# Nondestructive state-of-charge assessment of Lithium-ion batteries using quantitative ultrasound spectroscopy

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***Abstract*— The ability to detect and quantify the state of charge (SoC) of lithium-ion (Li-ion) batteries - the most common energy sources for portable devices - using fast and nondestructive evaluation techniques is crucial for the technology. Ten factory-new 18650 batteries were imaged at 100% and 0% SoC using a Vantage-256 system (Verasonics, Inc.) equipped with a 5-MHz and 64-element ultrasound array (Imasonic SAS). Quantitative ultrasound spectroscopy (QUS) parameters, i.e., midbandfit (MBf), spectral slope (SS), and intercept (I0), were obtained from the normalized power spectra of the backscattered ultrasound signals. A significant impact (ANOVA, $p<0.05$) of SoC on two spectral parameters (i.e., MBf and SS) was observed. The results from this study demonstrate feasibility and promising results of using linear-array ultrasound transducers in combination with QUS parameters for future nondestructive evaluation of SoC of Li-ion batteries.**

***Keywords—Quantitative ultrasound spectroscopy (QUS), lithium-ion batteries, state of charge, non-destructive evaluation***

## I. Introduction

Li-ion batteries were crucial for the revolution of portable electronics and are catalyzing the augmentation of electric vehicles and the decarbonization of the grid by allowing renewable capacity firming (tackling intermittency issues in renewable energies) as they are, by far, the most common energy storage option [1]. They are found commercially in different cell architectures: pouch cells are used in iPhones or Mac laptops, and prismatic and cylindrical cells are found in electric vehicle battery packs and stationary energy storage systems for grid scale applications.

One of the most crucial aspects in Li-ion batteries is the estimation of their lifetime or “rest of useful life”. To do this, two important parameters must be accurately estimated, which are state of charge (SoC) and state of health (SoH). SoC is the level of actual charge of a battery relative to its capacity, and it is usually expressed in percentage points (i.e., 0% empty; 100% full charge). SoH is a parameter used to track how the battery capacity decreases over time, which also corresponds to the degradation process during all its life. This capacity reduction is the result of battery aging caused by different mechanisms [2]. However, studies demonstrated that for most commercial lithium-ion batteries (i.e., batteries with graphite as material for anode and a lithiated transition metal oxide as material for cathode) varying the lithiation of graphite (which influences the SoC) during cycling has the biggest impact on battery aging and, therefore, on the SoH [3]. Thus, the SoC estimation is one of the most important features of today's battery management systems (BMS) [4], necessitating development of increasingly accurate analytical SoH models, due to the growing interest in implementing circular economy strategies for used batteries [5].

Li-ion batteries are complex systems, and their performance can be affected by several external factors such as the cut-off voltages during charge and discharge, temperature, the rate at which it is charged/discharged; and by internal electrochemical factors such as the electrochemical behavior of anode and cathode materials, their crystal structure and how they behave during lithium insertion/de-insertion [6]. The combination of these factors results in different degradation mechanisms inside the batteries, such as corrosion in the current collectors, or loss of active material due to dissolution in the electrolyte, among many other mechanical and electrochemical behaviors [7]. Estimating the SoC is not straightforward, often involving complex algorithmic processing. Furthermore, the hardware sensors of the BMS are expensive. Therefore, it is necessary to find low-cost and high-accuracy methods for estimating the charged state of lithium batteries.

Previous studies indicate that among nondestructive testing (NDT) methods, ultrasound is an excellent candidate for assessing SoC and SoH in batteries [8-12]. Davies et al. (2017), showed that time of flight (TOF) measurements using a through transmissions approach can be used to track the SoC in pouch cell Li-ion batteries [10]. In their study, TOF was directly correlated to the time taken by the battery to complete full cycles of charge (until it reached a cut-off voltage of 4.2V) and discharge (until it reached a cut-off voltage of 2.2V), which is a measure of the capacity and has an indirect relation to the SoC. A model has been developed by Copley et al (2021) to understand the nature of the ultrasound response. In their work they report an intelligent peak selection method to ensure that, independent of the ultrasound response, the measurements of the SoC are optimized by identifying signal regions with the best correlation of battery charge [13].

The aim of this study was to investigate the potential of quantitative ultrasound spectroscopy (QUS) in combination with an ultrasonic array for assessing SoC of 18650-Li-ion batteries. Similar methods, which are called quantitative ultrasound, are commonly and successfully used in biomedical applications for tissue characterization [14]. Examples include cancer detection and classification in prostate [15], thyroids [16], and lymph nodes [17].

