly reflect the remaining life of the battery under specific cycle times, current, voltage, temperature, discharge depth, and other conditions. Based on LOC (Life of Charge), using AI algorithm to accurately establish a single battery model, and using this as a starting point, establish a BMS system.

2. LOC model

The model is as follows:

$$LOC = C \times K_{EV} \times SOC / R_D$$

The single cycle lifetime LOC of a single battery is related to SOC, battery rated capacity C, and discharge rate. (It is an effective SOC coefficient) In addition, in the actual model, a weighting coefficient should be used to correct the above formula considering various operating conditions and stresses.

3. KEV fitting mathematical model:

When conducting charge and discharge cycle experiments on batteries, considering the irregularity of battery discharge during actual use and the regular working conditions during charging, this article uses the capacity of the battery during charging to calculate SOC. A total of 423 experiments were conducted. The comparison of battery appearance before and after the experiment is shown in Figure 1. The obtained LiFePO4 battery life test results are shown in Table 1. After many times of use, batteries will experience aging, and aging batteries will experience bulging. This is due to the degradation of battery performance after aging, and "overreaction" of chemical reactions within the battery, resulting in the generation of gas, deformation of the structure of the positive and negative electrodes of the battery, leading to bulging of the battery.

Table1.battery cycle life data

Number of experiments	Charging power	SOH(%)
10	13.24	110.3
50	13.92	116
100	13.72	114.3
150	13.85	115.4
200	13.75	114.5
250	13.36	111.3
300	12.6	105
350	11.79	98.25
400	11.04	92
410	9.32	77.67
423	7.66	63.83

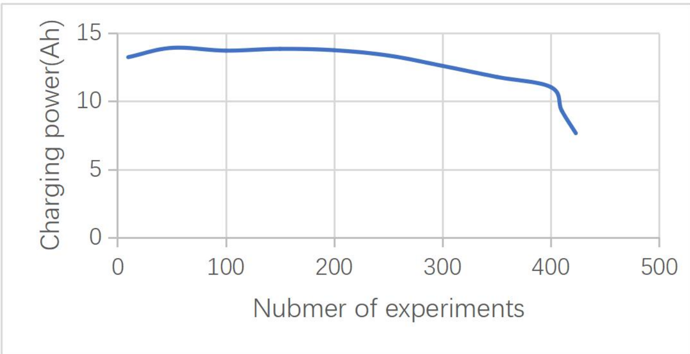

Fig.1. Available capacity of lithium batteries

4. Battery Capacity Model

The aging model of a battery simulates the decay of the battery's rated capacity during its cyclic use, i.e., the change of the battery's rated capacity with the number of cycles. Currently, there are two commonly used battery aging models: Exponential model and Polynomial model 5. The following is an analysis and discussion of the exponential model. The exponential model is obtained by fitting the capacity decay data obtained from the battery cycle aging experiment.

$$C_{ek} = b_1 \cdot e^{f_1 k} + b_2 \cdot e^{f_2 k}$$

Where C_{ek} is the rated capacity of the battery at the k-th cycle obtained from the exponential model, and a1, a2, a3, and a4 are unknown model parameters of the exponential model and the polynomial model, respectively, which need to be obtained through parameter identification. Table 1 shows the fitting results and fitting evaluation indicators of the exponential model. As can be seen from Table 1, the exponential model can well track the changes in measured values throughout the battery life cycle.

Table 2 Simulation Table

Parameters	Group One	Group Two	Group Three	Group Four	Group Five
b1	0.9931	0.9825	0.9801	0.9861	0.9610
f1	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002
b2	-5.123e-4	-5.34e-4	-5.230e-4	-5.318e-4	-5.267e-4
f2	0.0414	0.0476	0.0438	0.0513	0.0483
R2	0.9834	0.9845	0.9942	0.9935	0.9873
RMSE	0.0054	0.0069	0.0056	0.0047	0.0066

After simplification and normalization, the mathematical model of battery capacity was obtained by fitting the capacity decay data obtained from the battery cycle aging experiment.

Where b_1 value is in the range of 0.96-0.99, f1 is in the range of -0.002 to -0.003, b2 value is -5e-4, f2 is in the range of 0.04-0.05

5. Conclusion

With the increasing number of charging and discharging cycles, the available capacity and available energy of the battery have significantly changed. The usable capacity and energy of the battery reach the maximum value when the cycle period is close to 50 times. When the cycle period approaches 200 times, the performance of the battery changes significantly, and the available capacity and energy of the battery begin to undergo significant attenuation. This is due to an irreversible chemical reaction occurring inside the battery, resulting in a reduction in recyclable Li, which attenuates the battery's capacity.

$$K_{EV} = (1 - ROUND(\frac{0.01N}{500}))(1 - N/200)$$

Where N is the number of impulse discharges. ROUND is an integer.

6. Funding details

This work was partially supported by Guangdong Science and Technology Project (2016A040403028), Foshan polytechnic project (KY2020G07), Zhongshan polytechnic project (2019KQ20). Special projects in key fields of ordinary universities in Guangdong Province(518)，Foshan Engineering Technology Research Center(4), Guangdong Provincial First-class Post-Course Funding Program(YLKC202109)

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