Advances in Lithium Ion Cells for EV

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Is it possible to do fast-charging and get long life?

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Yes

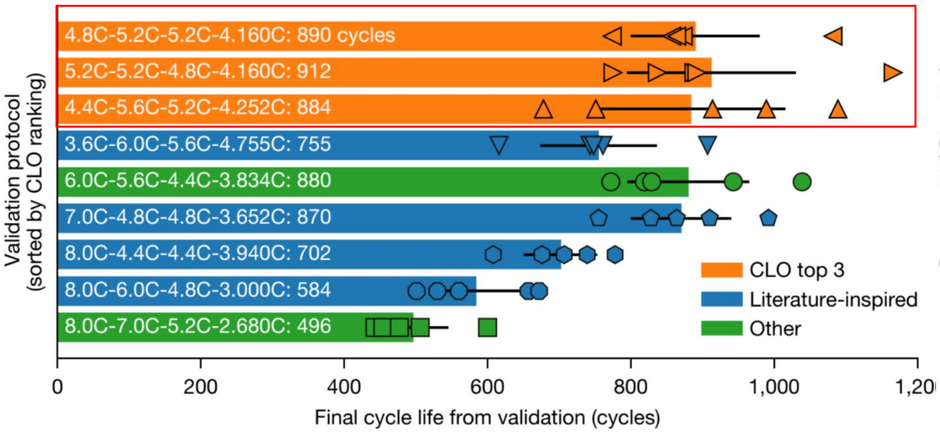
Attia, Grover et. al. Nature 2020

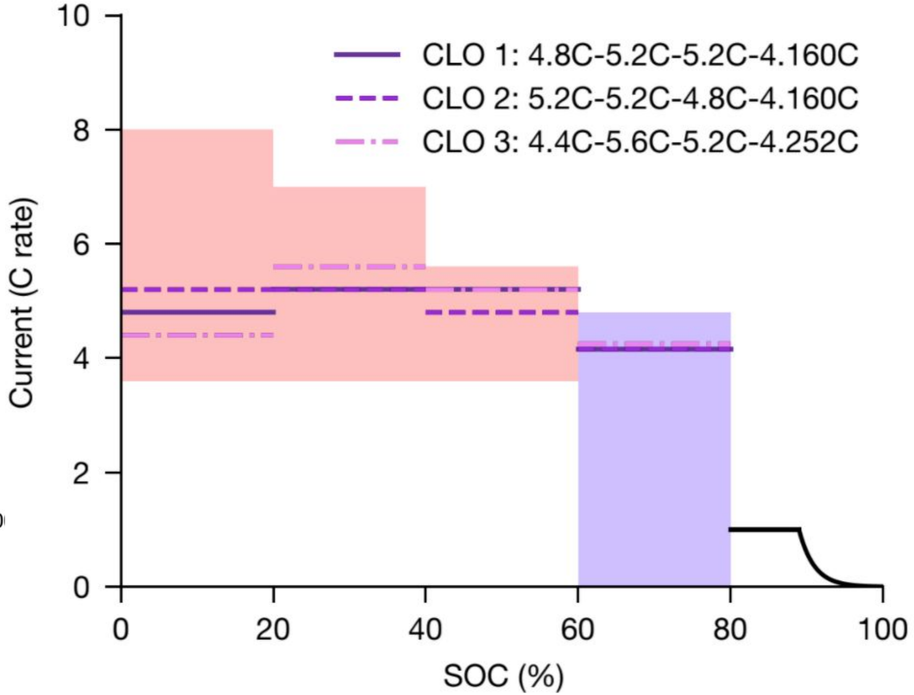
< 10 mins

What is fast charging?

3 discovered fast charging policies

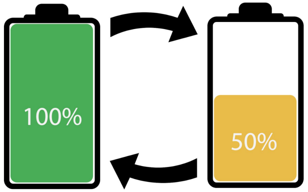
Attia, Grover et. al. Nature 2020



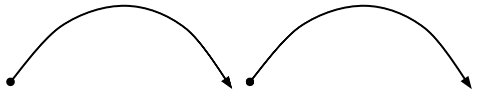


2 key ideas

- Early cycle life prediction model.
  - Predicts life of battery from beginning-of-life 100 cycles.
  - Reduces the number cycles required in each test.

