Abstract—Electrical impedance measurements provide useful information about the characteristics of a Li-ion battery. The classical method of measurement consists of performing electrochemical impedance spectroscopy (EIS) that relies on offline records of the response of the battery to a controlled current or voltage test signal. Although robust, it is considered as an expensive, complex, and very time-consuming method, particularly when used for an embedded system where a new whole measurement set should be carried once the impedance is to be tracked. To overcome these problems and to address embedded applications, we propose applying broadband excitation signals to perform such impedance measurements. Spectral coherence is an advanced parameter estimated to define the frequency bands where the transfer function of a system is accurately identified. The calculation of this parameter can also assess the normalized random errors on both the magnitude and the phase of the identified impedance since they are related by an explicit mathematical expression. After a brief review of some signal processing tools for identification with broadband excitation signals, we apply this method to identify the impedance of a Li-ion battery and to compare performances of various identification patterns on noisy simulated and experimental data.

Index Terms—Battery impedance, broadband signals, confidence limits, identification, Li-ion battery, spectral coherence, spectroscopy.

I. INTRODUCTION

Due to its higher power density and energy density, long cycle life, low cost of raw materials, and superior safety characteristics [1], [2], Li-ion battery technology is considered the most attractive for electric-vehicle (EV) and hybrid-electric-vehicle (HEV) applications since, in particular, batteries are their essential component. For reliable operation in these applications and very time-consuming method, particularly when used for an embedded system where a new whole measurement set should be carried once the impedance is to be tracked. To overcome these problems and to address embedded applications, we propose applying broadband excitation signals to perform such impedance measurements. Spectral coherence is an advanced parameter estimated to define the frequency bands where the transfer function of a system is accurately identified. The calculation of this parameter can also assess the normalized random errors on both the magnitude and the phase of the identified impedance since they are related by an explicit mathematical expression. After a brief review of some signal processing tools for identification with broadband excitation signals, we apply this method to identify the impedance of a Li-ion battery and to compare performances of various identification patterns on noisy simulated and experimental data.

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impedance. Several studies [12]–[15] point out the usefulness of this former quantity as a technique to enhance the estimation of battery states.

Current embedded methods only estimate the internal resistance of batteries by computing, for example, the ratio between battery voltage and current during a specific current step [3], [16]. In [17], values of EEC parameters were extracted using impedance measurements made at only three discrete frequencies (2, 25.18, and 158.9 Hz) based on a mathematical equation system. In addition, the Kalman filter (KF) is commonly considered a powerful and elegant solution for estimating the states of systems [18], [19], and the extended KF (EKF) method, in particular, has been first proposed in [20]–[22]. Nonetheless, the existing EKF algorithm does not account for variations in battery parameters due to variances in the electrochemical characteristic modifications caused by aging effect. Therefore, in [23], the EKF was combined with the per unit system that represents the electric variables as dimensionless values relative to a set of reference base values to identify accurately the battery model parameters and to enhance the SOC and SOH estimation.

Such impedance estimations are strongly limited because they do not represent the wealth of information inherently present in complex and broadband battery electrical impedance. This is the main reason why electrochemical impedance spectroscopy (EIS) is frequently used to better investigate battery states. Its general concept consists in the application of an electrical stimulus to the working electrode and the monitoring of its corresponding response. Many EIS experiments are performed by a stepwise change of frequency in an applied sinusoidal current, measuring the corresponding sinusoidal voltage and calculating at each frequency the electrochemical impedance (galvanostatic operating model) [24]–[26].

Concerning the aforementioned methods, each one has its own drawbacks in terms of accuracy, computational complexity, computation time, or compatibility with embedded systems.

