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Executive Summary of the Thesis

Advanced Online Diagnostics for Automotive Lithium Batteries

Laurea Magistrale in Electrical Engineering - Ingegneria Elettrica

Author: Alessandra Geroni

Advisor: Prof. Luigi Piegari

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1. Context and motivation

The growing interest in a sustainable future has led to the development of everyday technologies with an increasingly lower environmental impact. Among these, the growth of electric vehicles (EVs) stands out, as road transportation represents one of the major sources of pollution today. An increase in the use of EVs has opened the way to a growing interest in batteries. Among these, lithium-ion batteries (LIBs) offer a strong combination of high energy density and high power density, enabling their widespread development in the automotive sector. There are different chemistries within the family of LIBs, with the most widely used in the EV field being NMC and LFP batteries. Both chemistries present different characteristics, but they make them clearly superior to other technologies with regard to the transportation market [3]. In this context, battery diagnostic technologies are becoming increasingly important. There are several methods and approaches that allow the study of internal battery phenomena in order to estimate its state and possible aging. Among these, one of the most widely used techniques is electrochemical impedance spectroscopy (EIS). This diagnostic tool allows, through the analysis of the impedance frequency spectrum, to obtain an overall view of the internal electrochemical phenomena occurring within the cell. EIS measurements are traditionally performed by applying a controlled sinusoidal excitation signal, which can be either current or voltage. In the first case, it is referred to as galvanostatic electrochemical impedance spectroscopy (GEIS), while in the second case it is known as potentiostatic electrochemical impedance spectroscopy (PEIS). Considering the GEIS case, after applying the sinusoidal current signal, the corresponding voltage response is measured. The impedance value at a given angular frequency, and therefore frequency, is then calculated as the ratio between voltage and current. The excitation frequency is swept over a range that generally spans from 10 kHz to 10 mHz, allowing the analysis of the battery response over a frequency interval that contains information about all internal dynamics.

The battery is generally represented through an equivalent circuit model (ECM), where each circuit component is associated with a different region of the frequency spectrum. Figure 1 shows the Nyquist plot of the impedance spectrum of a lithium-ion battery together with the corresponding ECM. The high-frequency section ($\geq 1kHz$) is dominated by the effect of the inductor L and the ohmic resistance R_1, and it is correlated with ionic conduction through

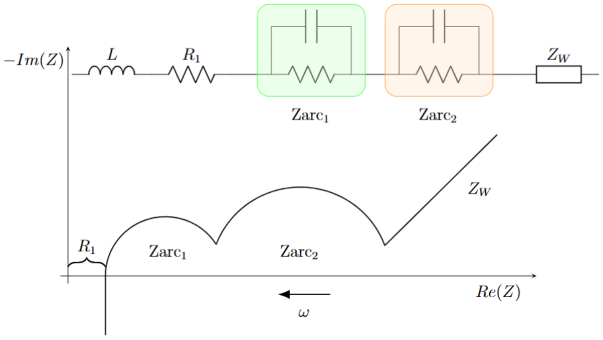


Figure 1: Ideal impedance spectrum of a LIB and an ECM with Zarc and Warburg element.

the electrolyte and the separator. Subsequently, in series with these components, many studies adopted a model based on Zarc and Warburg elements. The former consists of a parallel connection between a resistance and a constant phase element (CPE), and multiple Zarc elements can be connected in series, each characterized by its own time constant. These components dominate the mid-frequency region (approxiamtely from $\leq 1kHz$ and $\geq 100mHz$), where the semicircles are associated with charge transfer processes and double-layer capacitance. Lastly, Warburg elements are approximated as a series connection between a resistance and an RC element. The Warburg impedance characterizes the low-frequency region ($\leq 100mHz$) of the Nyquist plot, which is represented by a tail with a slope of 45° and reflects diffusion-controlled phenomena [2] [1].