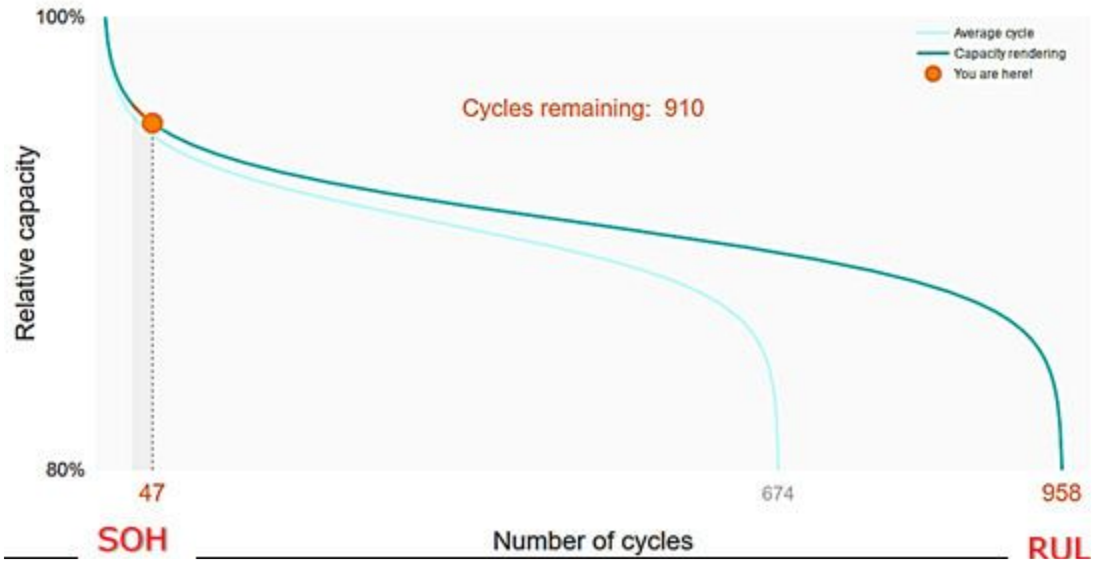


- Experimental design optimization.
  - Predicts next protocol/experiment to test.
  - Reduces the number of experiments.



Early life prediction

- Predict battery life given beginning-of-life 20 or 100 cycles.
- State of Health (SOH) : How many cycles has the cell lived through?
- Remaining Useful Life (RUL) : How many cycles will it last before EOL?



Experiment design optimization

- Predict cycle life for points in the parameter space.
- Identify set of parameters for next experiment
  - reduce uncertainty
  - higher cycle life

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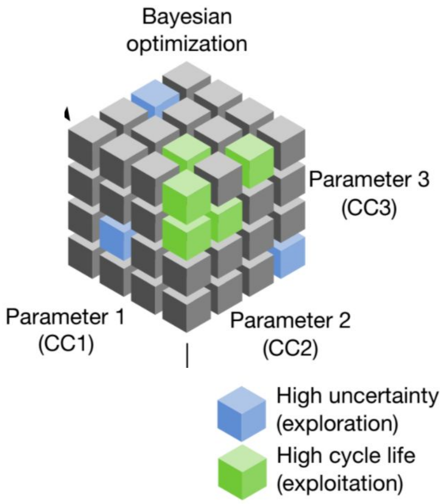

Parameter space: CC1, CC2, CC3

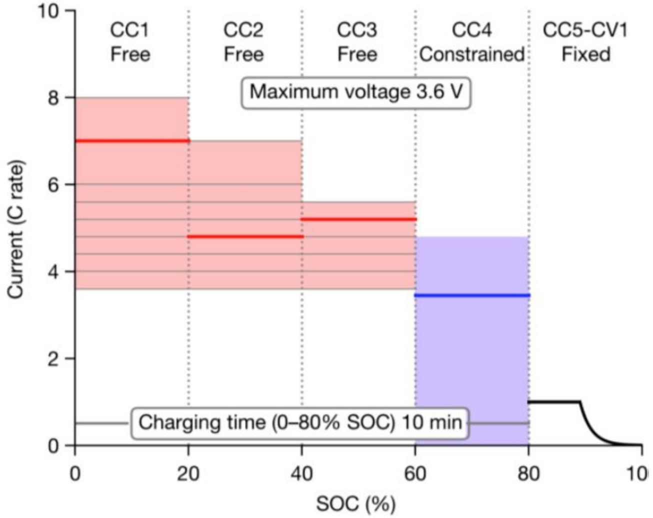

Fig. 2 | Structure of our six-step, ten-minute fast-charging protocols. Currents are defined as dimensionless C rates; here, 1C is 1.1 A, or the current required to fully (dis)charge the nominal capacity (1.1 A h) in 1 h. **a**, Current versus SOC for an example charging protocol, 7.0C–4.8C–5.2C–3.45C (bold lines). Each charging protocol is defined by five constant current (CC) steps followed by one constant voltage (CV) step. The last two steps (CC5 and CV1) are identical for all charging protocols. We optimize over the first four constant-current steps, denoted CC1, CC2, CC3 and CC4. Each of these steps comprises a 20% SOC window, such that CC1 ranges from 0% to 20% SOC, CC2

