calce™ BATTERY RESEARCH

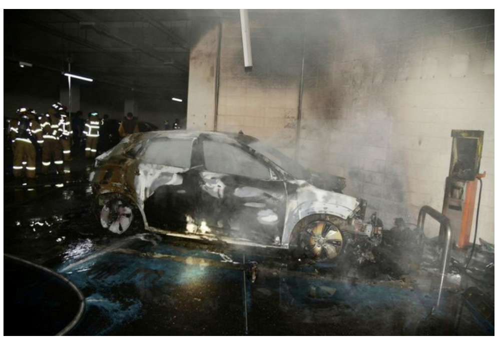
IMPROVING PERFORMANCE, RELIABILITY, AND SAFETY OF BATTERY-POWERED SYSTEMS

MARCH 2021

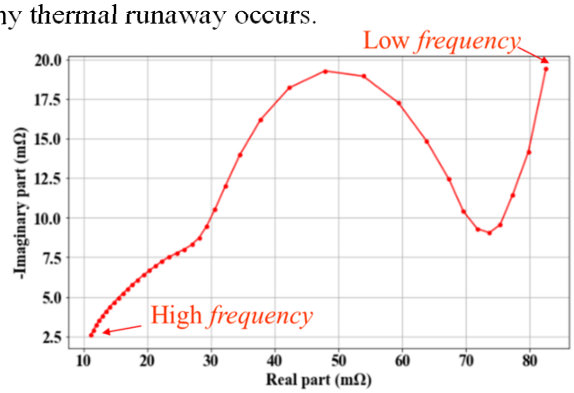
Using Machine Learning to Analyze Electrochemical Impedance Spectra of Lithium-ion Batteries

In October 2020, WM Motor, a startup electric vehicle producer backed by Tencent Holdings and Baidu, issued a recall of more than 1,000 vehicles after four of its automobiles caught fire in just a month, according to several news reports. Hyundai Motor Co. is being sued over a string of battery fires in its electric vehicles just as General Motors recalls nearly 70,000 electric vehicles that use batteries from the same maker, LG Chem Ltd.

One question has been raised for these issues — “is the battery management system (BMS) defective?”. If working properly, couldn’t they have flagged overheating battery cells, taken preventative measures, or provided alarms for users and EV suppliers? A BMS should monitor cell voltage, current, impedance, and temperature to detect suspicious cells and provide early warnings well before any thermal runaway occurs.



A burnt Hyundai Kona electric vehicle



EIS spectrum

Electrochemical impedance spectroscopy (EIS) is commonly employed to evaluate the transport phenomena and electrochemical reactions of lithium-ion batteries. As a non-destructive diagnostic technique, EIS can be applied before battery operation to prognose potential safety risks. For example, manufacturer defects and foreign objects in the cells can lead to internal shorts and will present a lower battery impedance than normal values. The aging of cell components will cause impedance rise and power decay. Both examples can result in battery overheating, swelling, and even thermal runaway, fire, and explosions.

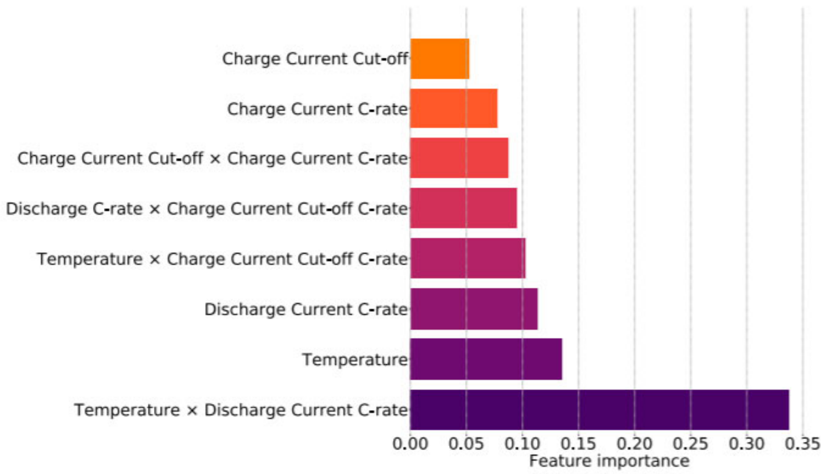
To identify attributes of the impedance spectrum that may be of value in understanding the electrochemical processes in batteries that traditional equivalent circuit models cannot provide, the CALCE battery team is applying machine learning and deep learning algorithms to analyze the EIS spectra for battery degradation analysis.

