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# Tracking of electrochemical impedance of batteries

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## HIGHLIGHTS

- The aim is to estimate and track the electrochemical impedance of batteries.
- We develop a wideband recursive estimation algorithm based on the Fourier transform.
- The method reaches good tracking and estimation performance on lithium ion batteries.
- The algorithm can easily be implemented in an embedded system.

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## ABSTRACT

This paper presents an evolutionary battery impedance estimation method, which can be easily embedded in vehicles or nomad devices. The proposed method not only allows an accurate frequency impedance estimation, but also a tracking of its temporal evolution contrary to classical electrochemical impedance spectroscopy methods. Taking into account constraints of cost and complexity, we propose to use the existing electronics of current control to perform a frequency evolutionary estimation of the electrochemical impedance. The developed method uses a simple wideband input signal, and relies on a recursive local average of Fourier transforms. The averaging is controlled by a single parameter, managing a trade-off between tracking and estimation performance. This normalized parameter allows to correctly adapt the behavior of the proposed estimator to the variations of the impedance. The advantage of the proposed method is twofold: the method is easy to embed into a simple electronic circuit, and the battery impedance estimator is evolutionary. The ability of the method to monitor the impedance over time is demonstrated on a simulator, and on a real Lithium ion battery, on which a repeatability study is carried out. The experiments reveal good tracking results, and estimation performance as accurate as the usual laboratory approaches.



## 1. Introduction

The recent and future expansion of electric vehicles or nomad devices inevitably leads to the development of efficient battery management systems (BMS). Such systems must continuously determine the state of the monitored battery from several measurements. However, in order to preserve the battery integrity, only non invasive and non destructive measurement methods are used, and most BMS measure external quantities such as the current flowing through the battery, the voltage across its terminals and its surface temperature [1,2]. From these measurements, one way to obtain interesting information representative of the current state of the battery is to estimate its electrochemical impedance [3]. Indeed this quantity describes the dynamic behavior of the battery and regularly changes with the evolution of its internal temperature, state of charge (SoC) and state of health (SoH) [4]. Consequently, the electrochemical impedance is used in many methods to estimate the internal temperature [5–7], the SoC [8–10] and the SoH [10,11] of the monitored battery. Usual procedures used to estimate a battery electrochemical impedance belong to the class of active identification methods [12]: known variations are added to the battery input, and the corresponding output variations are measured and used to estimate the unknown impedance on a given frequency band. In the rest of this paper, the battery impedance is

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estimated in galvanostatic mode: the current $i(t)$ flowing through the battery is considered as the input and the voltage $u(t)$ across the battery terminals as the output. This choice can be justified by the fact that the current can be easily driven by very simple and cheap electronic devices (such as a transistor for example), which is a strong requirement for embedded systems for which this work is developed. Active identification methods rely on two main assumptions:

- Firstly, variations of the additional current used to estimate the impedance are chosen sufficiently small for the battery to have a linear behavior with respect to these variations. Under this assumption, the battery can be considered as a linear system.
- Secondly, parameters on which the battery characteristics depend are assumed to remain constant during the measurement process. Under this assumption, the battery can be considered as a time-invariant system during the measurement time.

Jointly, these two assumptions allow to consider the battery as a linear and time-invariant (LTI) system regarding the additive input-output variations and during the measurement time. In that case, the battery admits a well defined frequency response function, corresponding to its electrochemical impedance $Z(f)$ and verifying the following frequency relationship:

$$Z(f) = \frac{S_{ui}(f)}{S_{ii}(f)} \text{ if } S_{ii}(f) \neq 0. \tag{1}$$

In this equation, $S_{ui}(f)$ is the cross power spectral density (CPSD) between voltage and current variations, while $S_{ii}(f)$ is the power spectral density (PSD) of current variations only [13,14]. Eq. (1) highlights the fact that $Z(f)$ can only be estimated in the frequency bands where the input current variations contain power, *i.e.* where their PSD is different from 0.

