Li-ion Battery Health Estimation Using Ultrasonic Guided Wave Data and an Extended Kalman Filter

2021 IEEE Applied Power Electronics Conference and Exposition (APEC) | 978-1-7281-8949-9/21/$31.00 ©2021 IEEE | DOI: 10.1109/APEC42165.2021.9487367

Anthony Bombik, Sung Yeon Sara Ha, Mohammad Faisal Haider, Amir Nasrollahi, and Fu-Kuo Chang
Aeronautics and Astronautics, *Stanford University*
Stanford, CA
ajbombik@stanford.edu

State estimation for Li-ion batteries is difficult due to the limited number of measurement parameters available: voltage and current. Furthermore, thus far, there is not a physical model to accurately and directly link the measurement parameters to the two battery states we would like to estimate, state of charge (SoC) and state of health (SoH). Several approximate models such as the equivalent circuit model and single-particle model have been developed to correlate SoC with the measurable parameters, but no such model exists for correlating SoH . Ultrasonic guided waves have been used in many nondestructive testing and evaluation applications. This work uses ultrasonic guided wave features to detect battery degradation and thereby measure battery SoH, introducing the opportunity to make online SoH estimation feasible. A novel set of state estimation parameters and transition equations is proposed and used with an Extended Kalman Filter (EKF) to compare with results from using only current and voltage measurements.

Keywords— Li-ion, State of Health, extended Kalman filter, EKF, ultrasonic guided waves

I. Introduction

Methods for SoH estimation can mainly be classified into three categories: (1) direct measurement, (2) model-based state estimation approaches, and (3) data-driven approaches [1-4]. In direct measurement, the batteries are fully charged and discharged to obtain the static battery capacity. Beyond that, resistance measurements are also used to evaluate battery SoH. This is a rather straightforward method, but it requires strictly constrained cycle testing conditions, and data can only be collected at the completion of each cycle, which is on the order of hours. The main concept of the model-based SoH estimation is to connect online battery signals with the battery's SoH using a battery model. In many cases, the SoH model parameters need to be estimated using a nonlinear state estimator; hence, the introduction of the EKF. Data-driven approaches are based on processing a great amount of multifaceted experimental data. These approaches have attracted increasing attention because of their flexibility and model-free characteristics but require a plethora of experimental data for training, which are slow to obtain in the case of SoH. Recent works have turned to ultrasonic guided wave signal processing to correlate changes in signal properties with battery material degradation and, therefore, SoH [5-6]. While this method shows promising correlations between measurable signal properties and SoH, the mechanical composition of each individual battery is unique and requires individual tuning. Other groups have tried hybrid methods such as directly measuring SoH at the end of every cycle while estimating SoC for all time, given the current estimate for SoH, but this only works in constant current discharge [7-8]. The work presented here introduces an empirical model correlating ultrasonic guided wave signal data with battery SoH. Rather than using copious amounts of experimental data to train an empirical model, the model parameters are entered as static states in an EKF that simultaneously estimate battery SoC and SoH while tuning the model parameters. A comparison between the various SoH estimation methods and their advantages and disadvantages is shown in Table 1.

II. Method of Approach

A. Ultrasonic Guided Wave Method

The method of ultrasonic wave propagation to sense atomic mechanical changes has been deployed in aerospace and civil nondestructive damage detection for years. The underlying principles when applying the ultrasonic method to Li-ion batteries remain the same: the ability for the ultrasonic wave to propagate through the material depends on the atomic structure.

TABLE I. Comparison between State of Health Estimation Methods

Method	Advantages	Disadvantages
Direct Measurement	Simple, model free, accurate in laboratory environment	Strict cycling conditions, updates on the time scale of a full charge/discharge cycle
Model-based State Estimation	Health related parameters can be measured frequently and nondestructively in any environment	Varying levels of accuracy depending on the model, available measurements, and operating conditions
Machine Learning	Accurate, model free, adaptive, frequent measurements	High dependency on the completeness, quantity, and quality of experimental training data
Ultrasonic wave based EKF	High accuracy model, adaptive, frequent measurements, no dependency on experimental training	Poor performance prior to model convergence

In aerospace composite structures, the change in the signal response is correlated to matrix cracking and delamination, while in Li-ion batteries, the change in signal response relates to the changing atomic structure of the battery electrode surfaces as the lithium ions intercalate between the electrode layers or the solid electrolyte interphase (SEI) layer grows in the process of battery degradation. The former correlates with SoC, while the latter correlates with SoH. Unfortunately, the two effects are indistinguishable; therefore, the ultrasonic data must either be taken at the same SoC value in consecutive charge/discharge cycles to track SoH, or SoC must be separately estimated in the current state and used to retract SoC effects from the ultrasonic signals.

