CALCE BATTERY RESEARCH

IMPROVING PERFORMANCE, RELIABILITY, AND SAFETY OF BATTERY-POWERED SYSTEMS

AUGUST 2020

Taking Lithium-ion Battery Datasheets with a Degree of Skepticism

A datasheet is a document provided with a product that lists information about the product for both informational and advertising purposes. Datasheets typically define the basic capabilities and performance characteristics, including product composition, methods of use, operating requirements, common applications, and product warnings.

A complete battery datasheet describes the requirements of the battery type to be supplied to customers by the battery manufacturer. Lithium-ion battery datasheets are not only used for selecting the most appropriate battery for an application but also serve as guidance for product manufacturers to develop battery management systems for enhanced performance, reliability, and safety.

A confusing term or parameter will make it difficult to verify the datasheet and may cause legal issues between buyers and battery manufacturers. Academia also tests commercial lithium-ion batteries per the datasheet for modeling and degradation/failure/protection mechanism analysis. However, no papers have explored the various problems in lithium-ion battery datasheets.

There are numerous problems with lithium-ion battery datasheets, including discrepancies in terminology, ambiguity, lack of critical performance parameters, and misleading statements. For example, there are up to five capacity terms specified in different datasheets, which are rated capacity, minimum capacity, typical capacity, nominal capacity, and standard capacity. However, the testing conditions that define these capacity terms are often not mentioned. Moreover, battery manufacturers often do not provide a datasheet to low-volume customers. Instead, these customers must search for the datasheet online and often find multiple different datasheets for the same battery type (e.g., Panasonic NCR18650B cells).

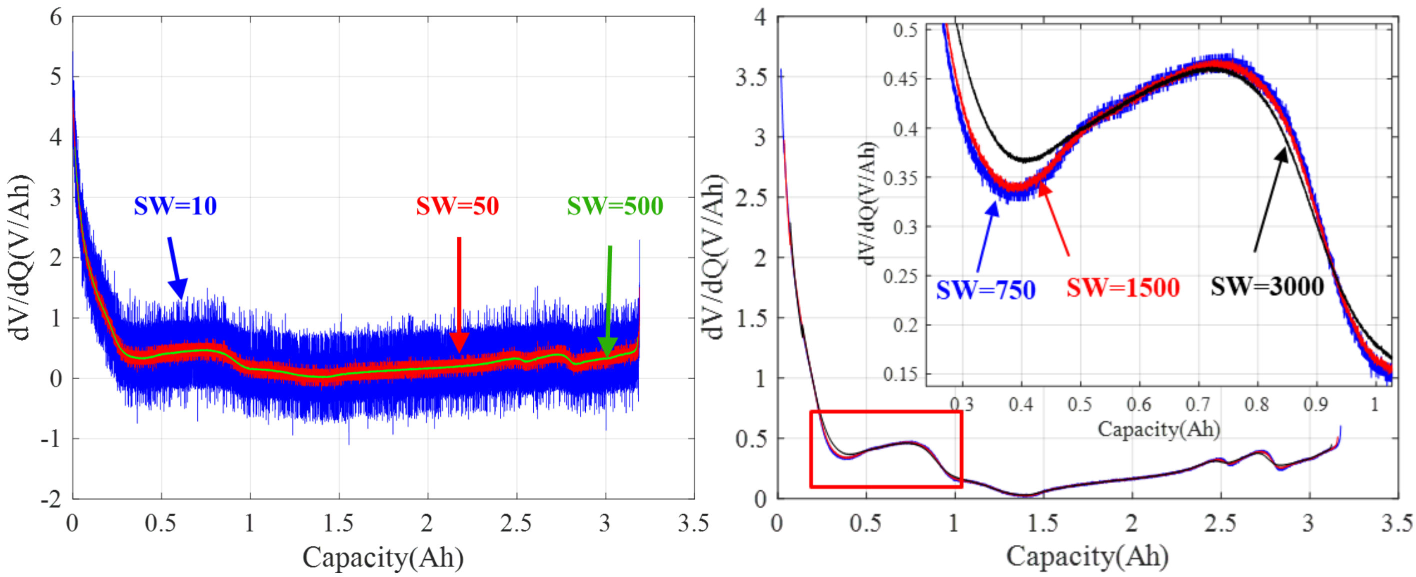
CALCE is reviewing and evaluating the datasheets of more than 20 different lithium-ion battery types from 9 major battery manufacturers. For more questions, please contact Weiping Diao: **wdiao@umd.edu**.

