Data-driven Prediction of Battery Cycle Life Before Any Capacity Loss Has Occurred

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Overview

Timeline

- Project Start Date 9/2017
- Project End Date 3/2019
- Percent Complete: 100%

Barriers

Life—Need to be able to predict life at an early stage in order to drastically shorten time required to test new charging protocols

Partners

MIT

Stanford

Toyota Research Institute

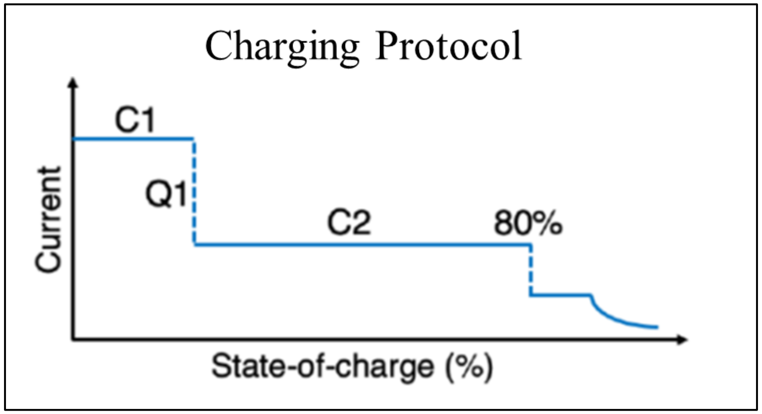
LBL

Relevance

- Project Objective
  - Drastically shorten the lab time required to test a new (extreme fast) charging protocol.
- Goal
  - Accurately predict the cycle life of a test battery even before any fade has been detected
- Impact
  - Enables identification of the best fast charge protocols
  - Enables faster adoption of EVs

Approach

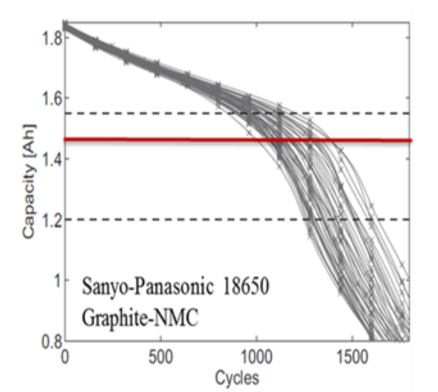
- Find the best extreme fast charge protocol
  - A123 LFP high power cells
  - 48 testing channels, 30A current per channel
  - 3.6 C to 6 C
  - *T*-controlled environment, but up to 10° C rise for individual cells



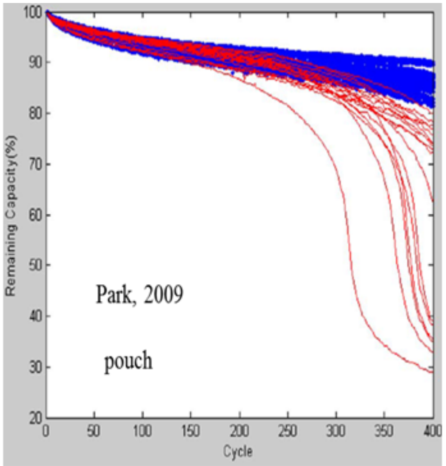
- 2-step extreme fast charging protocol (10 minutes to 80% SOC)
- C1 and C2 are the 1st and 2nd currents, Q1 is the SOC at switch point.
- Beyond 80%, charge at 1C to 3.6 V, then potentiostatically at 3.6 V

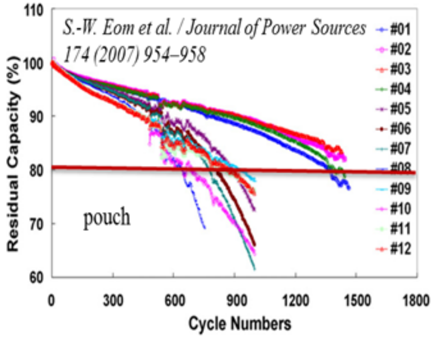
Technical Accomplishments
Predicting Cycle Life