Figure 1 shows the dependency of SoH on the different measurable qualities of the ultrasonic guided wave: time of flight (ToF) and signal amplitude (SA). For comparison, the relative independence of SoH and voltage is shown in Figure 1a to illustrate the difficulty of estimating SoH from the standard battery outputs. All cycle data was taken at full charge, SoC=100%. Because similar correlations exist between SoC and signal response, it is possible to separate the two states given the two features [5].

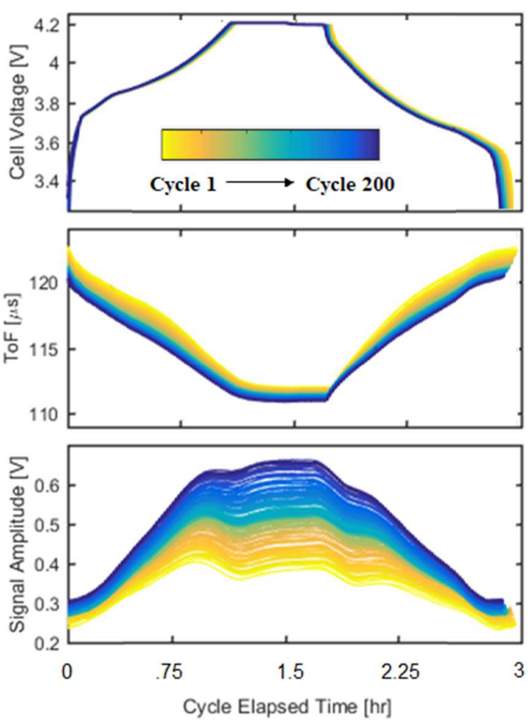

Figure 1: Evolution of ultrasonic signal parameters by cycle. top) cell voltage middle) signal travel time from actuator to sensor (ToF) bottom) signal amplitude

B. Experimental Setup

The proposed technique is evaluated on commercial Li-ion pouch cells in a 30°C temperature-controlled environment (graphite/NMC chemistry; 3,650 mAh capacity; free-standing and stationary condition). Figure 2 shows the schematic diagram of the experimental setup. The guided waves were propagated and sensed using low-profile, built-in piezoelectric disc transducers that can be retrofitted onto off-the-shelf batteries, as shown in Figure 2. In a two-sensor configuration, one sensor is used as an actuator and the other as the receiver (Figure 2). A 5-count tone burst signal at 125 kHz was used as an excitation signal. The ultrasonic data acquisition system (Scan-sentry) was synchronized in real-time with a high-accuracy battery analyzer that performs battery charging and discharging, allowing SoC to vary from 100% fully charge state to 0% discharge state (0.85 C discharging rate for 120 cycles). Voltage, current, and piezo measurements were taken every one minute for the duration of the discharge for use in the EKF algorithm.

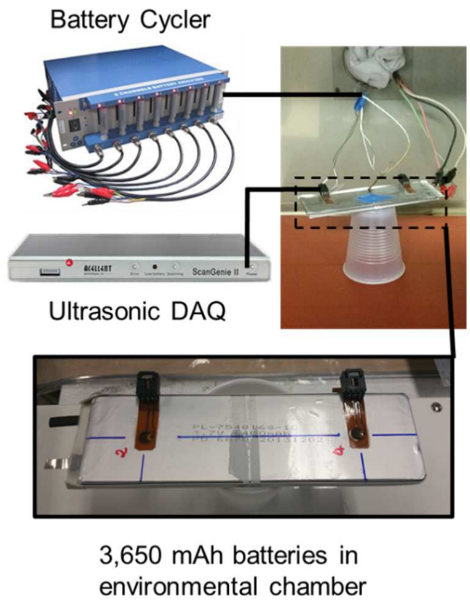

Figure 2: Experimental setup of the commercial pouch cell in thermally controlled environment with connected battery cycler and ultrasonic signal data acquisition hardware

C. Measurement Model

Signal amplitude and Time of Flight (ToF) from Figure 1 provide enough information to relate ultrasonic signal data to SoH, but the use of Gabor-dictionary-based matching pursuit decomposition provides access to more of the rich multidimensional data (time and frequency domain) available in the ultrasonic signal. This works by effectively deconstructing the complex wave response into several wave packet components - atoms - which can be recombined to match the full wave response [9].