INSIDE THIS ISSUE:

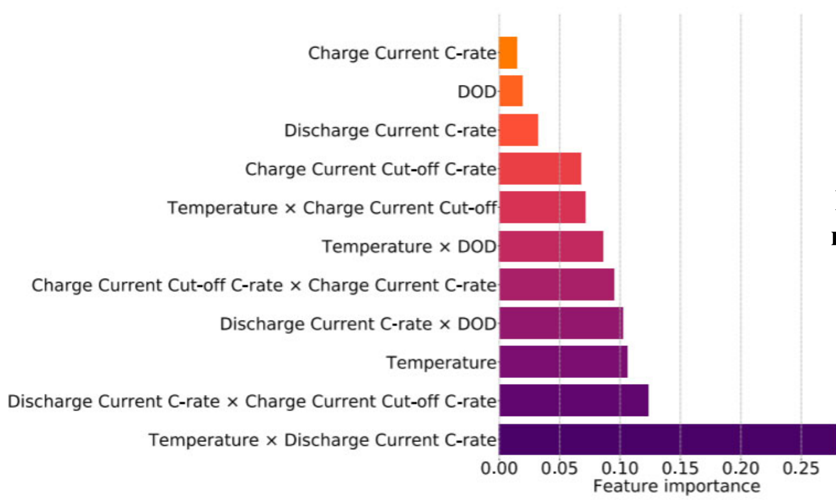
USING MACHINE LEARNING TO ANALYZE ELECTROCHEMICAL IMPEDANCE SPECTRA OF LITHIUM-ION BATTERIES	1
USING MACHINE LEARNING FOR BATTERY STRESS FACTOR RANKING AND ACCELERATED DEGRADATION TEST PLANNING	2
LITHIUM-IRON-PHOSPHATE BATTERY ELECTROCHEMICAL MODELLING UNDER A WIDE RANGE OF AMBIENT TEMPERATURES	3
LITHIUM-ION BATTERY FAILURE MODES, MECHANISMS, AND EFFECTS ANALYSIS (FMMEA)	4
RISK IDENTIFICATION OF CELL ACTIVATION VARIABLES USING PROCESS FAILURE MODES, MECHANISMS, AND EFFECTS ANALYSIS OF LI-ION POUCH CELLS	5
CALCE BATTERY DATABASE	6
CALCE BATTERY PUBLICATIONS WITH 50+ CITATIONS	6

Using Machine Learning for Battery Stress Factor Ranking and Accelerated Degradation Test Planning

Electronic device companies conduct qualification tests on lithium-ion battery samples for degradation assessment prior to mass purchase and deployment. Qualification testing involves repeated charge–discharge operation of the batteries, which can take more than three months if subjected to 500 cycles at a C-rate of 0.5C. Accelerated degradation testing can be used to reduce the qualification testing time, but its application requires a careful selection of stress factors. To address this challenge, stress factors are identified and ranked in terms of their effects on battery degradation (capacity fade) using half-fractional design of experiments and random forest algorithm. The random forest algorithm can identity the most significant input variables by outputting the feature importance.



Manufacturer 1: Random forest (RF) results for predictor variable (feature) ranking in decreasing order of importance



