Validation of Remaining Useful Life Prediction of Li-Ion Battery Based on the Voltage drop

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ABSTRACT

Batteries, which are used for the energy storage and power distribution, tend to degrade, and their capacity declines with repeated charging and discharging cycles. The battery is considered to fail when it reaches 80% of its initial capacity. In general, the battery state under operation can be characterized by identifying the state of health (SOH) and state of life (SOL), which refer the capacity degradation and remaining useful life respectively. Recently, authors have found that the SOH can be indirectly estimated based on the observation that the slope of voltage curve under charging is proportional to the capacity degradation. In the study, only the full charge and discharge cycles under room temperature were conducted with Li-ion battery, which is not the case in reality. In this study, more research is conducted to find out more reliable and robust measurement of the capacity and voltage drop that may be independent of the degradation conditions. Several tests are made under various C-rates, charging stabilization time and surrounding temperatures. Once succeeded, the regression model is established between the capacity and voltage drop, that is used in the estimation of the SOH. Adaptive Particle filtering (APF) framework is then applied during the battery usage to estimate the SOH and predict the RUL in the form of a probability distribution. In the APF, the recursive state transition and measurement functions are given by the empirical degradation model and the regression model, respectively. The APF performs the two functions at the same time which are the anomaly detection and prognostics. Experiments are conducted for a Li-ion battery by repeating full charge discharge cycles, in which a fault is imbedded to change the degradation pattern at a certain moment of the cycle to illustrate the technique.

1. INTRODUCTION

Batteries are core components of many machines and are critical to the system's functional capabilities. Battery failure could lead to reduced performance, operational impairment, and even catastrophic failure, especially in aerospace systems. An efficient method for battery monitoring would greatly improve the reliability of such systems (Goebel, 2008).

In this study, first step, we made a reliability of method for measuring the capacity, and voltage drop in discharging cycle are first explored for the purpose to obtain regardless constant value regardless of different degradation history of C-rates, temperatures and so on. From the regression model is then established, which represents a relationship between the capacity degradation and voltage slope change, that is used in the estimation of the SOH, is obtained. Own experiment—for an Li-ion battery under various conditions such as temperature are used for illustrating this technique.

Adaptive Particle filtering (APF) framework is then used applied during the battery usage to estimate the SOH and anticipate the RUL, which are given by using the form of a probability distribution.

2. RELIABLE MEASUREMENT OF THE CAPACITY

Capacity is an important parameter that represents battery degradation. The accurate measurement of the capacity is hence of paramount importance, which are usually obtained by integration of the current over time under full charge cycle. The measured value, however, can vary not only by the different charging conditions but also by the different degradation histories, which are imposed by the C-rate, temperatures and so on. The incorrect capacity may lead to the poor SOH estimation. In this study, a dependable method for capacity measurement is investigated which is reliable and constant regardless of the degradation history.

3. DISCHARGE VOLTAGE DROP

It is well known that during the capacity degradation with repeated charging and discharging cycles, the voltage drop in the discharge cycle increases as are shown in Figure 1 and Figure 2, which illustrate the shift of voltage curve and their slope increases over cycles respectively. This shows that the voltage drop change can be a key for the estimation of SOH. In order to have this as a good indicator for the SOH, it should be constant as long as we have the same capacity that have underwent various degradation cycles. This is examined in this study by measuring both the voltage drop and capacity after having various degradation conditions, and checking whether they show one to one correspondence regardless of the degradation paths.