Furthermore, each atom's properties can be defined by Gabor parameters - a, b, and u - and empirically tied to SoC and SoH. A linear regression is used to fit a fifth-order polynomial in SoH and SoC to the three Gabor parameters in each atom. In this work, we will assume that this empirical polynomial measurement model relating SoC and SoH to the various Gabor parameters is a static relationship. The correlation of one atom's Gabor parameters with SoC and SoH is illustrated in Figure 3. Adding atoms significantly increases the complexity of the state estimator; therefore, a single atom with its three Gabor parameters is used to represent the ultrasonic signal data in the measurement model.

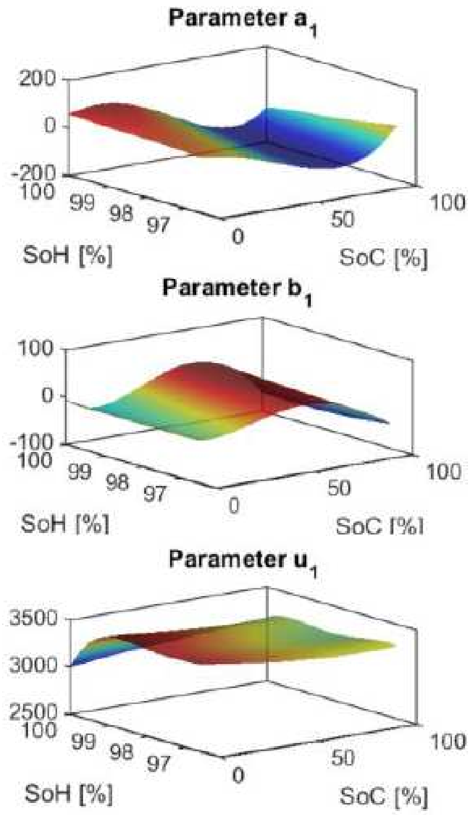

Figure 3: Fifth order polynomial empirical surface fit between the first ultrasonic signal atom Gabor parameters and SoC and SoH [9]

Voltage is the most common measurement used in SoC and SoH estimation. The dependency of cell voltage on SoC is well documented and often approximated with first-order linear ordinary differential equations [10-15]. However, this work uses a fifth-order polynomial in SoC for simplicity and consistency with the Gabor parameter measurement model. Note that the dependency of voltage on SoH is ignored here since the correlation is very weak in comparison to the dependency on SoC, as was shown in Figure 1.

$$V = \sum_{p=0}^{5} \gamma_p^V (SoC)^p \tag{1}$$

D. State Transition Model

The polynomial coefficients in the measurement model are assumed to be static and are just carried over from the last time step with noise. The SoC and SoH states, however, have documented approximate state equations. A typical approach for SoC estimation is Coulomb counting, where the amount of charge leaving the battery during discharge is calculated and compared to the initial full charge state. However, as the battery degrades, the full capacity at the beginning of a discharge cycle is lower, so the SoC propagates more rapidly. This dependency on SoH is represented in the SoC update dynamics (equation 2).

$$SoC_t = SoC_{t-1} - I\Delta t/(SoH_{t-1}Q_0) \tag{2}$$

Modeling SoH dynamics is more difficult, but other groups have used an empirical exponential model to try to match the typical capacity degradation curve for a batch of similar batteries, shown in Figure 4.

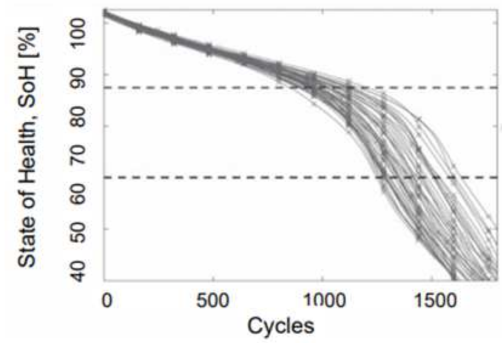

Figure 4: SoH degradation history for 48 virtually identical Li-ion batteries.