- Demonstrate that failure in commercial cells is statistical, not deterministic



T. Baumhöfer et al. / Journal of Power Sources 247 (2014) 332–338





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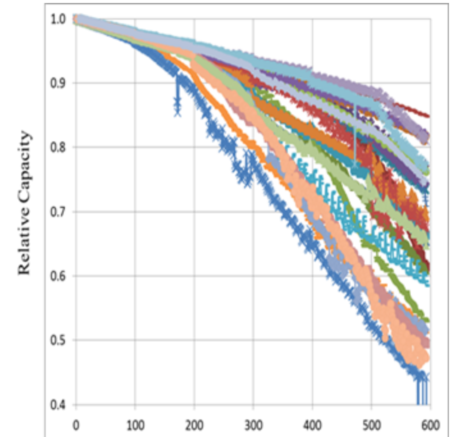
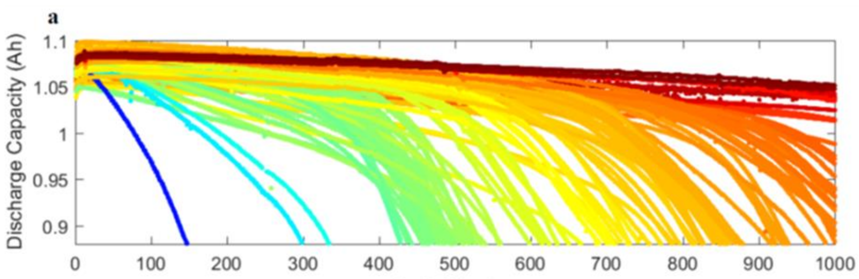


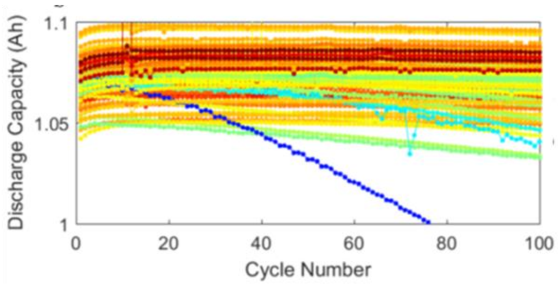
Harris et al, *Journal of Power Sources* **342** (2017) 589

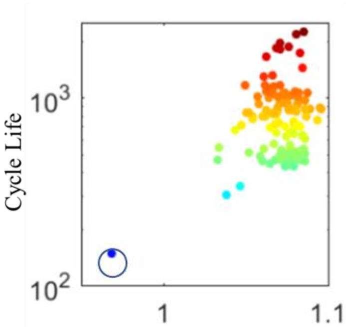
- Initially, all cells degrade linearly ~ the same rate. Then substantial variability sets in.
- With everything under strict control, we still can't predict a battery's life to much better than a factor of 2

Technical Accomplishments
Predicting Cycle Life

ANALYSIS







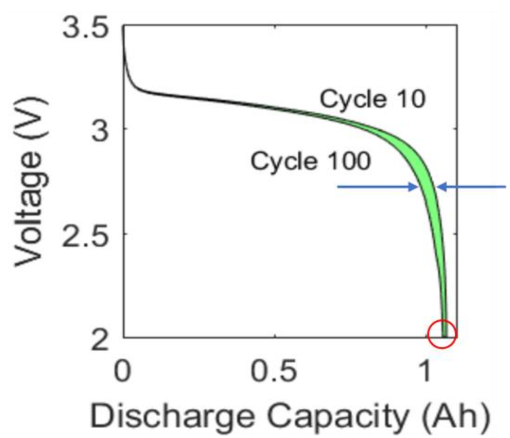
Discharge capacity at cycle 100 (Ah)

Cannot predict cycle life from capacity fade during the fist 100 cycles

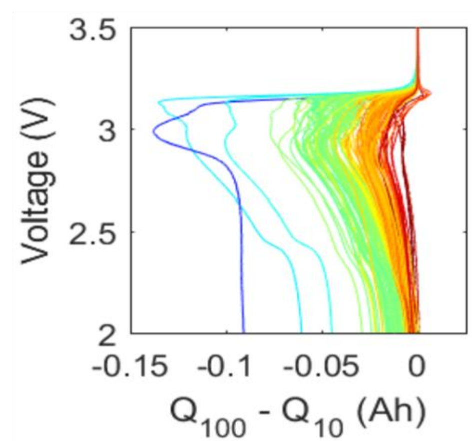
- How do we generate capacity fade data?
  - By throwing away almost all our information
  - All of the voltage information is ignored
- Difference curves capture information from the entire cycle