## II. Methods

### A. Batteries

Ten factory-new 18650-Li-ion batteries were divided into two groups (i.e., 5 samples each). The batteries in each group were charged and discharged using a constant-current constant-voltage protocol which involved charging at 700 mA until a cut-off voltage of 4.2 V (i.e., SoC 100%) and discharging at a constant current of 700 mA until a lower potential window of 2.5 V (i.e., SoC 0%) was reached.

### B. Ultrasound measurements

A Vantage-256 system (Verasonics, Inc.) equipped with a 5-MHz and 64-element ultrasonic array (Imasonic SAS) was used to measure the backscattered ultrasound signals. The array was placed longitudinally on the battery assuring that the imaging plane cut the diameter of the battery (Fig. 1). Ten ultrasound frames at a frame rate of 1 kHz were acquired for each battery using plane-wave imaging. The battery cell was then rotated, and measurements were repeated every 45 degrees resulting in a total of eight measurement locations per battery.

In a first group of experiments (Exp1) all measurements were conducted for the charged and discharged batteries of the two groups. Then the 5 charged batteries from Exp1 were discharged and the formerly discharged batteries were charged in a second experiment (Exp2) and measurements were repeated.

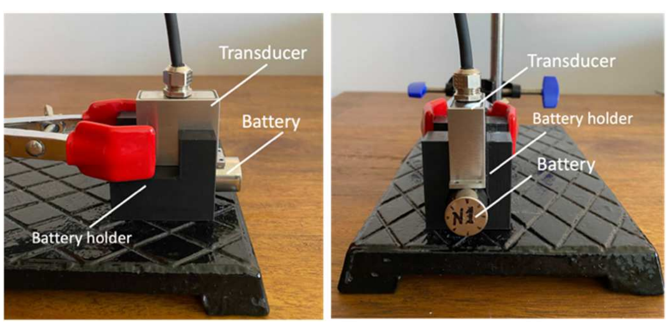


Fig. 1 Ultrasound setup with the ultrasonic array placed longitudinal on the batteries.

### C. QUS parameter estimation and statistics

In this preliminary study, backscattered signals were analyzed from the back-wall reflection of the batteries (i.e., between a constant TOF of 10 µs and 11 µs, Fig 2.). The signals were gated using a Hanning window centered at 10.5 µs and the 64-channel-averaged log-compressed power spectrum ($R(f)$) was computed for each measurement location.

To estimate system-independent quantitative ultrasound parameters the normalized power ($R_N(f)$) spectrum was computed using eq. 1.

$$R_N(f) = \frac{|R(f)|^2}{|R(f)_{ref}|^2} = \frac{|S(f)|^2 |BSC(f)|^2 |A(f)|^2}{|S(f)|^2 |BSC_{ref}(f)|^2 |A_{ref}(f)|^2} \quad (1)$$

In eq. 1, $R(f)$ is the power spectrum of the backscattered signal and $R(f)_{ref}$ is the power spectrum of a reference signal, $f$ is frequency in MHz.

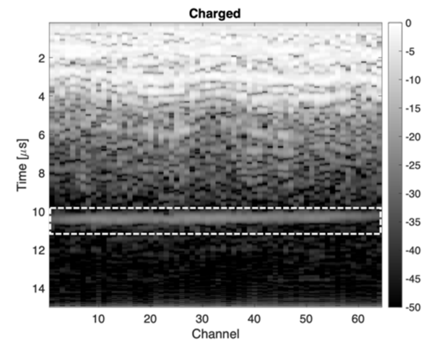


Fig. 2 Log-compressed power amplitude image of the RF signals for each of the 64 chanels.

The reference signal in this study was obtained from a battery of unknown charge. The backscattered signal can be modeled as a function of system dependent effects, $S(f)$, (e.g., pulse echo impulse response or diffraction pattern of the transducer), the backscatter coefficient, $BSC(f)$, and frequency dependent attenuation ($A(f)$). If the reference and the sample spectrum were acquired using the same system and settings, $R_N(f)$ will only depend on $BSC$ and $A$, and quantitative (i.e., system independent) measurements can be obtained.

A linear model was then fitted to $R_N(f)$ between 3.8 and 5.5 MHz (i.e., the average -6-dB range) to compute the spectral slope (SS), intercept at 0 MHz (I0) and mid-band fit (MBf). Fig. 4 shows representative power spectra and linear fits.