The use of EIS as a diagnostic tool is well established, as it allows the estimation of the battery state of health (SOH) through impedance analysis. Generally, impedance measurements are performed offline through laboratory tests conducted at fixed SOC and temperature conditions. These tests are highly effective because they allow the acquisition of the complete impedance spectrum of the cell over a wide frequency range. The main drawback of this approach is the duration, as conventional EIS requires long testing time in order for the cell to reach electrochemical equilibrium. For this reason, this approach is defined as offline, meaning that measurements are typically performed when the vehicle is turned off. Many researchers have proposed different methodologies to perform these measurements online; however, they all present limitations in terms of practical applicability, and often require dedicated hardware for proper operation. The objective of this work is to implement and validate a method for real-time estimation of EIS during normal battery operation through the use of the wavelet transform (WT).

2. Objectives and approach

To address the challenges associated with online EIS measurements discussed in Section 1, this work investigates an approach that combines laboratory testing and dynamic driving cycle simulations to analyze battery behavior under realistic operating conditions. The study focuses on the development of a wavelet-based methodology for online impedance spectrum estimation from power profiles. Additionally, a real SOC estimation approach based on differential voltage analysis (DVA) is developed, with particular focus on LFP cells.

2.1. Experimental framework

The first step consists in selecting three EVs with different technical characteristics in order to compare power profiles with various intensity levels. The selected vehicles are Tesla Model 3 Long Range AWD, Peugeot e-208 54 kWh, and Dacia Spring Electric 65. Moreover, to test the batteries, the worldwide harmonised light-duty vehicles test procedure (WLTP) cycles have been used in order to simulate real driving conditions. These cycles are divided into three main classes, and the classification is based on the value of a parameter called power-to-mass ratio (PMR), which is defined as the ratio between the nominal vehicle power and its curb mass [6]. An additional classification for vehicles belonging to Class 3 is based on the maximum vehicle speed. Consequently, Tesla and Peugeot are classified as Class 3b vehicles, while Dacia is classified as Class 3a. The profiles are provided as speed-versus-time curves; therefore, it is necessary to compute the corresponding power profiles using the following formula:

$$P(t) = F_{tot}(t)v(t) \tag{1}$$

where F_{tot} represents the total longitudinal force acting on the vehicle. The obtained power-versus-time profiles are then scaled according to the energy of the cells used in the laboratory in order to be applied in the experimental measurements. The final trends are illustrated in Figure 2.

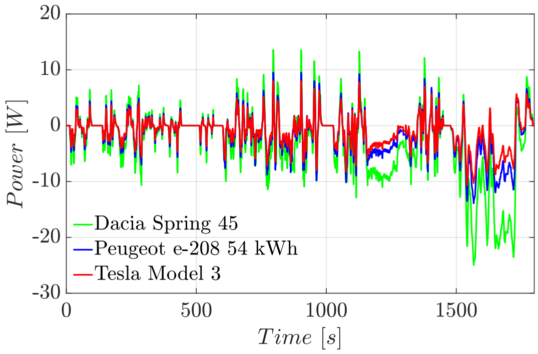


Figure 2: Cell-level scaled power profiles.

Subsequently, the cells to which the obtained power profiles are applied are selected. In the case of Tesla and Peugeot, two NMC cells (model INR21700-50E/2170) with a nominal capacity of 4.9 Ah are used. In the case of Dacia instead, an LFP cell (model FR32650/32700) with a nominal capacity of 6.5 Ah is tested. The cells have been initially activated through charge/discharge cycles at 0.5C. Afterwards, as a first test, EIS measurements are performed every 10% SOC. An additional 5% discharge step is applied to go from 10% down to 5% SOC. This procedure is applied also during charge up to the maximum cutoff voltage, which is 2.5 V for NMC cells and 2 V for the LFP cell. In the case of the NMC cell, due to the characteristic shape of the voltage profile during discharge, which does not exhibit a flat plateau as in LFP cells, a small change in SOC can cause a significant increase in voltage. For this reason, in the NMC case the cell does not reach 100% SOC at the end of charge, but approximately 88%. EIS measurements have been performed using the GEIS technique through BTLab software, which allows the application of a controlled sinusoidal current signal to measure impedance at each SOC level.
The second test performed represents the reference ground truth for the validation of the wavelet-based method. For all cells, EIS measurements were carried out at selected SOC levels of 100%, 75%, 50%, 25%, and 5%. This allows a comprehensive view of the impedance behavior across the entire battery charge range. The impedance measurement was performed before and after the application of a WLTP cycle such that it was possible to demonstrate that the WLTP does not change the electrochemical structure of the cell and the wavelet-method could be applied using these results.