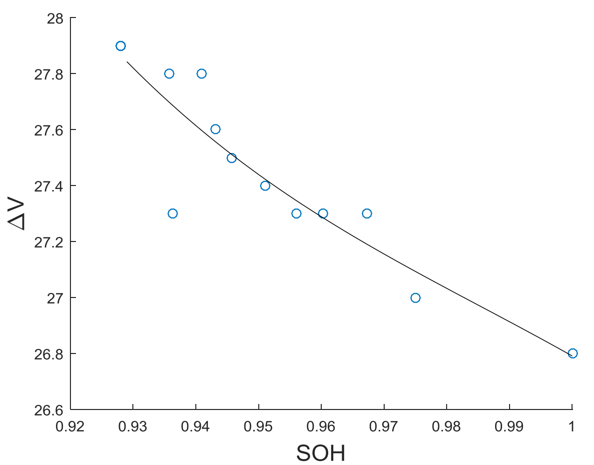

Figure 1. relationship between voltage drop and capacity

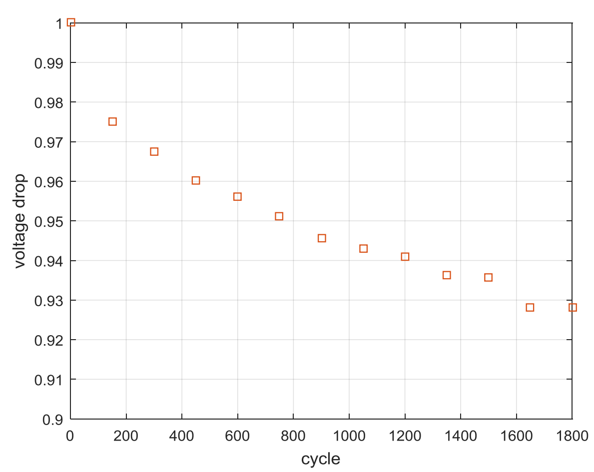

Figure 2. voltage drop increase over cycle

4. FEATURE EXTRACTION AND EXPERIMENTAL DATA

Figure 3. Experimental setup of battery degradation

Life-cycle test data for charging and discharging cycle have been collected for 1500mAh Lithium-ion cells at our own experimental test rig, which are shown in Figure 3. In the equipment, c (computer) plans charging and discharging cycles of b (batteries) and then a (programmable power supply) runs the charge and discharge cycles program from the computer to repeat the process. In order to investigate temperature effect, the batteries are operated in d (chamber).

5. ADAPTIVE PARTICLE FILTER(APF)

Adaptive particle filter algorithm predicts remaining useful life(RUL) until battery fails. As data added, RUL prediction improves. APF is more accurate than particle filter. New Adaptive Particle filter is developed to account for this, i.e., detect moment of condition change & account for it in the subsequent RUL prediction.

5.1. Prognostics Remaining Useful Life(RUL)

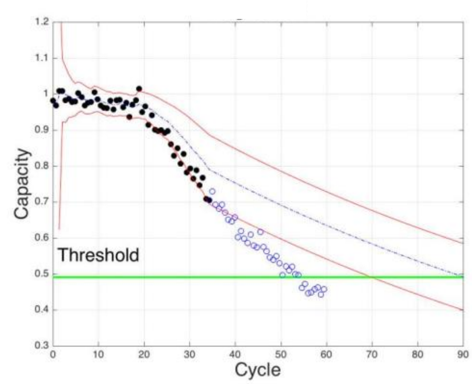

Figure 4. Traditional regression

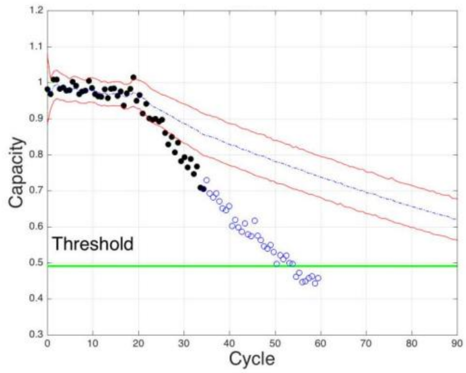

Figure 5. Ordinary particle filter

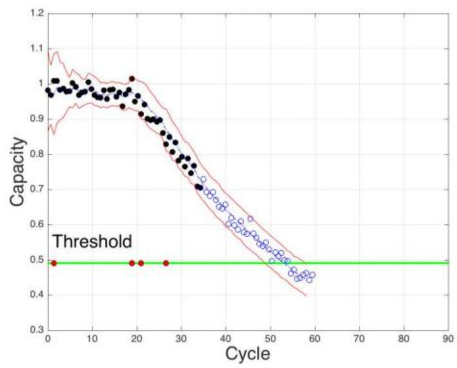

Figure 6. Adaptive particle filter

Simulation of battery capacity degradation is carried out to obtain the data which includes the condition change at the cycle 20 as shown in Figures 5 and 6. APF is applied to the data to estimate the model parameters, detect the moment of state change, and predict the RUL by accounting for this. The predictions are compared against the real end-of life thresholds to derive RUL. As seen in the figures, the result of Figure 6 by APF is much better than that by the ordinary PF of Figure 5.

Degradation data until EOL includes condition change at cycle 20. Traditional regression is no good since it makes average prediction for RUL.

Original PF does not change even after condition changes. APF detects & reflects the change real time and predicts RUL properly.

6. CONCLUSION

In this paper, reliable method to measure the capacity and voltage drop during the discharging cycle is investigated, in order to get one-to-one correspondence between the two features. Regression model is developed based on the results. Adaptive Particle Filter is applied by defining the state transition and measurement equations as the empirical degradation and regression model respectively. Experiments are conducted by repeating full charge and discharge cycles for a Li-ion battery, in which a fault is imbedded to change the degradation pattern at a certain moment of the cycle. The APF is applied to the data to estimate the SOH and predict the RUL. The result is validated by the real degradation data. The prognostic performance is evaluated by using the metrics introduced in (Saha, 2007).

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Nomenclature

SOH	Percentage of Health w.r.t. maximum charge
SOC	Percentage of charge w.r.t. maximum charge
SOL	Remaining Useful Life (RUL) until battery fails

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