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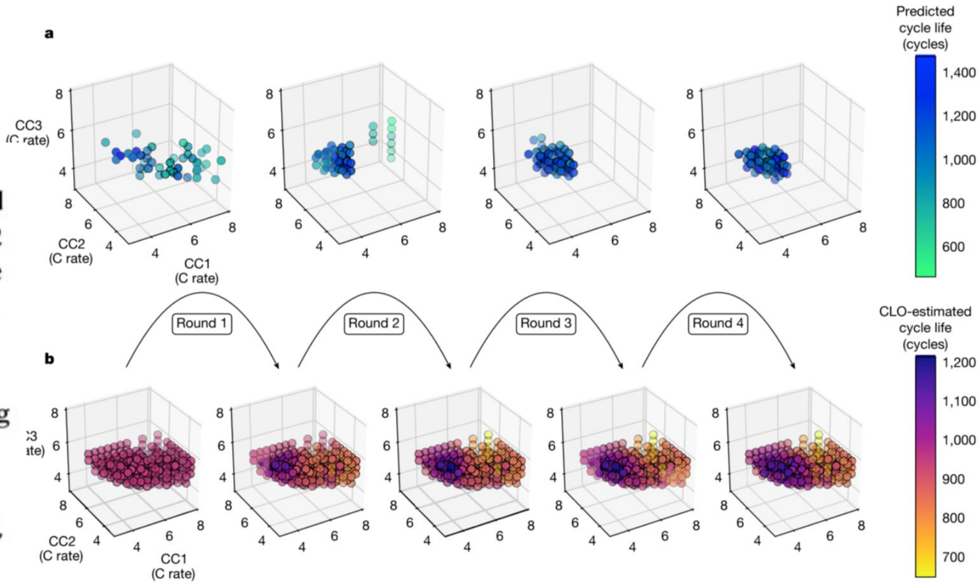
Design optimization

Fig. 3 | Results of closed-loop experiments. a, Early cycle life predictions per round. The tested charging protocols and the resulting predictions are plotted for rounds 1–4. Each point represents a charging protocol, defined by CC1, CC2 and CC3 (the *x*, *y* and *z* axes, respectively). The colour scale represents cycle life predictions from the early outcome prediction model. The charging protocols in the first round of testing are randomly selected. As the BO algorithm shifts from exploration to exploitation, the charging protocols selected for testing by the closed loop in subsequent rounds fall primarily into the high-performing region. **b**, Evolution of the parameter space per round. The colour scale represents cycle life, as estimated by the BO algorithm. The initial cycle life estimates are equivalent for all protocols; as more predictions are generated, the BO algorithm updates its cycle life estimates. The CLO-estimated mean cycle lives after four rounds for all fast-charging protocols in the parameter space are also presented in Extended Data Fig. 5 and Supplementary Table 3.