2.2. Wavelet-based online EIS

The Wavelet-based online EIS approach is developed to enable impedance estimation under non-stationary operating conditions such as realistic driving cycles. Unlike traditional frequency-domain techniques, which require stationary signals, the WLTP profile exhibits continuously varying frequency content due to rapid changes in current and voltage. For this reason, a time–frequency analysis based on wavelet transform is adopted, allowing the reconstruction of impedance information while preserving temporal localization of the signal dynamics [5]. Since the dynamic profile does not excite all frequencies with the same energy, the impedance estimation is more accurate in the high and mid-frequency regions, while low-frequency information is inherently more challenging to extract due to slower electrochemical dynamics. The proposed method is validated through comparison with laboratory EIS measurements performed at different SOC levels. Rather than a point-by-point comparison, the validation focuses on the physical consistency of the impedance trends and on the ability of the method to capture the main electrochemical processes within the cell. The results confirm that the application of the WLTP cycle does not significantly alter the electrochemical state of the cell after adequate rest, enabling a meaningful comparison between offline and online impedance spectra. Overall, the wavelet-based approach demonstrates its capability to extract diagnostically relevant impedance information during normal operation, providing a complementary tool to conventional laboratory EIS for real-time battery monitoring.

2.3. Differential Voltage Analysis

DVA is a conventional approach used to study the effects of capacity loss and battery aging. The main feature of this method is its ability to translate internal electrochemical phase transitions into peaks in the dV/dQ curve. In this work, DVA is applied to an LFP cell of the same model mentioned in Section 2.1. This chemistry has been specifically selected since it exhibits a characteristic flat voltage profile over a wide SOC range, approximately from 10% to 90%. Consequently, the voltage varies only slightly with SOC, meaning that even small measurement errors may translate into large SOC estimation errors. Under such conditions, OCV-based methods alone become inadequate, thus motivating the adoption of more advanced techniques such as DVA. The objective of this work is to identify a true electrochemical peak under real driving conditions. DVA generally achieves high accuracy when applied at very low current levels, where the voltage can be approximated to the open circuit voltage (OCV). Several studies have also demonstrated that meaningful results can be obtained at higher C-rates, although shifts in the DV curve may occur depending on whether the battery is in the charge or discharge phase [4].

In this context, it is initially necessary to compensate the highly dynamic WLTP voltage profile for the resistive voltage drop in order to obtain a quasi-OCV curve from which electrochemical peaks could be extracted. Furthermore, these peaks present a fixed position in terms of SOC, since capacity and SOC are related through a factor given by the nominal capacity Q_{nom} (Equation 2), while the corresponding $dV/dSOC$ curve is expressed by Equation 3.

$$SOC = \frac{Q}{Q_{nom}} \tag{2}$$

$$\frac{dV}{dSOC} = \frac{dV}{dQ} \cdot \frac{dQ}{dSOC} = Q_{nom} \cdot \frac{dV}{dQ} \tag{3}$$

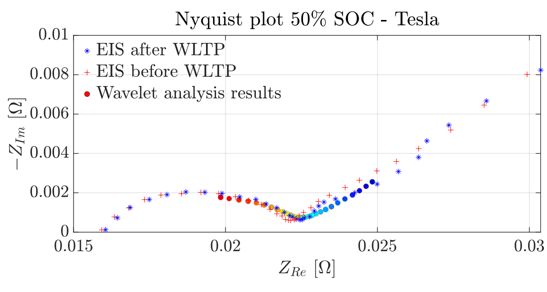
Two different methodologies were investigated to track the DV peaks under WLTP driving conditions. Despite their different implementation approaches, both methods identify consistent peak locations that agree with the reference $dOCV/dSOC$ profile. The identification of such peaks within a dynamic driving cycle represents a key diagnostic landmark, as their evolution over time provides insight into aging mechanisms such as lithium loss, structural changes, and overall cell degradation.

