Battery Diagnostic System and Complex Impedance Measurement Algorithm

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Abstract

This paper presents a novel parameter estimation algorithm for accurately and rapidly assessing a cell’s complex impedance and related estimation parameters, such as State-of-Charge (SoC) and State-of-Health (SoH); while diagnosing its propensity for failure, to improve overall reliability and safety. The measurement technique uses a low power microcontroller for evaluating analogue signals and performing calculations, in order to identify complex impedance parameter values from records of battery voltage variations caused by short duration, pulsed current excitation signals. The technique requires low amounts of memory and processing power, making it ideal for embedded applications and intelligent Battery Management Systems (BMSs), particularly for the automotive and aerospace industries. Experimental results on the influence of battery degradation and temperature variations with impedance are presented for a 1.5 Ahr (SLPB603870H) Lithium-Polymer (LiPo) Kokam cell, while issues around the practical implementation of a 40 Ahr (SLPB100216216H) LiPo cell in a hybrid-electric propulsion system for aircraft are also discussed.

Keywords: Battery impedance, Diagnostic system, System identification, State-of-Health, State-of-Charge

1. Introduction

Recent technological advances in electrochemical storage devices have enabled batteries to store increasing amounts of energy in smaller sizes, intensifying their exploitation over a wide range of industrial sectors. The affordability and availability of low impedance cells have recently influenced the development of high power systems for improving performance and promoting more sustainable, next generation designs [1]. Lithium-ion (Li-ion) batteries, in particular, have attracted significant interest in high power applications, such as Hybrid-Electric Vehicles (HEVs) [2, 3], smart-grid power distribution [4] and Hybrid-Electric Aircraft (HEA) [5]. However, growing concerns over battery reliability and potential failures have presented challenges to their successful implementation and widespread adoption in such high power systems.

Developing a good understanding of cell behaviour and ageing process, is critical when designing energy storage systems for hybrid / electric applications. To ensure safe and reliable operation with optimum performance, these systems usually rely on a BMS [6]. These typically combine both software and hardware systems, to control current flow
across individual cells, or clusters of cells in a battery pack, to ensure that temperature, voltage, and current limits are respected. However, BMSs commonly lack effective prognostic and diagnostic tools to identify faulty, or weaker cells within a battery pack which have a higher probability of failure [7].

Diagnostic systems can help reduce battery failures by correlating variations in its internal impedance with characteristics associated with particular damage modes, such as those induced by short-circuit and overcharge conditions. Furthermore, certain battery chemistries, such as LiCoO2, are more likely to experience catastrophic failures from thermal runaway conditions, if excessive heating occurs when abused [8, 9]. The use of high current rates results in excessive internal heating caused by resistive elements, and approximated by \( P_{\text{loss}} = R I^2 \). Consequently, unsafe conditions may emerge in high power applications, as a battery’s SoH decreases and impedance increases.

There have been several attempts to estimate SoH using a battery’s internal impedance \([10, 11]\), as they both reflect a cell’s ability to deliver and store a percentage of its maximal performance. SoH is a dimensionless parameter, with no absolute definition for representing the battery’s actual physical condition, making its calculation subject to interpretation. Systems often attempt to estimate SoH values with various degrees of accuracies, though it is generally defined as:

\[
\text{SoH}(\%) = \frac{\text{Present condition}}{\text{Initial condition}} \times 100
\]

The purpose of this paper is to present an effective method for accurately identifying a battery’s complex impedance, with minimum processing power and memory requirements; in order to develop on-board battery diagnostic techniques for improving the reliability and safety of energy storage systems in high power applications.

2. Battery Dynamic Model

Batteries are dynamic systems, subject to physical and chemical changes, often leading to lower performance and altered electrical properties \([12]\). These systems are usually characterised by establishing a mathematical relationship between time-varying input-output signals, given by \( u(t) \) (i.e. current) and \( y(t) \) (i.e. voltage) respectively. A series of discrete signals \( u(n) \) and \( y(n) \) are acquired through sampling, with sampling rate \( T_s^{-1} \) and number of samples \( N \).

2.1. Equivalent Circuit Model

The time-domain representation of a battery’s dynamic response varies as a result of electrochemical concentration and polarisation effects, with factors such as SoC, ageing, and temperature. Equivalent circuit models (ECMs) are often included in BMSs to both predict, and improve battery performance, through a network of discrete circuit components. The dual-polarisation (DP) ECM, shown in Figure 1, is commonly used for battery related applications as it is suitable for many battery chemistry types, such as Nickel-Metal-Hydride (NiMH) and Lead-acid batteries \([13]\). Even though higher order models may be used, the DP model is simple enough to minimise the error between the measured and estimated data within an acceptable range, while maintaining minimal amounts of nonlinearities and low computational complexities.