The aim of this paper is to search for a new technique for measuring battery electrical impedance, which can be easily implemented on a BMS for HEVs and EVs and tends to reduce measurement time. In this paper, we propose applying broadband excitations. The concept is to measure the system response at multiple frequencies at the same time. Since the measurement time to get a specified accuracy depends on the measured SNR, it is important to select excitations with a high SNR on a wide frequency band. To the authors’ knowledge, broadband excitation approaches were applied to measure electrochemical impedance in a rather limited number of investigations [27]–[29]. Indeed, the advantages of such methods over the conventional single-sine excitation methods are not that obvious in the EV community. However, if implemented following a recursive form, they allow not only the reduction of necessary computation time but also the tracking of battery impedance variations without the need of carrying a whole new measurement. In particular, Pintelon and Schoukens in [30] explained that the use of broadband signals satisfying specific conditions of energy transmission in the band of interest can reduce the measurement time, particularly in the case of a good SNR. Undoubtedly, this consideration alone is of significant importance in the context of an embedded BMS.

This paper focuses on the test and comparison of broadband excitation signals concerning their performance for battery electrical impedance estimation. Section II recaps nonparametric broadband identification basics for linear and time-invariant systems. The corresponding frequency algorithms are also presented, and their estimation performance is evaluated due to advanced spectral quantities such as spectral coherence. Next, these algorithms are applied to simulated data in Section III, where the results obtained with different broadband excitation signals are also compared with each other. Finally, Section IV gives experimental results that validate the relevance of this approach.

II. NONPARAMETRIC IDENTIFICATION METHOD

A. LTI Systems

A single-input–single-output (SISO) system \( \mathcal{H} \) is shown in Fig. 1, where \( x[n] \) and \( y[n] \) are discrete signals verifying Shannon’s sampling theorem.

If \( \mathcal{H} \) is linear and time invariant (LTI), it is completely characterized by its impulse response \( h[n] \) or its frequency response function \( H(\lambda) \), which are related by a Fourier transform as follows:

\[
H(\lambda) = \sum_{n=-\infty}^{+\infty} h[n] e^{-j2\pi \lambda n},
\]

In this equation, \( j = \sqrt{-1} \), and \( \lambda \in (-1/2; 1/2) \) is the normalized frequency, leading to frequency \( f \) (in hertz) when multiplied by the sampling frequency.

Indeed, for periodic deterministic and stationary random signals, input–output relationships in the time and frequency domains are, respectively, given as

\[
y[n] = \sum_{k=-\infty}^{+\infty} h[k] x[n-k]
\]

(2)

\[
S_{yx}(\lambda) = H(\lambda) S_{xx}(\lambda)
\]

(3)

where \( S_{xx}(\lambda) \) is the power spectral density (PSD) of \( x[n] \), and \( S_{yx}(\lambda) \) is the cross PSD (CPSD) between \( x[n] \) and \( y[n] \).

Equation (3) gives the frequency-domain input–output relationship for the LTI system and is the foundation of nonparametric identification of such systems in the frequency domain.

B. Nonparametric Identification Principle

The goal of frequency-domain nonparametric identification of LTI systems is to estimate the frequency response function \( H(\lambda) \) from input and output measurements without the use of any model.

The general principle of this method is shown in Fig. 2. A known input signal \( x[n] \) is applied to the unknown system \( \mathcal{H} \), and a noisy version \( z[n] \) of the corresponding output \( y[n] \) is measured at the same time. The unknown additive measurement

![Fig. 1. SISO system.](image-url)
noise \( b[n] \) is supposed to be uncorrelated with \( x[n] \) and therefore with \( y[n] \). Due to this last assumption, (3) then becomes

\[
S_{xx}(\lambda) = S_{yx}(\lambda) = H(\lambda)S_{zz}(\lambda).
\]  
\[ \text{(4)} \]

Therefore, on the frequency bands, where the input PSD \( S_{xx}(\lambda) \neq 0 \), the unknown frequency response function \( H(\lambda) \) can be calculated through

\[
H(\lambda) = \frac{S_{xx}(\lambda)}{S_{zz}(\lambda)} \text{ if } S_{xx}(\lambda) \neq 0.
\]  
\[ \text{(5)} \]

This finally leads to the frequency-domain identification of the unknown system \( \mathcal{H} \). Equation (5) clearly shows that it is advantageous to use broadband input signals \( x[n] \) since they allow the computation of \( H(\lambda) \) on a wide frequency band as a whole.