3. Key results and discussion

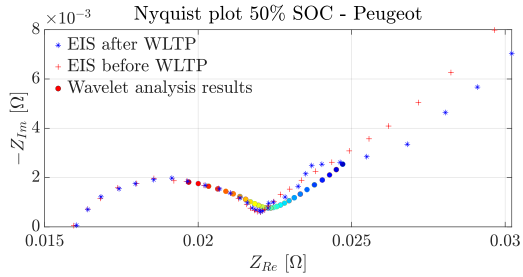
The results obtained from offline EIS measurements represent the reference for the electrochemical behavior of the investigated cells across different states of charge. The wavelet-based online method is validated under WLTP operating conditions, showing a strong physical consistency with laboratory measurements within the analyzed frequency range. Moreover, the DVA applied with two different algorithms highlights the possibility of identifying stable electrochemical features even under dynamic conditions, confirming the diagnostic potential of the proposed approaches.

3.1. Validation of wavelet-based EIS

The validation of the wavelet-based method for online impedance spectrum estimation was carried out by comparing the obtained results with offline EIS measurements performed at fixed states of charge. For clarity, only the results at 50% SOC are shown for each vehicle in Figure 3. The results corresponding to the remaining SOC levels are nevertheless consistent within the analyzed frequency range. The colored markers represent the impedance estimates obtained through the wavelet-based method, where red indicates the highest frequency point and blue the lowest one. The power profiles were sampled at a frequency of 500 Hz; therefore, according to the Nyquist theorem, the wavelet analysis allows the excitation signal to be analyzed up to a maximum frequency of 250 Hz. The wavelet approach extracts impedance-related information within a frequency range limited by technical constraints.



(a)



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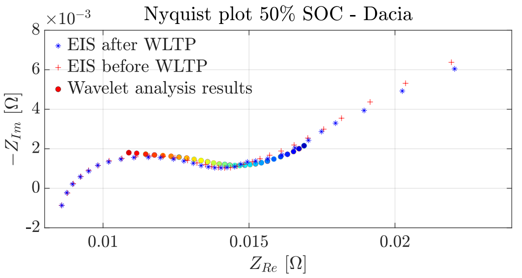


(c)

Figure 3: Comparison of offline EIS and wavelet-based online impedance estimation at 50% SOC for the three EVs: (a) Tesla; (b) Peugeot; (c) Dacia.

While the upper frequency limit is determined by the Nyquist criterion, at very low frequencies the wavelet tails begin to overlap, preventing the extraction of meaningful results. Nevertheless, the online estimation shows a pattern consistent with the laboratory measurements within the frequency range that is most relevant under real driving conditions.

3.2. DVA-based peak identification results

The DVA analysis performed in this work starts from the construction of the OCV(SOC) curve obtained from stepwise measurements during rest conditions. The profile is interpolated using a shape-preserving approach to ensure numerical stability and to avoid artificial oscillations. The derivative of the OCV with respect to SOC highlights a single stable electrochemical peak located at approximately 62.8% SOC, corresponding to a phase-equilibrium condition of the cell (Figure 4). This peak represents a key diagnostic landmark, as its position is expected to shift with battery aging. To enable the application of DVA under realistic driving conditions, the WLTP voltage signal is corrected for the resistive voltage drop using a constant ohmic resistance equal to $20m\Omega$. This chosen value represents a good approximation for cells with capacity in the range 5-10 Ah. The compensation allows the extraction of a quasi-OCV profile that preserves slower electrochemical dynamics while attenuating high-frequency contributions.