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Closed loop optimization

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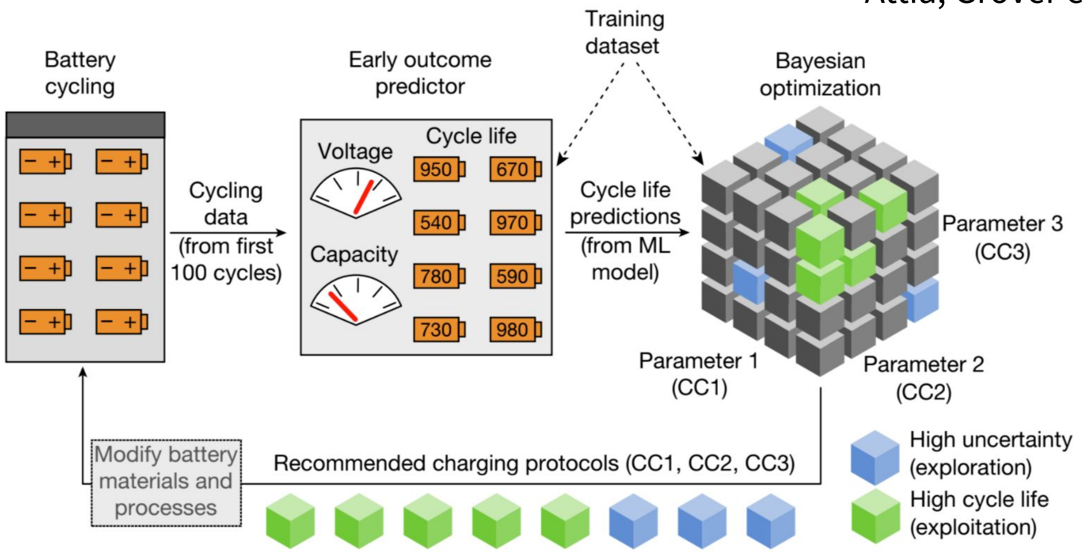
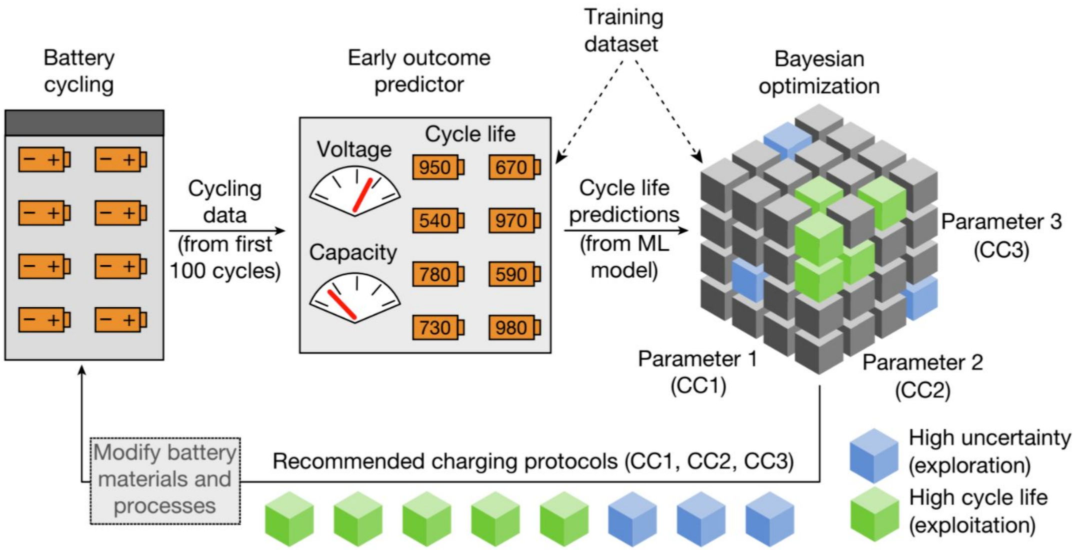


Fig. 1 | Schematic of our CLO system. First, batteries are tested. The cycling data from the first 100 cycles (specifically, electrochemical measurements such as voltage and capacity) are used as input for an early outcome prediction of cycle life. These cycle life predictions from a machine learning (ML) model are subsequently sent to a BO algorithm, which recommends the next protocols to test by balancing the competing demands of exploration (testing protocols with high uncertainty in estimated cycle life) and exploitation (testing protocols with high estimated cycle life). This process iterates until the testing budget is exhausted. In this approach, early prediction reduces the number of cycles required per tested battery, while optimal experimental design reduces the number of experiments required. A small training dataset of batteries cycled to failure is used both to train the early outcome predictor and to set BO hyperparameters. In future work, design of battery materials and processes could also be integrated into this closed-loop system.

Early life
prediction model



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Key steps

- Early cycle life prediction model.
    - Predicts life of battery from beginning-of-life 100 cycles.
    - Reduces the number cycles required in each test.
- Experimental design optimization.
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Need data.

Generate data.

What is fast charge? - Tolerable time 10mins

Battery capacity - C is Ampere hrs - rating of battery - charge holding capacity

Pumping charge is current, Time is known

What should be the current to charge battery to capacity in a given amount of time. If battery takes 60 mins charge and you want to charge 10 mins - this is 6C charge

Premise: Typically fast charging negatively battery life.

Discovery: There exists a fast charging policy that is capable of retaining long life.

There exists a policy of charging the battery that can be used to charge battery fast and get long life.

That policy is atypical and complex.

How can we discover the policy for a given battery?

Given battery → particular design, material, make, conditions are fixed

You can build a model

Conditions that

What are the conditions that need to be known?

- Temperature range in which battery operates
- Charge / Discharge current range
- Voltage at which battery is going to operate

We can build a model based on generating lots of data under these conditions.

How to minimize the number of experiments during data collection?