An essential quantity in such a method is the spectral coherence between measured signals \( x[n] \) and \( z[n] \)\cite{31,32}

\[
|c_{xz}(\lambda)|^2 = \frac{|S_{xx}(\lambda)|^2}{S_{zz}(\lambda)S_{zz}(\lambda)}.
\]  
\[ \text{(6)} \]

This statistical quantity is bounded by 0 and 1 and measures the linear dependence or correlation between \( x[n] \) and \( z[n] \) at each frequency \( \lambda \)\cite{31,32}. Moreover, it can be also interpreted as an LTI system detector between \( x[n] \) and \( z[n] \)\cite{33}. In that case, \( |c_{xz}(\lambda)|^2 \) becomes

\[
|c_{xz}(\lambda)|^2 = \frac{S_{yy}(\lambda)}{S_{yy}(\lambda) + S_{bb}(\lambda)} = \frac{\text{SNR}_o}{1 + \text{SNR}_o}.
\]  
\[ \text{(7)} \]

where \( \text{SNR}_o = (S_{yy}(\lambda)/S_{bb}(\lambda)) \) is the output SNR quantifying the additive noise \( b[n] \) relative to \( y[n] \). Equations (6) and (7) can be interpreted as follows.

- When \( |c_{xz}(\lambda)|^2 \rightarrow 1 \), \( x[n] \) and \( z[n] \) are strongly correlated, and \( \text{SNR}_o \rightarrow +\infty \) at \( \lambda \). In that case, \( b[n] \) is negligible compared with \( y[n] \), and the LTI model for the unknown system \( \mathcal{H} \) is totally justified around this frequency.
- When \( |c_{xz}(\lambda)|^2 \rightarrow 0 \), \( x[n] \) and \( z[n] \) are uncorrelated, and \( \text{SNR}_o \rightarrow 0 \) at \( \lambda \). This corresponds to an important measurement noise \( b[n] \) dominating the system output \( y[n] \). In that case, the LTI model of \( \mathcal{H} \) cannot be easily justified around this frequency.

Another interesting property of the spectral coherence is that it is closely related to estimation errors obtained when identifying \( H(\lambda) \). This is used in the following to compute confidence limits for different spectral estimators.

C. Nonparametric Identification Algorithm

Equations (5) and (6) show that PSD and CPSD are necessary to compute the desired frequency response function and spectral coherence. Such quantities can be easily estimated through the well-known Welch modified periodogram \cite{32}. Measured signals are first split up into \( L \) data segments of length \( N \). All these segments are then windowed by a window function \( w[n] \) of length \( N \), and the Fourier transform of each windowed segment is computed by the use of an algorithm with discrete Fourier transform and fast Fourier transform. Finally, the products of these Fourier transforms are averaged to estimate the desired spectral quantities. As an example, the corresponding estimator of the CPSD between \( x[n] \) and \( z[n] \) is given by

\[
\hat{S}_{xz}(\lambda) = \frac{1}{L} \sum_{k=Q}^{L-Q} S_k(\lambda)X_k^*(\lambda)
\]  
\[ \text{(8)} \]

where \( A \) is a normalization factor; \( Z_k(\lambda) \) (resp. \( X_k(\lambda) \)) is the Fourier transform of the \( k \)th windowed segment of \( z[n] \) (resp. \( x[n] \)); and \( * \) denotes the complex conjugate.

Similarly, the estimator of the PSD of \( x[n] \) \( \hat{S}_{xx}(\lambda) \) is obtained by replacing \( Z_k(\lambda) \) by \( X_k(\lambda) \) in (8).