$$\int \Delta Q_{100-10}(V)dV = Energy\ lost \sim \mu$$

$$Var = \sigma^2 = \int \Delta Q_{100-10}^2(V)dV - \mu^2$$



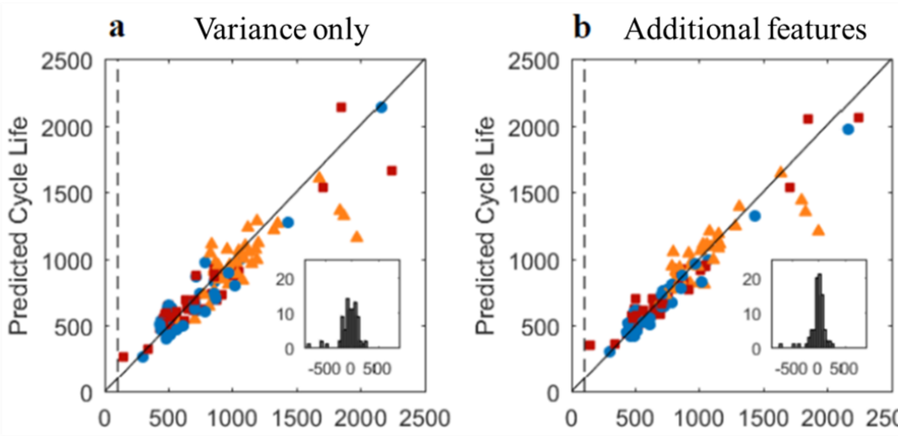
Difference Curves



Technical Accomplishments
Predicting Cycle Life

PREDICTIONS MADE AT CYCLE 100

- Variance alone can make excellent predictions
- Other features that can improve the predictions include
  - $\min(Q_{100} - Q_{10})$
  - Slope of the discharge curve, cycles 2-100
  - Intercept of the discharge curve, cycles 2-100
  - Discharge capacity, cycle 2
  - Average charge time, first 5 cycles
  - Integral of temperature, cycles 2-100



13% average error

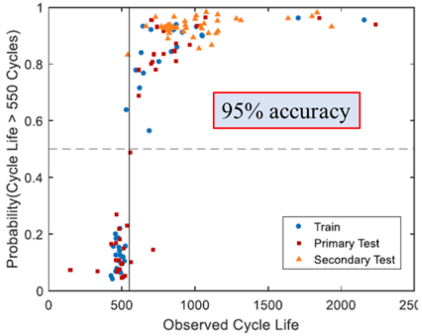
9% average error

PREDICTIONS MADE AT CYCLE 5

Classify cells at the factory (a few hours at 5C) into:

"Economy" cells for reduced cost

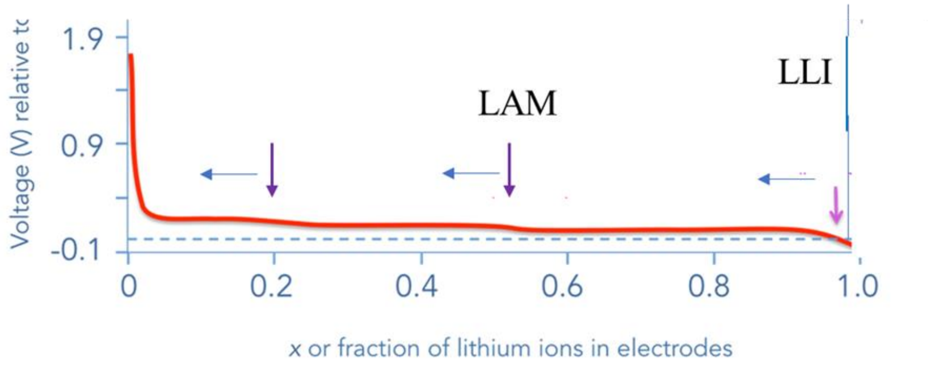
"Premium" cells for improved range (greater SOC window)

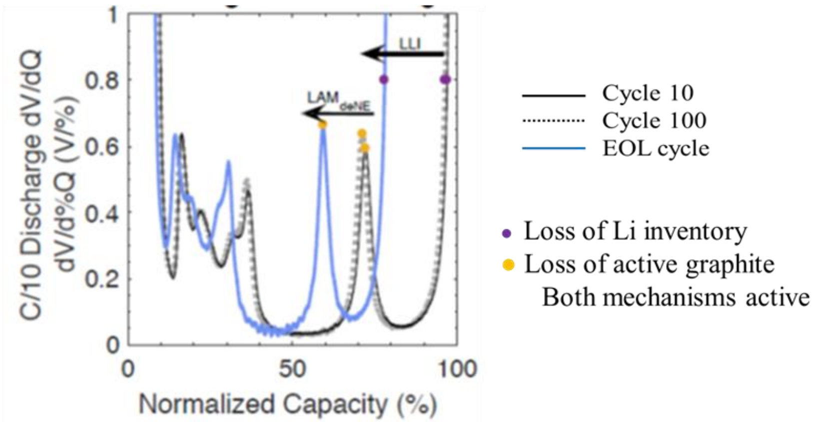


Technical Accomplishments
Predicting Cycle Life

INTERPRETATION

- How can we predict fade at cycle 100, before there is any fade?
- Identify a degradation mode that changes` the voltage profile, but that does not affect the capacity





Remaining Challenges and Barriers

- A purely data-driven model made successful early life predictions
  - But only for a single battery chemistry, LFP
  - Only for a specific pair of failure modes

- Can a data driven model be successful for other chemistries and more complex failure modes?

Future Plans

- Test our data-driven approach for NMC
  - How much can we rely on machine learning and how much physical insight do we need?

- Determine best fast-charge protocols
  - Where we require a relatively small number of cycles to evaluate any given protocol

Any proposed future work is subject to change based on funding levels

Summary and Conclusions

- Data-driven modelling can predict battery life
- Early prediction (at 100 cycles) permits rapid evaluation of new chemistries and protocols
- In-factory classification (at 5 cycles) permits cells to be labeled “economy” or “premium”
- The secret? Don’t throw away all the voltage data