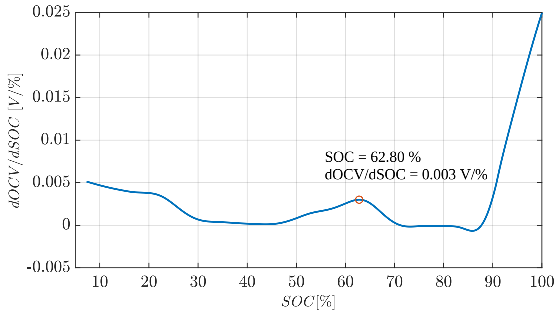
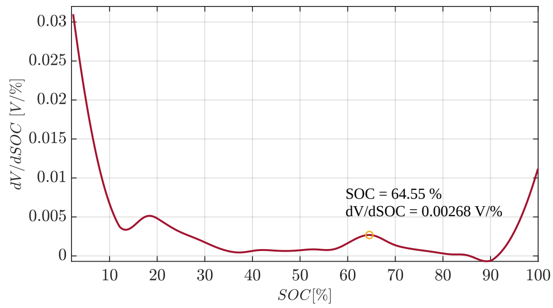
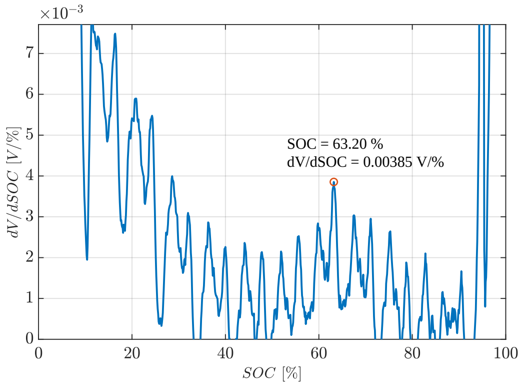


Figure 4: Differential open-circuit voltage curve $dOCV/dSOC$ as a function of SOC with the identified electrochemical peak highlighted.

Two methodologies are then investigated to extract the differential voltage peak from the differential dynamic profile. The first approach, based on SOC binning and statistical averaging, provides a highly robust peak detection by reducing the impact of noise and uneven data distribution. It is based on the costruction of a binned SOC, where an avarage value of voltage is computed for each bin. At this point the derivative is computed and using the findpeaks MATLAB function the electrochemical peak is found. The second approach instead is based on signal interpolation and filtering, it offers a simpler implementation with lower computational cost but shows higher sensitivity to filtering choices. It is based on the usage of a moving average filter which permits to remove easily most of the oscillations given by the dynamics of the signal.



(a)



(b)

Figure 5: Peak identification results: (a) bin-avaraged DVA approach; (b) zoomed view interpolated signal-filtered DVA approach.

In Figure 5 the final results of the two approaches are illustrated. Despite their different implementations, both methods identify consistent peak locations within the SOC range of interest, confirming the validity of the proposed analysis framework. The extracted peak represents a meaningful electrochemical signature that can be used as a diagnostic reference for tracking internal battery processes under dynamic operating conditions.

4. Conclusions and future perspectives

This work evaluated the feasibility of a diagnostic framework aimed at extracting impedance-related information in real time under realistic driving conditions through wavelet-based analysis. The results demonstrate a strong physical consistency between the impedance estimated online and conventional offline EIS measurements within the analyzed frequency range. Despite the inherent limitations associated with the dynamic excitation profile and sampling constraints, the proposed method successfully captured the main electrochemical signatures linked to SOC variations during WLTP operation. The main limitations of the approach are related to the restricted observable frequency bandwidth and the reduced sensitivity to very low-frequency processes. However, these constraints do not significantly affect the reliability of the methodology, since the most diagnostically relevant impedance features lie within the analyzed range.

From the DVA perspective, the analysis performed on the LFP cell enabled the identification of a stable electrochemical peak associated with phase equilibrium conditions. Both peak-detection approaches investigated provided physically meaningful and diagnostically consistent results, confirming their effectiveness for tracking electrochemical features under dynamic conditions. Nevertheless, peak identification remains inherently challenging under highly dynamic profiles, where detection may not always be guaranteed.
Overall, the results establish a physically consistent and reliable framework for online diagnostics of lithium-ion batteries, demonstrating that meaningful impedance information and electrochemical signatures can be extracted during normal vehicle operation without the need for dedicated excitation signals.

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