![Figure 1: Second order ECM battery model](image)

Considering that the individual model parameters, shown in Figure 1, represent major electrochemical processes occurring within the cell, a correlation
between parameter variations and battery degradation may be established [10]. The ECM parameters therefore change with SoC, temperature, and degradation (i.e. ageing).

For practical reasons, the impact of mass transport (i.e. ionic diffusion) on polarisation behaviour is not considered throughout this paper, as the phenomenon requires long acquisition times to measure it with reasonable accuracy [12]. However, with appropriate sampling rates and acquisition times, the proposed method can be adapted to characterise such effects.

2.2. ECM Transfer Function

Transfer functions are frequently used to characterise a Linear Time Invariant (LTI) system’s dynamic behaviour in the frequency domain. Rational transfer functions have been used extensively in many battery applications [10, 14], where system models are characterised by differential and difference equations. Rational transfer functions also provide extensive flexibility for estimating model parameters over a wide range of conditions, while its accuracy can be adjusted according to the order of polynomials in the numerator and denominator [14].

\[ H(s) = \frac{B(s)}{A(s)} = \frac{\sum_{k=0}^{M} b_k s^k}{\sum_{k=0}^{N} a_k s^k} \]  

(1)

Rational functions, given by Equation (1), will be used to analyse battery electrochemical variations with SoC, degradation, and temperature. Assuming that all DC voltage and current signals are removed throughout the analysis, the normalised (i.e. \( a_0 = 1 \)) ECM’s impedance transfer function is given by:

\[ Z(s) = \frac{b_3 s^3 + b_1 s + b_0}{a_2 s^2 + a_1 s + 1} \]  

(2)

Where:

\[
\begin{align*}
&b_0 = R_0 + R_1 + R_2 \\
&b_1 = C_1 R_0 R_1 + C_1 R_1 R_2 + C_2 R_0 R_2 + C_2 R_1 R_2 \\
&b_2 = C_1 C_2 R_0 R_1 R_2 \\
&a_1 = C_1 R_1 + C_2 R_2 \\
&a_2 = C_1 C_2 R_1 R_2 \\
\end{align*}
\]

Substituting the discrete-time equivalent of the Laplace variable \( s \) in Equation (2), with the bilinear transform (also known as Tustin’s method), into \( Z(s) \), transforms it into its corresponding discrete-time representation \( Z(z) \):

\[
Z(z) = \frac{(ak^2 + bk + c) + (2e - 2ak^2)z^{-1} + (ak^2 - bk + c)z^{-2}}{(k^2 - dk + e) + (2e - 2k^2)z^{-1} + (k^2 - dk + e)z^{-2}}
\]

Where:

\[
\begin{align*}
a &= R_1 & e &= \frac{1}{C_1 C_2 R_1 R_2} & k &= \frac{2}{T_s} \\
b &= \frac{C_1 R_0 R_1 + C_1 R_1 R_2 + C_2 R_0 R_2 + C_2 R_1 R_2}{C_1 C_2 R_1 R_2} \\
c &= \frac{R_0 + R_1 + R_2}{C_1 C_2 R_1 R_2} & d &= \frac{C_1 R_1 + C_2 R_2}{C_1 C_2 R_1 R_2}
\end{align*}
\]

Assuming that all transfer function coefficients are known, the above expressions represent a set of simultaneous equations, which can be used to estimate individual impedance variables (i.e. \( R_0, R_1 \), etc.). However, parameter extraction cannot be obtained directly through mathematical manipulations, but instead, nonlinear solving techniques must be used to obtain corresponding values.

2.3. Impedance System Identification

The following section discusses an Infinite Impulse Response (IIR) adaptive filtering technique for calculating battery impedance values from voltage and current samples, acquired from an instantaneous event. A wide range of methods can be used to compute coefficient values from the discrete transfer function \( Z(z) \), but the discussion here will only cover the Steiglitz-McBride method.