The problem with this model is that even a batch of virtually identical batteries from the same production line can have different degradation rates. Thus, the parameters for the aging model need to be updated at each time step to reflect the degradation of the specific cell being tested. However, updating the exponential coefficients can lead to divergence if not properly constrained. For simplicity, a coulomb counting method is proposed for SoH estimation (equation 3). This puts more weight on the measurement accuracy rather than the accuracy of an empirical model.

$$SoH_t = It/(1 - SoC_{t-1})Q_0 \tag{3}$$

III. Results

The experimental data used in this study kept track of true SoC and SoH through coulomb counting and direct measurement. The SoC, input current, and output voltage are available at each time step, while the SoH is updated once at the end of each cycle. Initial conditions for the SoH model parameters were calculated from curve fitting the SoH transition function to the average degradation curve of similar experimental cells. The SoC and SoH were initiated to be 100%, while the Gabor model coefficients were assigned to arbitrary non-zero initial conditions. The state transition noise covariance was carefully chosen to represent high confidence in the initial conditions, while the model parameters are assigned a much larger covariance due to their arbitrary initial conditioning. The augmented EKF state estimator was run on 120 cycles of constant current discharge battery cycling data, and the true SoC and SoH were compared with the estimated values. The convergence of the augmented EKF is shown in Figure 5. For comparison, Figure 6 shows results using only voltage measurements to predict SoC and SoH [16].

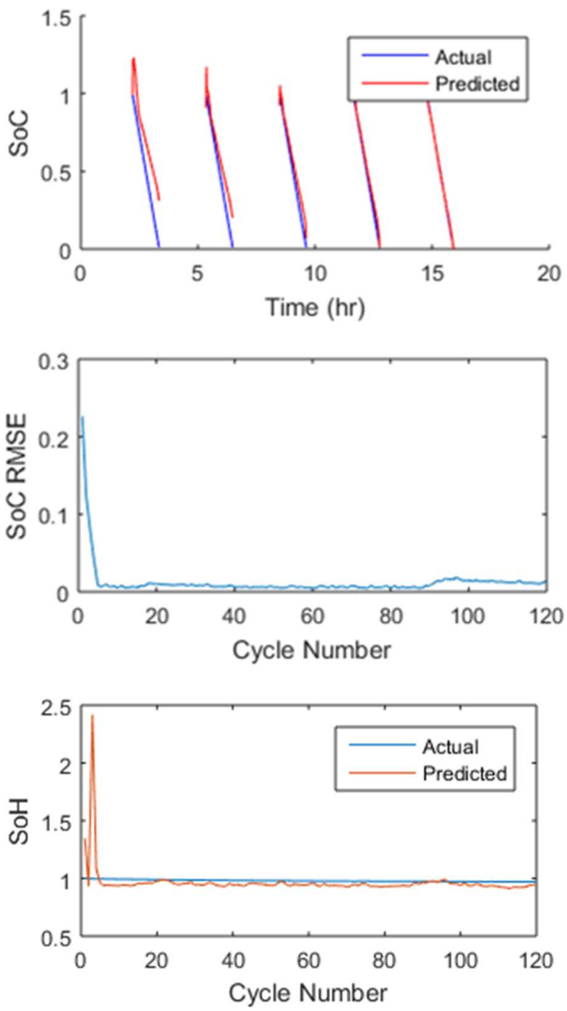

Figure 5: State estimation results for the augmented EKF model: top) First 5 cycles SoC estimation vs time middle) RMSE of SoC of each cycle, bottom) SoH estimation vs time

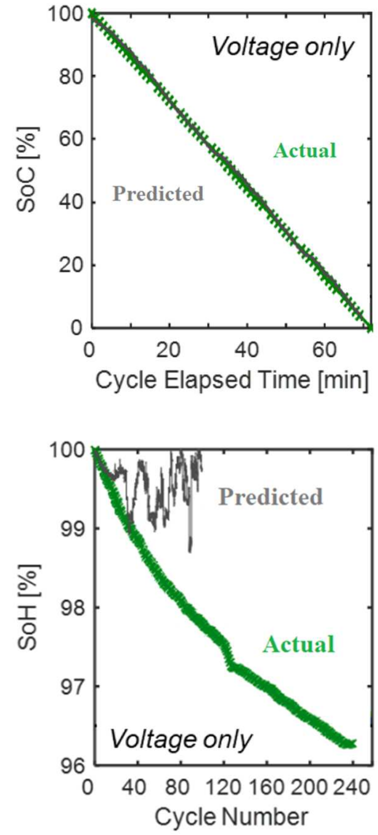

Figure 6: State estimation results for a state estimator using only voltage to predict SoC (top) and SoH (bottom)

IV. Conclusion

The augmented EKF performs quite well despite arbitrary initial conditioning on the parameters of the Gabor measurement model. The initial parameters of the Gabor measurement model are poorly defined and hence provide a poor initial estimate for both SoC and SoH, but as the Gabor parameters update and converge on the correct model, both the SoC and SoH estimation improves dramatically, converging and tracking well within five cycles. Meanwhile, the conventional approach of using only voltage measurements to estimate SoH fails to track the experimental data without any sign of converging.