The impact of SoC on the spectral parameter was assessed using analysis of variance (ANOVA) and results were considered significant at $p<0.05$.

## III. Results

Comparing spectral parameter estimates between charged and discharged batteries revealed a significant impact of SoC on the parameters, MBf and SS. Both parameters showed significant smaller values for the charged batteries when compared to the discharged batteries. The difference between MBf(discharged) - MBf(charged) was ~ 5.5 dB and SS(discharged) - SS(charged) was ~2.2 dB/MHz. The ANOVA box plots are shown in Fig 4.

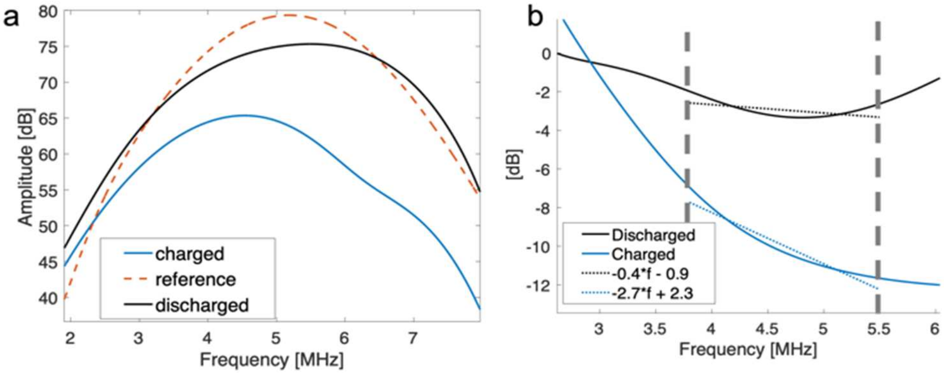


Fig. 3 (a) Averaged log-compressed poewr spectrum of a charged (blue), discharged (black) and a reference spectrum (dashed red). (b) normalized power spectrum (R)

Comparing Exp1 (i.e., batteries 1-5 charged, batteries 6-10 discharged) and Exp2 (i.e., batteries 1-5 discharged, batteries 6-10 charged) confirmed the same effect of significant lower MBf and SS values for the charged batteries vs. discharged batteries.

No significant difference between discharged and charged batteries was observed for the intercept (I0). The results of Exp1 and Exp2 are shown in Fig. 5

## IV. Discussion

To the best of the authors knowledge this is the first study that uses QUS parameters to assess the SoC in li-ion batteries using a linear ultrasound array. The significant difference of two of the three spectral parameters for charged vs. discharged batteries is very encouraging and may lead to future classification systems that will allow an accurate estimation of the SoC of the batteries. We anticipate that QUS parameters may provide a key parameter in future BMS.

Although we are currently improving the measurement protocols and further experiments are being conducted to confirm these preliminary results, with the current study we could show that QUS-based assessments are feasible using linear ultrasonic arrays in backscatter-acquisitions setups. Backscatter-acquisition setups are easier than through transmission setups since they only require one ultrasound array and prevent transducer-alignment problems. By measuring the TOF of the back-wall reflection, the speed of sound could also be assessed and may be combined with QUS parameter estimations to develop multi-parameter classification approaches.

This study focused only on the signals originated from the back-wall reflection of the batteries. However, traditional quantitative ultrasound techniques assess Rayleigh-scattering rather than geometrical scattering as observed from the backwall reflection. More studies are required to analyze the backscattered signals from within the batteries. The layered structure of the batteries with several sheets of cathode and anode embedded in electrolyte fluid may cause complex ultrasound propagation and backscatter phenomena including guided, fast, and slow waves. Numerical ultrasound simulations [18] may provide better insights and could help develop better ultrasound-backscatter models that then can be used to extract QUS parameters that are better predictors than the parameters obtained from the linear model as described in this study.