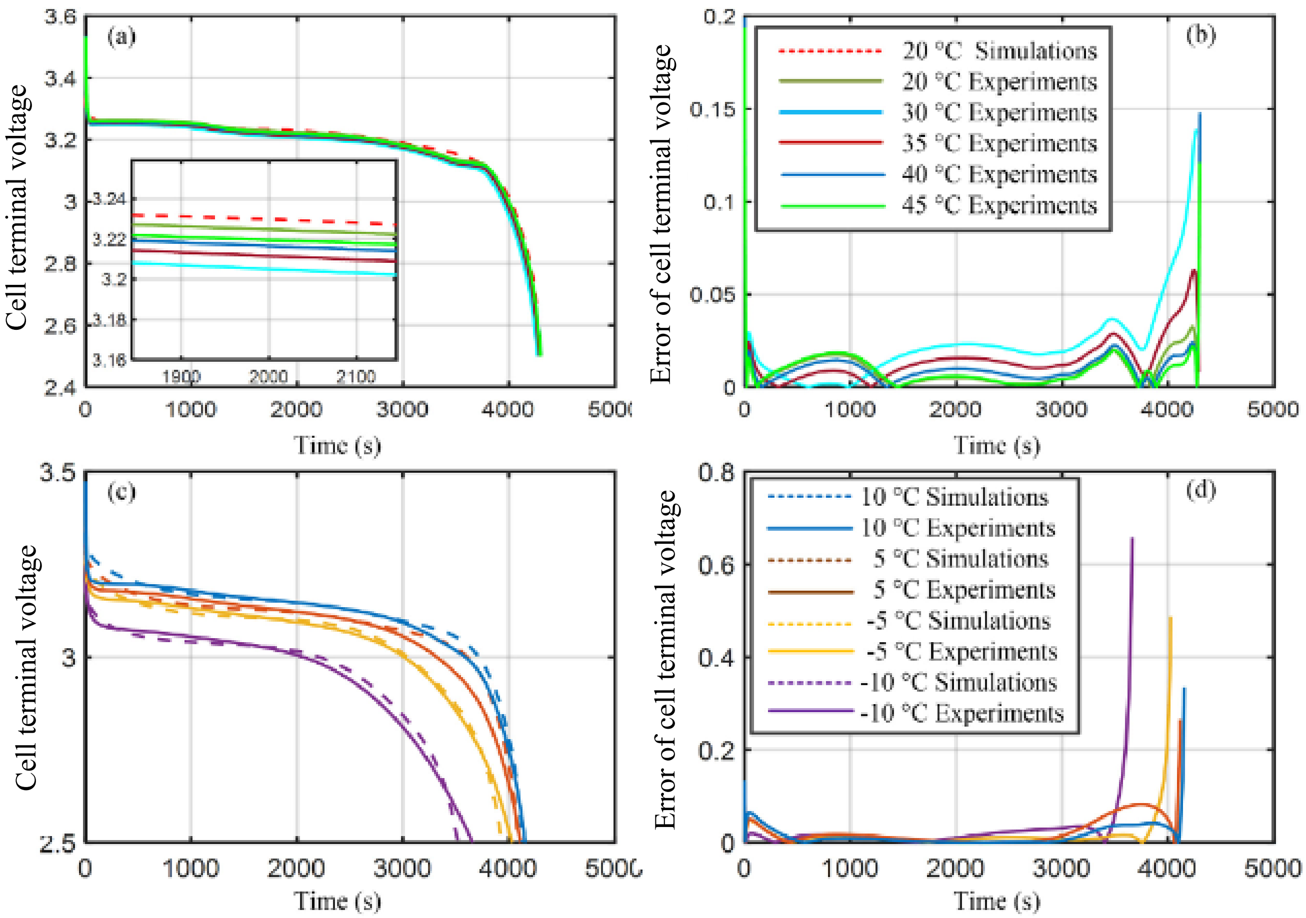
Manufacturer 2: Random forest (RF) results for predictor variable (feature) ranking in decreasing order of importance

Two case studies are presented involving 96 lithium-ion batteries from two different manufacturers, tested under five different stress factors. Results show that neither the individual (main) effects nor the two-way interaction effects of charge C-rate and depth of discharge rank in the top three significant stress factors for the capacity fade in lithium-ion batteries, while temperature in the form of either individual or interaction effect provides the maximum acceleration.

The study is published in Energies.

Lithium-iron-phosphate Battery Electrochemical Modelling that Works under a Wide Range of Ambient Temperatures

The performance of lithium-iron-phosphate batteries changes under different ambient temperature conditions and deteriorates markedly below 10 ℃. This work models and simulates the discharge characteristics of lithium-iron-phosphate batteries under ambient temperatures ranging from -10 ℃ to 45 ℃. Modifications based on an existing electrochemical model are carried out to reduce the simulation error compared to the measurement values at temperatures below 10 ℃. Excitation response analysis and a multi-group particle swarm optimization algorithm are used to identify the model parameters.



