In-Operando Variable Charge Rate Monitoring and Prognostics for Battery Safety

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Benefits of Li-ion Batteries [1]

- Lithium-ion batteries have higher energy densities and greater design flexibility
- Different cell chemistries provide higher energy, power, and cycle life for different applications

Potential Hazards of Li-ion Batteries

LIB shipment fire [2]

USS Bonefish [4]

Boeing 787 [3]

Samsung Galaxy Note 7 [5]

EV crash fire [6]

Testing Standards

- NAVSEA 9310 [7], Sandia FreedomCAR [8], SAE International Surface Vehicle Recommended Practice [9], United Nations Manual of Tests and Criteria Section 38.3 [10]
  - Electrical abuse tests (overcharge/discharge, high rate charge/discharge, short circuit, separator integrity)
  - Thermal abuse tests (high temperature, thermal shock, thermal stability)
  - Mechanical abuse tests (penetration, drop, immersion, roll-over, mechanical shock, vibration, impact, pressure, crush)

Knowledge gaps

• Limited research on the use of machine learning algorithms for in-operando cycle life prediction of LIBs on a BMS incorporating accident effects.

• Limited investigation on the in-operando performance of machine learning models using public data for battery life prediction.

• Lack of publicly available datasets with high-quality data for training the neural network models for predicting battery capacity and life cycle.
Outline

• Battery Health Monitoring System helps track
  - Voltage
  - Current
  - Temperature

• Prediction of LIB capacity
  - CD-Net model developed at Interfacial Multiphysics Laboratory.

• Edge-cloud communication
  - Advanced Encryption Standard (AES) encrypted data transfer
BMS and SOH

- SOC and SOH monitoring are the main concerns and the basis to improve reliability and ensure LIB safety.
- Online measurement of chemical parameters inside batteries is limited to inputs from BMS- [Current, Voltage, Temperature]
- SOH estimation infers if LIBs need to be replaced with new ones.
  - SoH is the maximum possible charge a battery can hold compared to the rated capacity

\[
\text{SoH} = \frac{Q_{\text{max}}}{Q_{\text{nominal}}}
\]

Where:
- \(Q_{\text{nom}}\) : nominal capacity of the un-aged battery
- \(Q_{\text{max}}\) : maximum available capacity in battery

Safety Map – Lab Base Data

Risk Assessment Matrix

<table>
<thead>
<tr>
<th>Probability</th>
<th>Expected</th>
<th>Likely</th>
<th>Possible</th>
<th>Unlikely</th>
<th>Rare</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Med-low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Expected</td>
<td>Med-low</td>
<td>Medium</td>
<td>Med-low</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Likely</td>
<td>Low</td>
<td>Med-low</td>
<td>Medium</td>
<td>Med-high</td>
<td>Med-high</td>
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<tr>
<td>Possible</td>
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<td>Med-low</td>
<td>Medium</td>
<td>Med-high</td>
<td>Med-high</td>
</tr>
<tr>
<td>Unlikely</td>
<td>Low</td>
<td>Med-low</td>
<td>Medium</td>
<td>Med-high</td>
<td>Med-high</td>
</tr>
<tr>
<td>Rare</td>
<td>Low</td>
<td>Low</td>
<td>Med-low</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Negligible</td>
<td>Minor</td>
<td>Moderate</td>
<td>Considerable</td>
<td>Significant</td>
<td></td>
</tr>
</tbody>
</table>

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Background

Predicting battery health is divided into three distinct styles [12]

• Experimental
• Physical Models
• Data-Driven Machine Learning

With recent advancements in machine learning and big data technology, data-driven algorithms have gained substantial popularity.

Requirements for modern RUL prediction approaches [13]

• Voltage
• Current
• Temperature


Background: BMS

Disadvantages to modern designs [19]

- Limited local computing resources
- Lack of flexibility in usage
- Hard-programmed models


https://doi.org/10.3390/batteries8020019
Review of Recent Testing

• Random forest regression [20]
  – Features from charging voltage and capacity measurements are used in a random forest regression to estimate capacity without requiring preprocessing

• Incremental capacity analysis for capacity estimation [21]
  – Incremental capacity peaks are used to develop a relationship with state of charge and estimate capacity

• Charging current for capacity estimation [22]
  – Adaptive capacity estimation method using incremental capacity curves from multiple charging conditions and cells with differing ages


Review of Recent Testing

- Failure mechanism during nail penetration [23]
  - Penetration at the center of a cell causes the most severe thermal runaway, surface temperature not positively correlated with penetration depth

- Thermal runaway induced by nail penetration [24]
  - Maximum temperature is higher and is reached in less time for radial penetrations as opposed to axial

- Deformation and failure under axial nail penetration [25]
  - Two possible failure modes (pinching or puncturing electrode layers), nail velocity has no clear effect on failure properties

Battery Health Monitoring System

Temperature Sensor

Voltage & Current Sensor

MAX31865

INA219

Micro-controller
Arduino Uno Rev 2

V, I, T

Encryption

Communicaton Platform
(ThingSpeak)

No-go operational signal

Edge-Cloud BMS
for Device swarm
at IML
Battery Health Monitoring System

Communication Platform (ThingSpeak)

CD-Net

© Interfacial Multiphysics Laboratory, CD-Net algorithm developed by Sudarshan et al.(Refer to paper) [26]

CD-Net testing on open source

Filtering Techniques

Unprocessed

Processed

Prediction Improvement

Unprocessed

Processed
Experiments - ground

Voltage (V) vs. Time (hrs)

Current (mA) vs. Time (hrs)

Temperature (°C) vs. Time (hrs)

Capacity (mAh) vs. Cycle Number
Experiment - Drone
Conclusion

**BHMS**

- BHMS showed close results to the Battery Analyzer values for the voltage and current.
- Edge and cloud communication was successfully established.

**CD-Net**

- Predicted capacity shows comparable values of capacity over the 10 cycles.
- By filtered data the prediction of CD-Net can be improved.

**Drone versus ground**

- Random current discharge were performed
- Discharge rate was at most 4C
- No-go signal based on SoC of battery
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Questions?
Background: Battery Cycling

Lithium-ion batteries degrade over time as they cycle
• A full cycle consists of a discharge and charge
• CC and CCCV are common charge algorithms
• C-rate of a battery
Lithium-ion Battery: Benefit and Market

Lithium-ion Battery World Markets: 2022-2032[2]

[1] Figure by Multiphysics Lab, data from http://batteryuniversity.com/learn/archive/whats_the_best_battery
To practice safe operation of LIB batteries
   - State of Health needs to be examined during battery abusing operations.
   - Thermal runaway needs to be detected.
- Continuous monitoring of LIB is necessary!

Data loggers (DAQs) exist, but they are bulky, expensive, and application-specific

- National Instruments
- Omega Eng
- Battery Analyzers (BAn)

Figure : omega Engineering USB DAQ [16]

Figure : Neware BTS400 Battery Analyzer [14]

Figure : National Instruments DAQ options [15]

Edge-Cloud communication

Data transfer from edge and cloud is Encrypted with AES.

CBC encryption [1]

Integrating LIB abuse

- Mechanical abuse testing, nail penetration
  - Previous study by Dr. Casey at Interfacial Multiphysics Lab

- Future work-
  - use nail penetration integrated with BHMS.