INSIDE THIS ISSUE:

Smoothing Metrics for Differential Voltage Curves and Incremental Capacity Curves

Li-ion batteries have successfully employed as power sources in a variety range of applications ranging from smartphones to electric vehicles (EVs). The irreversible capacity loss during calendar life and cycle life is still the critical scientific focus of Li-ion battery technology. It is common to perform post-mortem analysis by disassembling the battery to interpret the capacity degradation mechanism. However, non-destructive investigations have drawn attention in both industry and academia to characterize the state of health and understand the degradation mechanism without the efforts of opening batteries.

Differential voltage (DV) analysis and incremental capacity (IC) analysis are widely used non-destructive analysis methods that take identify degradation mechanisms for the on-going tested Li-ion batteries. However, the charge/discharge data at low currents with a subtle voltage/capacity change makes the DV/IC curves very noisy, which will affect the subsequent features extraction and mechanism analysis.



Smoothing results under the smoothing window(SW) from 10 to 3000.

The above figures show the smoothing results for a DV curve using the moving average method under smoothing windows (SW) from 10 to 3000. Increasing the smoothing windows from 10 to 500 can decrease the noise but from 750 to 3000 deform the shape of the DV curve. Not only the smoothing window but also the data quality (e.g., charge/discharge current, data sampling frequency), and smoothing algorithms (e.g., moving average, least-squares, and Savitzky-Golay filter) influence smoothing results. It is challenging to select the appropriate smoothing window for the DV/IC curves just by trial-and-error methods.

The DV/IC curves smoothing results of the same charge/discharge data may vary from person to person because there is no evaluation metrics for the smoothed results. The ideal smoothing results should have high signal-to-noise ratios and remain the primary peaks/valleys information. CALCE is currently designing metrics to evaluate the smoothed DV/IC curves for adaptive DV/IC curve smoothing.

Li-ion Battery Degradation Analysis using Voltage-Temperature Colormap and Differential Capacity Analysis

Differential analysis of electrical cycling data in li-ion batteries is a non-destructive method to measure degradation. The shifts and change in the peaks and valleys obtained from the differential data provides insight on electrode level degradation, voltage slippage, phase equilibrium (cathode and anode), etc. It has been reported that the changes in peak of the differential curve has direct correlation with the state-of-health of battery and have been quantified to measure loss in individual electrode capacity, or loss of Li-ions. However, the complexity of battery degradation depends on imposed operational conditions and the differential curve can evolve due to multiple degradation mechanisms contributing in an inter-dependent fashion. Even changing simple operational conditions like the current, temperature, or voltage may result in subtle path differences in the evolution of these differential curves. In this research, we use 22 different test conditions to obtain 50,000+ cycling data which is then converted to voltage-temperature colormap as stress factor (shown in figure 1) and the corresponding differential capacity curve as the effect (capacity and power fade) caused due to these stress factors (shown in figure 2). Machine Learning algorithms are then employed to predict the evolution of these differential curves after training on first few cycles of each test condition. Accurate long-term cycling/calendar life prediction through first few cycles allows us to cut our future test times by a factor of 10.