The validity of the LTI assumption for the battery and equivalently the validity of Eq. (1) can be checked by using the notion of magnitude squared spectral coherence [15] defined as:

$$C_{ui}(f) = \frac{\left|S_{ui}(f)\right|^2}{S_{uu}(f)S_{ii}(f)}, \tag{2}$$

where $S_{uu}(f)$ is the PSD of voltage variations.This frequency domain function is a statistical quantity normalized between 0 and 1, that can be interpreted as the magnitude squared correlation coefficient between the spectral components of the voltage and the current around a given frequency $f$. It gives a normalized measurement of how linearly the spectral components of these two signals are related to each other. It has been shown for example in Ref. [15] that in case of low measurement noise, the identified system can be considered as LTI in frequency bands where the magnitude squared coherence is close to 1, while the LTI assumption can be rejected in frequency bands where it remains close to 0. This quantity has been used to check the LTI assumption for batteries in Ref. [16].

Several methods have been developed to estimate the impedance, such as the time domain step response. The disadvantage of this approach is related to the measured response to an impulse or step input that often have a small amplitude in comparison to the noise, especially when the battery impedance is low. That is why this technique requires extra-large inputs to reach good signal to noise ratios and finally good estimation performance. These large inputs often induce non-linear behavior, explaining why this approach is not used in this study.

One of the authoritative methods for battery impedance measurements is the narrowband electrochemical impedance spectroscopy (FFT-EIS) [17,18]. In this method, a single sine wave with low amplitude and fixed frequency is used as input signal. Eq. (1) is then valid at the sine frequency only, and $Z(f)$ can be estimated at that particular frequency only, justifying the term “narrowband”. If $Z(f)$ must be estimated for several frequencies, the same measurement process has to be sequentially done for each desired frequency. An efficient way to avoid this sequential implementation and estimate the impedance for a discrete set of frequencies at one time is to use a multisine approach [14]. In that case, the input signal consists of a sum of sines which frequencies correspond to the desired set.

For wideband method, input signals are wideband in the sense that their PSD is different from 0 on a continuous frequency band. In that case, Eq. (1) is valid all over that frequency band, where $Z(f)$ can be estimated whatever $f$. Several options are available to choose a wideband input signal for system identification, the most popular being swept sines, random noises and pseudorandom binary sequences (PRBS) [14].

Eqs. (1) and (2) clearly show that the estimation of $Z(f)$ relies exclusively on basic spectral quantities such as PSD and CPSD. A simple and efficient estimator usually used for such quantities is the Welch modified periodogram [19]. The signals are first divided into $L$ consecutive blocks of same length by using a time window. The discrete Fourier transform (DFT) of each block of data is then computed by using a fast Fourier transform algorithm. Finally, the $L$ obtained DFTs are multiplied, averaged, and normalized correctly to obtain the desired result. As an example, Eq. (3b) gives the expression of the voltage-current CPSD estimator $\widehat{S}_{ui}(f)$:

$$\widehat{P}_{ui_k}(f) = AU_k(f)I_k^*(f), \tag{3a}$$

$$\widehat{S}_{ui}(f) = \frac{1}{L}\sum_{k=0}^{L-1}\widehat{P}_{ui_k}(f), \tag{3b}$$

where $A$ is a normalization factor, $^*$ denotes complex conjugation, and $U_k(f)$ ($I_k(f)$ respectively) is the DFT of the $k^{th}$ block of voltage (current respectively) signal. In Eq. (3a), $\widehat{P}_{ui_k}(f)$ is the cross-periodogram of the $k^{th}$ blocks of voltage and current signals, and Eq. (3b) clearly shows that the estimated CPSD is given by an arithmetic averaging of the $L$ cross-periodograms obtained from the acquired data. Obviously, same type of estimators can be obtained for the current and voltage PSDs $\widehat{S}_{ii}(f)$ and $\widehat{S}_{uu}(f)$ by using exclusively $U_k(f)$ or $I_k(f)$ in Eq. (3a).A simple impedance estimator $\widehat{Z}(f)$ is obtained by using Eq. (3b) in the impedance definition given by Eq. (1).

$$\widehat{Z}(f) = \frac{\widehat{S}_{ui}(f)}{\widehat{S}_{ii}(f)} \text{ where } \widehat{S}_{ii}(f) \neq 0. \tag{4}$$

Following the same principle, Eq. (3b) used in Eq. (2) leads to the estimator of the magnitude squared spectral coherence between battery voltage and current:

$$\widehat{C}_{ui}(f) = \frac{\left|\widehat{S}_{ui}(f)\right|^2}{\widehat{S}_{uu}(f)\widehat{S}_{ii}(f)}. \tag{5}$$

Therefore, Eqs. (3b), (4) and (5) form together the battery identification algorithm:

- Eqs. (3b) and (4) give access to the battery impedance estimate in the frequency band of interest,