Simple estimators can now be obtained to estimate spectral coherence \( |c_{xz}(\lambda)|^2 \) and frequency response function \( H(\lambda) \) by using (8) in (5) and (6), i.e.,

\[
|\hat{c}_{xz}(\lambda)|^2 = \frac{|\hat{S}_{xz}(\lambda)|^2}{\hat{S}_{xx}(\lambda)\hat{S}_{zz}(\lambda)} \quad \text{and} \quad \hat{H}(\lambda) = \frac{\hat{S}_{xx}(\lambda)}{\hat{S}_{zz}(\lambda)} \quad \text{if } \hat{S}_{xx}(\lambda) \neq 0.
\]  
\[ \text{(9)} \]

The last relation also allows the estimation of gain \( \hat{G}(\lambda) = |\hat{H}(\lambda)| \) and phase \( \hat{P}(\lambda) = \arg[\hat{H}(\lambda)] \) of the frequency response function \( H(\lambda) \). Moreover, it has been shown in \cite{32,34,35} that, under general conditions, the variance of these two estimates is directly related to the spectral coherence by the following expression:

\[
\text{var} \left\{ \hat{P}(\lambda) \right\} = \text{var} \left\{ \ln \left( \hat{G}(\lambda) \right) \right\} = \frac{1}{2L} \frac{1 - |\hat{c}_{xz}(\lambda)|^2}{|\hat{c}_{xz}(\lambda)|^2}.
\]  
\[ \text{(10)} \]

This interesting result shows two important things. First, the estimation errors of the frequency response function are inversely proportional to the number of data segments \( L \) used in the Welch estimator of (8). Second, estimation errors are closely related to the spectral coherence; more precisely, the higher the spectral coherence is, the smaller the estimation errors are. Equation (11) has been used in \cite{34} to compute upper and lower 95% confidence limits for the gain and phase estimates \( \hat{G}(\lambda) \) and \( \hat{P}(\lambda) \) by replacing the true spectral coherence \( |c_{xz}(\lambda)|^2 \) by its estimated value \( |\hat{c}_{xz}(\lambda)|^2 \), i.e.,

\[
\log_{10} \left\{ \hat{G}(\lambda) \right\} \pm 1.96 \sqrt{\frac{(\log_{10}(e))^2}{2L} \frac{1 - |\hat{c}_{xz}(\lambda)|^2}{|\hat{c}_{xz}(\lambda)|^2}}
\]  
\[ \text{(12)} \]

\[
\hat{P}(\lambda) \pm 1.96 \sqrt{\frac{1}{2L} \frac{1 - |\hat{c}_{xz}(\lambda)|^2}{|\hat{c}_{xz}(\lambda)|^2}}.
\]  
\[ \text{(13)} \]
Finally, (8) and (10) constitute the “identification algorithm” in Fig. 2, which is used to estimate the frequency response function $H(\lambda)$ of an unknown LTI system through its input $x[n]$ and noisy output $z[n]$. Equations (9), (12), and (13) are used to evaluate the algorithm performance by computing the 95% confidence limits of the previous estimators.

In the following, batteries are modeled as electrical LTI systems whose input is their current and whose output is their voltage. This choice is based on practical considerations since the control of current and the measurement of voltage stages of a battery are already present in currently developed BMS. The corresponding frequency response function is the electrical impedance of the battery and this quantity is estimated using the previous set of equations.

III. BROADBAND IDENTIFICATION OF ELECTRICAL IMPEDANCE FOR LI-ION BATTERIES

A. Battery Modeling

In this paper, modeling a battery is aimed at reproducing its electrical behavior through an EEC [36]. These models, the so-called gray box models, reproduce the dynamic behavior of batteries based on an analogy between their physicochemical phenomena and common electrical or nonelectrical elements. For electrical engineers, such a model is commonly used to characterize electrochemical phenomena and leads to a quick analysis and prediction of the battery behavior in both frequency and time domains [37].

