MACHINE LEARNING PREDICTION OF BATTERY CYCLE LIFE

Kristen A. Severson[1*], Peter M. Attia[2*], Norman Jin[2], Nicholas Perkins[2], Benben Jiang[1], Zi Yang[2], Michael H. Chen[2], Muratahan Aykol[3], Patrick K. Herring[3], Dimitrios Fraggedakis[1], Martin Z. Bazant[1], Stephen J. Harris[4], William C. Chueh[2†], Richard D. Braatz[1†]

* These authors contributed equally to this work

† Corresponding authors: wchueh@stanford.edu, braatz@mit.edu

Affiliations:

1 Department of Chemical Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA

2 Department of Materials Science and Engineering, Stanford University, Stanford, CA, USA

3 Toyota Research Institute, Los Altos, CA, USA

4 Materials Science Division, Lawrence Berkeley National Lab, Berkeley, CA, USA

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Abstract

Lithium-ion batteries are widely deployed in applications due to having low and falling costs, high energy densities, and long cycle lives (Dunn et al., 2011; Nykvist and Nilsson, 2015; Schmuch et al., 2018). Accurate prediction of cycle life using early-cycle data would unlock new capabilities in battery manufacture, optimization, and use. For example, manufacturers could accelerate the cell development cycle, perform rapid validation of manufacturing processes, and sort/grade new cells by their expected lifetime. Likewise, end users could estimate the battery lifetime expectancy (Peterson et al., 2010; Ramadesigan et al., 2012; Waag et al., 2014). The task of predicting cycle life for lithium-ion batteries is challenging because of nonlinear degradation with cycling and wide variability, even when controlling for operating conditions (Schuster et al., 2015; Harris et al., 2017; Baumhöfer et al., 2014).

Approaches using statistical and machine learning techniques to predict cycle life are mechanism-agnostic alternatives. A growing body of literature (Waag et al., 2014; Wu et al., 2016) applies machine learning techniques for predicting the remaining useful life of batteries using data collected under both laboratory and real-world conditions. Predictions are made after accumulating data corresponding to degradation of at least 25% along the trajectory to failure (Hu et al., 2014; Zhang et al., 2018) or using specialized measurements at the beginning of life (Baumhöfer et al., 2014). Accurate earlier prediction of cycle life – when significantly less degradation has occurred – is challenging due to nonlinearities in the battery degradation, uncertainties in degradation processes, and the limited availability of datasets that span a limited range of lifetimes (Saha and Goebel, 2007). For example, capacity values at cycle 80 were only weakly correlated to capacity values at cycle 500 for 24 cells exhibiting nonlinear degradation (Harris et al., 2017). Opportunities for improving upon state-of-the-art prediction models include higher accuracy, earlier prediction, greater interpretability, and broader application to a wide range of cycling conditions.

This poster summarizes recent work in the construction of data-driven models that accurately predict the cycle life of commercial lithium-iron-phosphate (LFP)/graphite cells using early-cycle data, with no prior knowledge of degradation mechanisms (Severson *et al.*, 2019). Cycle life (or equivalently, end-of-life) is defined as

the number of cycles until 80% of nominal capacity. A dataset was generated that consisted of 124 cells with cycle lives ranging from 150 to 2300 by using 72 different fast-charging conditions. For quantitative prediction of cycle life, our feature-based models achieved prediction errors of 15% using only discharge voltage curves from the 10^{th} and 100^{th} cycles, at which point most batteries have yet to exhibit capacity degradation. The test error reduced to 9.1% by incorporating data from additional cycles, internal resistance, and temperature measurements. We also demonstrate classification into low- and high-lifetime groups with a test error of 4.9% only by using data from the first 5 cycles. These results illustrate the power of combining data generation with machine learning to predict the behavior of complex systems far into the future.

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