The effects seen in this study are most likely explained by frequency dependent attenuation with stronger frequency dependent attenuation in the charged batteries. However, the

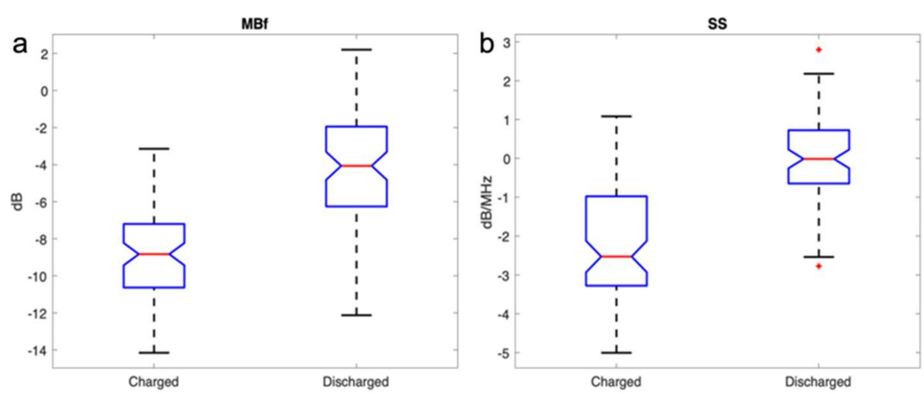


Fig. 4 ANOVA box plots results with significant differences between charged and discharged batteries for MBf (a) and SS (b). Results are obtained from combined experiment Exp1 and Exp2

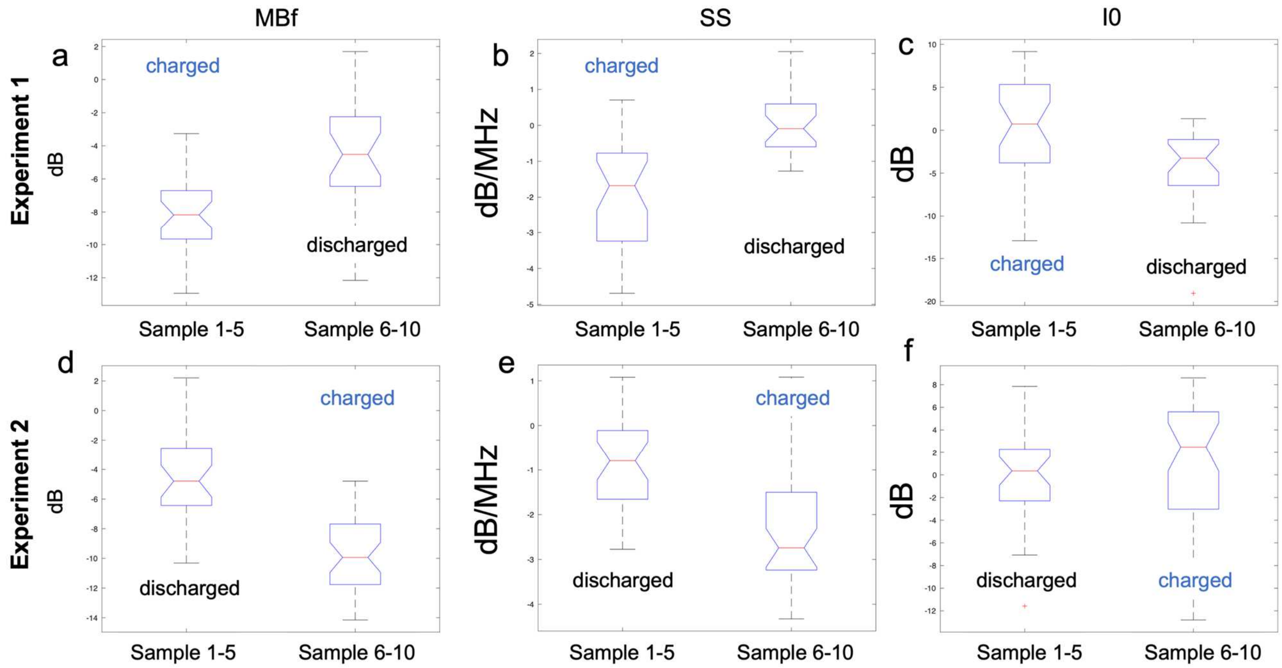


Fig. 5 Box plots of Experiment 1 (a-c) and Experiment 2 (d-f) comparing SoC impact on spectral parameter between discharged and charged batteries for MBf (a, d), SS (b,e) and I0 (c,f).

reasons for these effects are difficult to explain at this point and would require several more experiments and analysis.

Since QUS parameters appear to relate the SoC (as demonstrated in this study) and SoC is an important factor for the SoH batteries, we hypothesize that QUS will provide a useful tool in SoC assessment but also SoH and may be a significant contributor to improve BMS in the future.

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