Many electrochemical studies focus on fine association between impedance spectrum parts and fundamental physicochemical processes. Some authors [38]–[41] consider that the anode effects appear in high frequencies more than in low frequencies, whereas the cathode reacts more in low frequencies. Randles [42] proposed an EEC based on physicochemical processes. It includes the modeling of connectors and electrolyte $R$ and $L$ charge transfer $R_{tc}$ and double-layer phenomena $C_{dl}$ [43]. The open-circuit voltage depends on current intensity and battery SOC and can be tabulated using a lookup table. Finally, the diffusion phenomenon is modeled by the Warburg impedance [43]. Usually, constant phase elements (CPEs) are introduced to accurately reflect the behavior of the battery observed through impedance spectroscopy measurements [44], [45]. For Li-ion batteries, an additional electrochemical process is observed, i.e., the passivation film [46], [47]. In [48]–[51], it was suggested that this latter process should be modeled by an $R_f$/CPE$_f$ cell. Buller [48] and Moss et al. [51] consider that the first semicircle associated with the passivation film does not depend on the current intensity and slightly varies with the SOC. Based on those ascertainties, Dong et al. [37] proposed using an adapted Randles circuit (see Fig. 3), which we adopt in this paper. In [37] an excellent fitting is demonstrated between measured impedance spectra of a graphite/LiFePO4 battery and this model under specific operating conditions, such as limited temperature range and frequency band, allowing the voltage contribution associated with diffusion processes to be disregarded.

Finally, a nonlinear optimization method is used to estimate the value of each EEC parameter from the measured electrical impedance. In [52], we address the uniqueness issue of this inverse problem and propose an efficient two-step optimization approach to improve the convergence rate and accuracy. A statistical study has been performed and has revealed that this new algorithm presents a very good convergence rate and leads to unbiased estimates of model parameters. Experimental data have also been used to validate this new approach. The corresponding EEC parameters obtained using this algorithm for a SOC of 60% and a polarization discharge current of 1 A are given in Table I.

B. Spectroscopy

EIS [48] commonly used in the laboratory consists of exciting the battery with a small sinusoidal current $i(t)$ of frequency $f$, i.e., $i(t) = I_{\text{max}} \sin(2\pi ft)$, superimposed to a dc, and measuring its voltage response $v(t) = V_{\text{max}} \sin(2\pi ft - \varphi)$ [53]. Therefore, the voltage/current ratio in the frequency domain is expressed as complex impedance, i.e.,

$$Z_{\text{est}}(f) = \frac{V_{\text{max}}}{I_{\text{max}}} \cdot \exp(-j\varphi).$$

Although the results are robust and precise, EIS is not suitable for EV and HEV applications due to several reasons. First, an expensive complex electronic device is needed to generate sine waves. Second, a large frequency band scan with fine frequency resolution takes a long time to complete, particularly when systems with large time constants are studied since it is necessary to wait until transients disappear after each frequency step. Finally, for an embedded system (particularly for EV and HEV applications in this paper) where the battery impedance evolves and where the BMS should track the impedance evolutions, the use of the EIS technique imposes a new whole measurement to get an online estimation.
alternative solution based on broadband identification techniques presented in Section II is proposed in the following.

C. Broadband Excitation Signals

The selection of optimal excitation signals is an important step in designing the embedded system. In Section II, it was shown that, to estimate the whole electrical impedance at once, they should be able to excite the system with an almost flat power spectrum in the frequency band of interest. This is the main reason why sine waves should be avoided for this application. Here, broadband signals are introduced as identification patterns that can be used to overcome the spectroscopy drawbacks noticed earlier. We consider five broadband signals that are frequently used in system identification applications: 1) random white noise; 2) pseudo random binary sequences (PRBSs); 3) swept sine; 4) swept square; and 5) a square wave [30]. The fifth signal is not a broadband signal but is considered because its harmonics are in the frequency band of interest. Such signals allow the estimation of the frequency response function of LTI systems, particularly battery impedance, over a large bandwidth from a single set of measures.

1) Random White Noise: A white noise presents a flat power spectrum over all frequencies. Moreover, we filter it to inject only power in the frequency band of interest [30].

2) Pseudo Random Binary Sequence: PRBS is a deterministic periodic sequence of length $N$ that switches between two levels +A and -A. Using $n_r$ registers, a sequence of length $N = 2^{n_r} - 1$ can be generated. In addition, by choosing the time for a bit $T_b$, the highest frequency that will be excited is $f_{\text{max}} = 1/T_b$, whereas the lowest frequency is $f_{\text{min}} = f_{\text{max}}/n_r$. PRBS presents an almost flat power spectrum over the frequency band $[f_{\text{min}}, f_{\text{max}}]$ [30].