Simulations of terminal voltage and errors for cell B3

The simulation results indicate that when the ambient temperature is 20 ℃ or above, the mean absolute errors of the terminal voltage are within 20 mV. At lower temperatures of −10 ℃ to 10 ℃, the mean absolute errors of the terminal voltage are 9–14 mV for single cells and 11–21 mV for battery packs. Analytic function methods including Hermite interpolation, polynomial fitting, and sinusoidal fitting are adopted to handle the uncertainties of model parameters at different ambient temperatures for practical application. This work is useful for establishing an accurate battery state of charge estimator with an efficient parameter identification method under a wide range of ambient temperatures.

The study is published in the Journal of Power Sources.

Lithium-ion Battery Failure Modes, Mechanisms, and Effects Analysis (FMMEA)

Lithium-ion batteries have various applications in modern society ranging from smartphones to grid storage. In the past decades, the energy density of single lithium-ion cells increased. And battery packs are being used beyond portable devices. Battery packs contain thousands of cells are also used in electric vehicles and energy storage systems. Along with the lithium-ion battery market's growth, the severity of and possible damage from potential battery-related incidents are also increasing. Battery systems can fail in various ways. In the moderate failure case, several cells' malfunction may cause the downtime of a facility or equipment. However, in the worst situation where the battery causes a fire or explosion, resulting in property damage or physical injury, or death. A list of all possible failure modes of a battery is necessary to take proactive methods to improve the design and prevent the battery from operating in dangerous zones. Although battery packs may contain more subsystems than just batteries, such as the battery management system and the cooling system, conduct the initial analysis on the single cell level is fundamental.

The failure modes, mechanisms, and effects analysis (FMMEA) of lithium-ion batteries can provide a rigorous framework to define how lithium-ion batteries can fail, how failures can be detected, what processes cause the failures, and how to model failures for failure prediction. In addition, FMMEA gives priority to failure modes needed to guide the design, operation, and maintenance in practice. For conducting the FMMEA analysis, the battery components are identified. The analysis will be conducted hierarchically from the cell level and the system level. In consideration of the battery design and its operation, battery failure can cause capacity decay, electrical resistance increase, copper dissolve, short circuit, gas generation, aluminum dissolve, shutdown, electrolyte dry out, open circuit, fire/explosion. These failure modes can be prioritized based on likelihood, suddenness, the difficulty of detection, and severity, as shown in the table below. For quantitative analysis, scores are assigned to the different levels (1-low, 2-moderate, 3-high). A battery FMMEA analysis can enable the battery health and safety prediction and also facilitate the failure mitigation.

Failure Modes	Likelihood of occurrence	Severity of occurrence	Difficulty of detection	Suddenness	Scores
Capacity decay	High	Moderate	Low	Low	7
Resistance increase	High	Moderate	Low	Low	7
Copper dissolve	Low	Moderate	High	Low	7
Short circuit	Low	High	Low	Moderate	7
Gas generation	High	Moderate	High	Moderate	8
Aluminum dissolve	Low	Moderate	High	Low	7
Shutdown	Low	High	Low	High	8
Electrolyte dry out	Low	Moderate	Moderate	Low	6
Open circuit	Low	Moderate	Low	High	7
Fire/Explosion	Low	High	Low	High	8