The primary benefit of this approach is the proven ability to learn the measurement model parameters during the battery state estimation. This allows for the ultrasonic measurement model to adapt over time with the individual battery characteristics rather than remaining as the empirical average of a comparative batch of experimental test cells. The augmented EKF also avoids having to run many experimental tests to train a machine learning model, allowing it to function online while the cell is aging. In future work, the online capability of the algorithm will be tested along with improved state transition models and battery end-of-life prognosis.

Acknowledgment

This work was supported by the Advanced Research Projects Agency – Energy (U.S. Department of Energy) [grant number DE-AR0001151] and our industry partners: Airbus, Embraer, Dassault Systemes, Acellent Technologies, Marubeni, and Eaglepicher Technologies.

REFERENCES

[1] Xiong, Rui, Linlin Li, and Jinpeng Tian. "Towards a smarter battery management system: A critical review on battery state of health monitoring methods." Journal of Power Sources 405 (2018): 18-29.

[2] Berecibar, M., I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche. "Critical review of state of health estimation methods of Li-ion batteries for real applications." Renewable and Sustainable Energy Reviews 56 (2016): 572-587.

[3] Hu, Xiaosong, Jiuchun Jiang, Dongpu Cao, and Bo Egardt. "Battery health prognosis for electric vehicles using sample entropy and sparse Bayesian predictive modeling." IEEE Transactions on Industrial Electronics 63, no. 4 (2015): 2645-2656.

[4] Ungurean, Lucian, Gabriel Cârstoiu, Mihai V. Micea, and Voicu Groza. "Battery state of health estimation: a structured review of models, methods and commercial devices." International Journal of Energy Research 41, no. 2 (2017): 151-181.

[5] Ladpli, Purim, Fotis Kopsaftopoulos, and Fu-Kuo Chang. "Estimating state of charge and health of lithium-ion batteries with guided waves using built-in piezoelectric sensors/actuators." Journal of Power Sources 384 (2018): 342-354.

[6] Wu, Yi, et al. "Ultrasonic health monitoring of lithium-ion batteries." Electronics 8.7 (2019): 751.

[7] Hu, Chao, Byeng D. Youn, and Jaesik Chung. "A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation." Applied Energy 92 (2012): 694-704.

[8] Xiong, Rui, Fengchun Sun, Zheng Chen, and Hongwen He. "A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion polymer battery in electric vehicles." Applied Energy 113 (2014): 463-476.

[9] Ladpli, Purim, et al. "Estimating lithium-ion battery state of charge and health with ultrasonic guided waves using an efficient matching pursuit technique." 2018 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific). IEEE, 2018.

[10] He, Hongwen, Rui Xiong, Xiaowei Zhang, Fengchun Sun, and JinXin Fan. "State-of-charge estimation of the lithium-ion battery using an adaptive extended Kalman filter based on an improved Thevenin model." IEEE Transactions on vehicular technology 60, no. 4 (2011): 1461-1469.

[11] Xiong, Rui, Xianzhi Gong, Chunting Chris Mi, and Fengchun Sun. "A robust state-of-charge estimator for multiple types of lithium-ion batteries using adaptive extended Kalman filter." Journal of Power Sources 243 (2013): 805-816.

[12] Du, Jiani, Zhitao Liu, and Youyi Wang. "State of charge estimation for Li-ion battery based on model from extreme learning machine." Control Engineering Practice 26 (2014): 11-19.

[13] Di Domenico, Domenico, Giovanni Fiengo, and Anna Stefanopoulou. "Lithium-ion battery state of charge estimation with a Kalman filter based on a electrochemical model." In 2008 IEEE International Conference on Control Applications, pp. 702-707. Ieee, 2008.

[14] Sun, Fengchun, Xiaosong Hu, Yuan Zou, and Siguang Li. "Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles." Energy 36, no. 5 (2011): 3531-3540.

[15] He, Wei, Nicholas Williard, Chaochao Chen, and Michael Pecht. "State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation." International Journal of Electrical Power & Energy Systems 62 (2014): 783-791.

[16] Ladpli, Purim. MULTIFUNCTIONAL ENERGY STORAGE COMPOSITES WITH BUILT-IN HEALTH MONITORING CAPABILITIES. Diss. STANFORD UNIVERSITY, 2019.