3) Swept Sine: The swept sine, which is also called periodic chirp, is a sine whose frequency is swept up and/or down from one period to another. A logarithmic variation of frequency (from $f_{\text{min}}$ to $f_{\text{max}}$) with respect to time is chosen. An almost flat spectrum is also provided over frequency band $[f_{\text{min}}, f_{\text{max}}]$ [30].

4) Swept Square: Similar to the swept sine, this is a square with a logarithmic sweep of its fundamental frequency in the band $[f_{\text{min}}, f_{\text{max}}]$. 5) Square: Although a square is not precisely a broadband signal, by a correct choice of its fundamental frequency, one can use the frequencies that correspond to its odd harmonics to excite several discrete frequencies in the band of interest.

To get a better understanding of the nature of the former signals, we compare each signal using its PSD, which is estimated through (8). As an example, we focus on the frequency band from 136 to 819 Hz. All the signals have a total time duration of approximately 160 s and sampling frequency $f_s$ is 8190 Hz. These signals are split up into $L = 2059$ disjoint segments of length $N = 630$ samples. Consequently, each segment has a time duration of $T = (N/f_s) = 0.0769$ s, which results in a frequency resolution of $1/T = 13$ Hz. This former quantity should be chosen so that it is possible to distinguish two consecutive harmonics of the square wave. Moreover, (11) indicates that the number of data segments $L$ should be chosen as large as possible to minimize the estimation error of the electrical impedance. The five resulting PSDs are shown in Fig. 4. Under the assumption of constant power for the excitation signals, we note that the spectral information is different concerning levels and frequency bandwidths.

D. Simulink Simulator

The analytical expression of the impedance can be computed from the EEC in Fig. 3 and is taken as the theoretical value for estimation. This quantity is a function of the SOC and the intensity of the dc. The implementation in Simulink of this model simulates the behavior of a graphite/LiFePO4 battery supplied with a given input current composed, in our case, of a dc added with one of the broadband signals described earlier.

In the context of the nonparametric identification method presented in Section II, the system must be LTI during the whole measurement time. Therefore, this condition should also be respected during simulations. It forces limiting of the time duration of the excitation signals so that, according to the dc level, there is only a little variation of the battery SOC. Consequently, we chose a time duration that does not load or upload the battery from over 2% (value usually considered for EIS). This time constraint has two consequences on the proposed method. First, it is difficult to excite the battery with very low frequencies under high dc since, in that case, the whole measurement time has to be very short. Second, it limits the number of data segments $L$ and can increase eventual estimation errors.

The simulations are undertaken under the same operating conditions of SOC (60%) and dc (1 A), and the same values as those given in Section III-C are chosen ($L = 2059, N = 630, = 8190$ Hz, and $T = 0.0769$ s). To simulate additive measurement noise, white Gaussian noise with zero mean and several levels of variance is added to the output voltage signal. Spectral coherence and electrical impedance are then estimated from this noisy voltage and the excitation signals through (9) and (10). Estimated electrical impedance values are finally compared with the theoretical impedance value to evaluate the quality of the identification process.

E. Coherence Results

We first consider reasonable measurement noise of SNR = 0 dB. Fig. 5 shows the coherence estimated with the five
excitation signals defined earlier, and it can be clearly noticed that the results are different, although excitation signals are designed to excite the same frequency band.

Although the white noise preserves a high coherence value over the excited frequency band, it is difficult to generate with a simple electronic device and thus cannot be used in our application. The PRBS is able to excite frequencies lower than the lowest limit of the selected band \( f_{\text{min}} \) and injects less power in the frequencies near the upper limit \( f_{\text{max}} \). This could be useful when the aim of the measurement is to estimate the electrical impedance around the lowest frequencies of the selected band. Although other signals can be designed to excite low frequencies, by using a PRBS, a better estimate is obtained near \( f_{\text{min}} \) with the same time duration. The swept square and the swept sine roughly present the same behavior upon the frequency band of interest. For these two excitation signals, the coherence slightly decreases with the frequency, but they still inject more power than the PRBS in the frequencies close to \( f_{\text{max}} \). It can also be noted that, due to its harmonics, the swept square weakly excites frequencies beyond the selected band. This could be useful in finding information localized at high frequency. As expected, the coherence obtained with the square wave is only significant at its fundamental frequency and its odd harmonics.