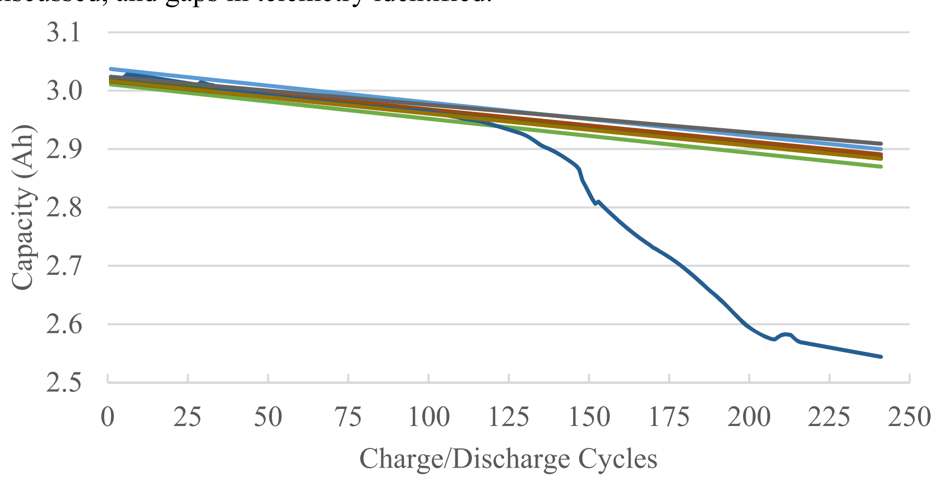
Risk Identification of Cell Activation Variables Using Process Failure Modes, Mechanisms, and Effects Analysis of Li-ion Pouch Cells

Increased demand for Li-ion batteries has a downside; to meet the industry's needs, Li-ion battery manufacturers need to increase throughput. The increase in throughput can come at the expense of quality control leading to potential risks to the end customer. We identify the risks inherent at each manufacturing step and provide a qualitative assessment of which steps are most critical to customers' safety and satisfaction. The formation process is one of the critical steps of manufacturing that can affect the Li-ion battery at all stages of its useful life, playing a critical role in determining the useful life.

The industry understands that there are safety risks when using Li-ion batteries. However, the genesis of the safety risks is not as well understood. It is crucial for device manufactures to know that not all Li-ion battery manufacturers are the same and that much of the performance and safety concerns in the application are affected by the Li-ion battery manufacturing process. Li-ion battery failures related to manufacturing errors are a common occurrence, examples of recalls due to manufacturing defects include the Samsung Galaxy 7, Sony notebook computers, and hoverboards. Risks may be reduced when manufacturers follow best practices, however, the gap in practices between top tier and lower-tier manufacturers is significant enough that entire processes may be skipped.

Lithium-ion battery cell activation is a multistep process made up of wetting, aging, cycling, and degassing. There are four goals of a cell activation process: electrolyte absorption, solid electrolyte interphase (SEI) formation, gas removal, and performance verification. Of primary interest is the SEI formation, which occurs during the subprocess step called the formation process. The formation process describes the first charging and discharging cycles of the battery cell and is responsible for creating an interface layer between electrolyte and electrode (SEI layer) necessary for Li-ion cell function. Lithium/carbon intercalation compounds on the negative electrode are unstable in all known electrolytes, and therefore the surfaces, which are exposed to the electrolyte, must be protected by SEI layers. The formation process is treated as a trade secret by cell manufacturers. Overall, the cell activation process varies for each cell manufacturer and is dependent on cell design and chemistry.

This work is exploring the process, and relative operational failure mechanisms, used during cell activation. The process, types of failures, and resulting failure mechanisms are being identified and analyzed regarding the steps taken during the formation process and how the SEI layer is generated. Variables of interest for each failure will be discussed, and gaps in telemetry identified.



Capacity retention after 250 cycles

As an experiment of manufacturing consistency, capacity retention was tested for ten Li-ion batteries from the same vendor, built during the same work order, and operating the same test profile on the same test equipment. The graph to the left shows an anomalous sample that passed the manufacturers exit criterion. The outlier illustrates the risk of manufacturing variance. A PFFMEA will be performed to identify the process step that would introduce this variance.

Open Access to CALCE Battery Data

CALCE is interested in growing the body of knowledge to improve battery reliability and safety. To this end, CALCE is providing open access to its battery test data. The CALCE Battery Database contains data from our research and experiments. 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, and we encourage others to do the same. The cycling data has been generated using Arbin, Cadex, and Neware battery testers. Impedance data has been collected using the Idaho National Laboratory's Impedance Measurement Box (IMB). For questions on the CALCE Battery Database, contact Michael Pecht (pecht@umd.edu).

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