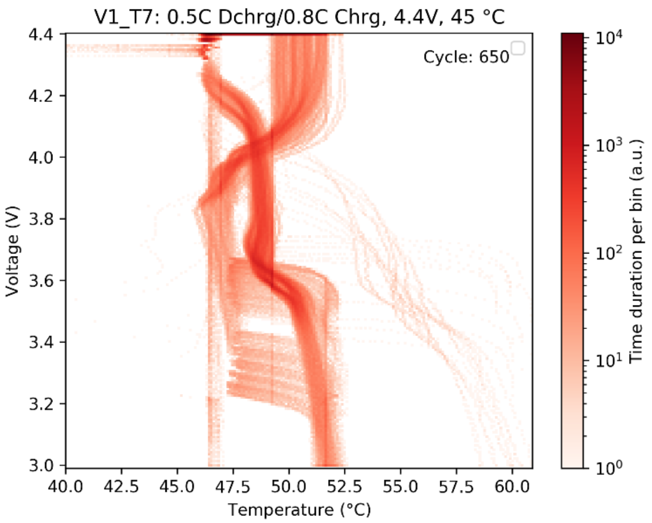


Figure 1. Battery Voltage-Temperature colormap as stress factors.

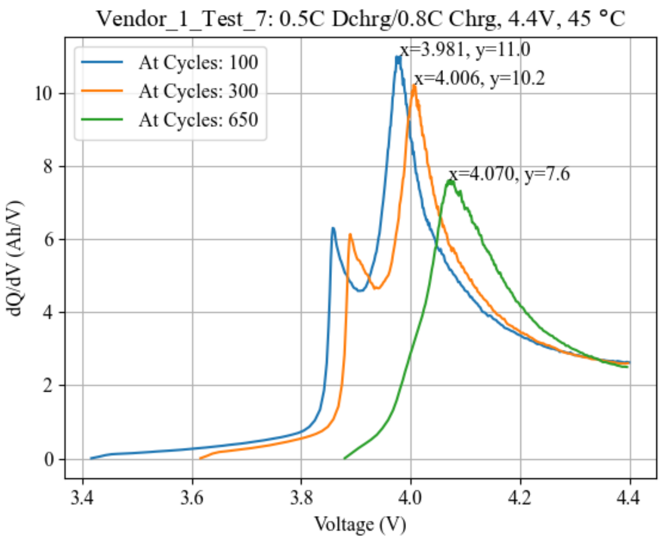


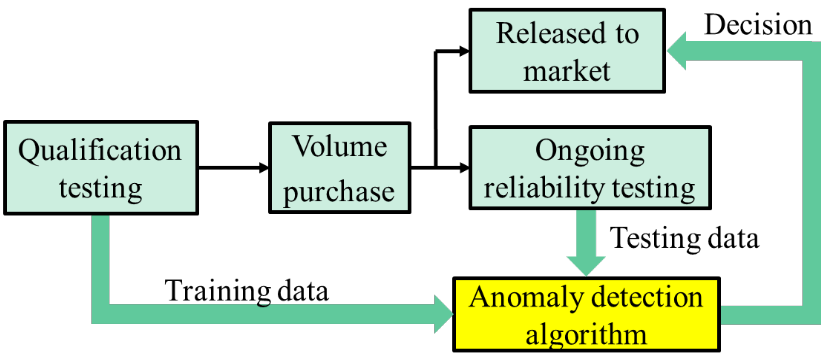
Figure 2. Evolution of battery Differential Capacity curve with cycling.

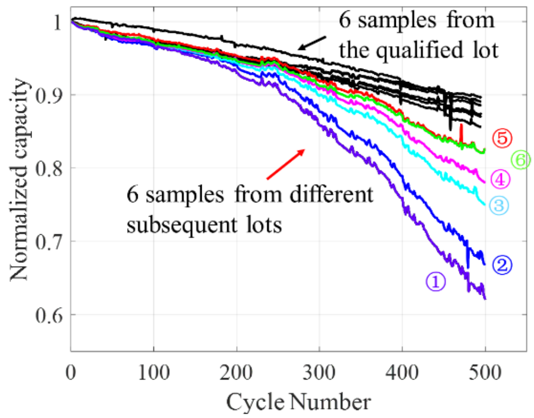
Figure 1 shows the accumulated cycling data as histogram and binned to fill voltage-temperature nodes (the damaging factors, this graph has 40,000 such nodes) which contain the length of time the batteries were in these nodes during cycling. The data points in the input are cumulatively added to signify the accumulating damage in the battery.