To touch upon some applications where these signals are useful, one can be reminded that, in the literature, it is assumed that SOC is estimated using information contained in lower frequencies, whereas the SOH is tied to higher frequencies. Hence, PRBS could be suitable for SOC estimation, whereas swept square is more dedicated to SOH estimation. In addition, another approach can be proposed: to identify impedance only on several discrete frequencies and to fit a model to build the whole frequency response. This approach can be addressed with a square signal, providing that the fundamental frequency and its first harmonics tie to the selected frequencies of interest.

F. Confidence Limits Results

Confidence limits upon gain and phase factors quantify the estimation performance reached by this identification method and can be easily computed using (12) and (13). Here, the results concerning the gain factor are given as an illustrative example, and they are exclusively represented in the selected frequency band. Results concerning the phase factor are very similar.

In Fig. 6, it is shown that the PRBS [see Fig. 6(a)] has large confidence limits near the upper limit of the band \( f_{\text{max}} \), which confirms the coherence results in Fig. 5. Moreover, tight confidence limits are observed upon the whole selected frequency band using white noise [see Fig. 6(b)], a swept square [see Fig. 6(c)], or a swept sine [see Fig. 6(e)]. The square wave [see Fig. 6(d)] provides, as expected, tight confidence limits only around its odd-harmonic frequencies.

We infer from those results that broadband impedance can be identified with signals composed of square patterns (PRBS, swept squares, and square waves) with as a good quality as that of classical signals (white noise and swept sine). Such signals are easy to apply to a battery from simple electronic components, e.g., by using electronic switches. Therefore, we only consider square waves, swept squares, and PRBS in the following.

G. Noise Effect

The given results were presented with simulated voltage measurement noise such that \( \text{SNR} = 0 \text{ dB} \). Here, we study the effect of this noise by varying the level of its variance.

From (7), it is obvious that the measurement noise affects the coherence function. The higher the noise variance is, the lower the coherence value is. In addition, the coherence decreases with the noise variance, the confidence limits become larger, and the identification performance finally decreases. These effects could be removed by increasing the number of averaging blocks \( L \). However, such an operation will increase the time duration of the measurements and may modify the system state by loading or unloading the battery of more than 2%. The hypothesis of the LTI system may be thus wrong. Therefore, in this paper, the length of the different signals remains the same whatever the noise quantity.

To study the noise influence, a statistical study is performed. For each SNR level, we simulate \( r = 100 \) realizations of the output additive noise, and we plot the estimation MSE (in percentage) (see Fig. 7) defined by (15). This error quantifies the averaged normalized difference between the estimated impedance \( \hat{Z} \) and its theoretical value \( Z \) over the selected frequency band and for a specific excitation signal, i.e.,

\[
\text{Error}(k) = \frac{1}{r} \sum_{f} \left| \frac{\hat{Z}(k, f) - Z(f)}{|Z(f)|^2} \right|^2
\]

\[
\text{MSE}_{\%} = 100 \times \text{mean}_k (\text{Error}(k))
\]

where \( \hat{Z}(k, f) \) is the estimated electrical impedance with the \( k \)th noise realization.

We first note that, the identification performance obtained with the three chosen input signals presents the same behavior as the SNR varies. Indeed, each error decreases when the
Fig. 6. Ninety-five percent confidence limits results using: (a) PRBS, (b) white noise, (c) swept square, (d) square, and (e) swept sine as excitation signals with measurement SNR = 0 dB.

Fig. 7. Estimation MSE (in percentage) for different output SNR. The average value is taken over 100 noise realizations.

measurement noise decreases. Moreover, estimation error obtained with a PBRS is always higher than the error obtained with swept squares and square signals. This is coherent with the results previously obtained on confidence limits. Finally, this identification method reaches very good estimation performance as soon as the output SNR is higher than or equal to 0 dB since, whatever the excitation signal, the estimation error is lower than 1%.

In the following, the proposed identification method is experimentally applied to a battery cell to validate the proposed method and the previous simulation results.

IV. EXPERIMENTAL RESULTS

A. Hardware and Implementation

The work was realized on a graphite/LiFePO4 cell with a nominal capacity of 2.3 Ah (an ANR26650m1 battery from A123 Systems Company Ltd.). To evaluate the performance of broadband signals for the identification of this battery impedance, experiments have been carried out at room temperature under the same operating conditions as those taken during simulations (SOC of 60%, dc of 1 A, number of blocks $L = 2059$, and $T = 0.0769$ s). A sampling frequency of 10 240 Hz was used because of experimental device constraints, so that the block size in samples was set to $N = 787$ to obtain the same time duration $T$ as in simulations. An electronic circuit was designed to perform the experiments and to allow the application of input current with squared patterns, particularly swept squares and PRBSs. The acquisition of the input current and the corresponding output voltage response has been performed with an important SNR level due to an OR-36, which is a high-performance acquisition device (24 bits).

During each experiment, three consecutive realizations of a single excitation signal ($3 \times 2059$ blocks) are applied to study the variability of the estimation. It should be noted that such solicitation with a polarization current of 1 A affects the SOC during the test (on the order of 6%) and may thus disrupt the conditions under which the battery can be approximated by the LTI system. However, referring to the experiments in [37], within the SOC interval [50%, 60%] we can assume that the impedance is quite constant. Coherence information will be studied to verify this last assumption.
B. Experimental Results

1) PRBS: During the first experiment, a PRBS is used as the input current. The corresponding estimated coherence is plotted in Fig. 8, whereas the estimated electrical impedance is shown in Fig. 9. The coherence is clearly close to 1 all over the specified frequency band. This shows that the battery can be considered an LTI system under these operating conditions, and that its electrical impedance will be correctly estimated. It can be also noticed that, as shown by simulations in Section III, the use of a PRBS current induces a decrease in the coherence near the upper limit frequency $f_{\text{max}}$. This is also visible in Fig. 9, where the variability of the estimated impedance with the different realizations is very small all over the frequency band, unless near the upper frequency.

2) Swept Square: The input current during the second experiment is a swept square signal. Figs. 10 and 11 show, respectively, the corresponding estimated coherence and electrical impedance. As predicted in Section III, the use of a PRBS current induces a decrease in the coherence near the upper limit frequency $f_{\text{max}}$. This is also visible in Fig. 9, where the variability of the estimated impedance with the different realizations is very small all over the frequency band, unless near the upper frequency. As predicted in Section III, this particular input signal leads to higher coherence values and better estimation performance all over the frequency band.

Based on the high coherence values obtained during experiments, this battery can be considered as an LTI system within the chosen frequency band and under the chosen operating conditions. Moreover, confidence limits of impedance estimators are sufficiently small to affirm that the electrical impedance is accurately identified all over the frequency band.

V. Conclusion

This paper focuses on the usefulness of broadband excitation signals for the identification of Li-ion battery electrical impedance. A nonparametric identification method has been theoretically introduced, together with advanced parameters, such as spectral coherence function and confidence limits, that are able to evaluate the identification performance reached by this method. Simulation results indicate that identification patterns on input currents can be selected on the basis of their frequency characteristics, such as power in the lowest frequencies of a selected band or flatness of their PSD over the whole band. This choice can be made by each user regarding the final use of the impedance measurement. Signals based on a square pattern such as a swept square and a PRBS lead to correct broadband identification and are particularly well suited for electronic implementation. Experimental results ascertain the possibility of applying such a method to real batteries. Future works will focus on a comparative study to quantify the performance of the method by comparing it with standard electrical impedance spectroscopy in terms of precision, robustness, and computation time. Meanwhile, the proposed method will be implemented following a recursive form.


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