Figure 2 shows differential curve (in right) after 100th, 300th, and 650th cycle. The green line in fig 2 corresponds to the evolved differential curve due to accumulated degradation from figure 1. The differential capacity curve shows changes and shifts in the peaks as the degradation accumulates signifying capacity and power fade.

Early Detection of Anomalous Degradation Behavior in Lithium-ion Batteries

Before lithium-ion batteries are purchased in volume, they are typically tested (qualified) to determine if they meet the life-cycle reliability requirements for the targeted applications. To ensure that subsequent production lots of batteries continue to meet the reliability requirements, ongoing reliability testing is often conducted on production lot samples. However, a key challenge is how to quickly determine if the samples have substantially similar reliability as those batteries that were initially qualified, and, in particular, how to detect early signs of unacceptable degradation. This paper uses five data-driven methods (regression model with prediction bound, one-class support vector machine, local outlier factor, Mahalanobis distance, and sequential probability ratio test) to detect anomalous degradation behavior of samples from actual production lots subjected to ongoing reliability tests. An ensemble approach was then developed because it was observed that no single method always gave the earliest warning. The approach can be used by device companies for warranty, recall, and technical decisions. **The paper is recently published in the Journal of Energy Storage.**





Aging Modes Analysis and Physical Parameter Identification Based on a Simplified Electrochemical Model for Lithium-ion Batteries

Due to the limited measurements, battery internal failures are hard to quantitatively assess. This work develops a method to quantitatively analyze battery aging modes under different aging conditions and selectively extract the internal indicators to track the battery health state. Considering the changes in physical parameters can reflect the deterioration inside a battery, a simplified electrochemical model that has good identifiability of battery model parameters is introduced, and battery physical parameters are obtained via their functional relationships with the model parameters. The battery aging modes under different aging conditions are then analyzed according to the variations of physical parameters during a battery's lifetime. Lastly, analysis of the correlations between physical parameters and battery state of health is conducted, and health indicators are correspondingly selected. This work can quantificationally analyze the degree of different aging modes from a mechanism perspective, help accurately estimate battery state of health, and predict battery remaining useful life, which has important theoretical significance and practical value for improving the technical level of battery management. **The paper is recently published in the Journal of Energy Storage.**

Open Access to CALCE Battery Data

CALCE is conducting a study in collaboration with six battery manufacturers and two consumer electronics manufacturers to develop accelerated qualification test plans to reduce overall testing time. Multiple stress factors, including temperature, discharge C-rate, and rest time during cycling, have been used in this study to characterize battery degradation behavior and find novel test methods to accelerate the testing. The data from this study is available on the CALCE Battery Database website free of charge.

The CALCE Battery Database contains data from previous studies and experiments as well. The data from these tests can be used for battery state of charge and health estimation, remaining useful life prediction, accelerated battery degradation modeling, and reliability analysis. CALCE has published many articles using this data. The following researchers are among those who have used CALCE battery data for their research: Prof. Daniel T. Schwartz from the Department of Chemical Engineering at the University of Washington, Prof. Malcolm D. McCulloch from the Department of Engineering Sciences at the University of Oxford, Dr. David Flynn from Heriott-Watt University, and Dr. Datong Liu from the Department of Automatic Test and Control at Harbin Institute of Technology. The cycling data has been generated using Arbin, Cadex, and Neware battery testers. Impedance data has been collected using Idaho National Laboratory's Impedance Measurement Box (IMB). For questions on the CALCE Battery Database, contact Michael Pecht (pecht@umd.edu).

Recent CALCE Battery Publications

The following are recent CALCE publications on Li-ion batteries. For more information, visit the CALCE battery website: https://calce.umd.edu/battery-publications.

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- Li, J., Wang, L., Lyu, C., Wang, D., Pecht, M. (2019). Parameter Updating Method of a Simplified First Principles-Thermal Coupling Model for Lithium-ion Batteries. Applied Energy, 256, 113924.
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