The Steiglitz-McBride algorithm [15] is an iterative technique for identifying the parameters of discrete LTI systems from samples of input-output variations, by minimising the mean-squared-error (MSE) between the system’s predicted and measured output. The methodology is based on the equation error formulation, but uses prefilters to linearise the
minimisation problem to one which involves output errors [16], as illustrated in Figure 2, where:

$$y_n = Z(z)u_n + \xi_n$$  \hspace{1cm} (3)

where \(\{\xi_n\}\) is some stochastic sequence which is statistically independent of the input sequence \(\{u_n\}\), and \(Z(z)\) is the battery impedance’s impulse response from the second order ECM:

$$Z(z) = \frac{B(z)}{A(z)} = \frac{\sum_{k=0}^{2} b_k z^{-k}}{1 + \sum_{k=1}^{2} a_k z^{-k}}$$  \hspace{1cm} (4)

The minimisation problem is given by the MSE between the predicted output and the observed output of the system being identified:

$$\min_x \sum_{n=0}^{N-1} e_n^2 = \frac{1}{2\pi j} \int \left| \frac{B(z)}{A(z)} U(z) - Y(z) \right|^2 \frac{dz}{z}$$  \hspace{1cm} (5)

Where the contour of integration is on the unit circle \(|z| = 1\) and \(x\) is the estimation parameter vector for the system’s minimisation problem:

$$x = [a_1 \ a_2 \ b_0 \ b_1 \ b_2]^T$$  \hspace{1cm} (6)

And:

$$e_n = y_n + \sum_{k=1}^{2} a_k y_{n-k} - \sum_{k=0}^{2} b_k u_{n-k}$$  \hspace{1cm} (7)

However, Equation (5) is a highly nonlinear regression problem, which cannot be solved directly. Steiglitz et. al. proposed an algorithm for computing a z-domain rational model with an iterative procedure which modifies coefficient values by carrying out linear minimisations with the use of prefilters to form the following problem:

$$\min_x \sum_{n=0}^{N-1} e_n^2 = \frac{1}{2\pi j} \int \left| B(z)U'(z) - A(z)Y'(z) \right|^2 \frac{dz}{z}$$

Where \(i\) is the number of iterations and:

$$U'(z) = \frac{1}{A_{i-1}(z)} U(z) \hspace{1cm} Y'(z) = \frac{1}{A_{i-1}(z)} Y(z)$$

Convergence for this iterative procedure corresponds to the sequence of polynomials \(A_i(z)\) and \(B_i(z)\) as they approach their limit [16], denoted by \(A_\infty(z)\) and \(B_\infty(z)\), resulting in the original nonlinear objective function presented in Equation (5):

$$\min_x \sum_{n=0}^{N-1} e_n^2 = \frac{1}{2\pi j} \int \left| B_\infty(z)U_\infty'(z) - A_\infty(z)Y_\infty'(z) \right|^2 \frac{dz}{z} = \frac{1}{2\pi j} \int \left| \frac{B_\infty(z)}{A_\infty(z)} U(z) - Y(z) \right|^2 \frac{dz}{z}$$

After convergence, the solution to the above least squares minimisation problem represents the discrete form transfer function, which describes the relationship between the battery’s input current and output voltage (i.e. impedance), thereby forming a set of simultaneous equations:

$$a_0 = 1 \hspace{1cm} b_0 = \frac{ak^2 + bk + c}{k^2 + dk + e}$$
$$a_1 = \frac{2e - 2k^2}{k^2 + dk + e} \hspace{1cm} b_1 = \frac{2c - 2ak^2}{k^2 + dk + e}$$
$$a_2 = \frac{k^2 - dk + e}{k^2 + dk + e} \hspace{1cm} b_2 = \frac{ak^2 - bk + c}{k^2 + dk + e}$$

A trust-region dogleg approach [17] was used to extract individual impedance values from the above nonlinear set of simultaneous equations, though other techniques can be used instead [9].

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**Figure 2: Steiglitz-McBride flow diagram**

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2.4. Bandwidth & Input Signals

An appropriate input excitation signal should be chosen, so that impedance estimations are accurate and consistent with each other. This is accomplished by selecting a signal with a wide frequency range, where a sufficient span of frequency components are available to adequately represent the battery impedance model.

The excitation signal may originate from any instantaneous events, transient events or triggered events, which would occur naturally or induced by the transfer of energy to a load, or from a source, thus allowing a system to regularly update impedance values, while monitoring for proper non-faulty operation. For example, common events in HEVs, such as acceleration, deceleration, and engine startup [10], can provide the necessary high transient voltage changes for identifying a battery’s internal impedance. While a wide range of input signals can be used, pulsed signals are typically preferred, as they are easily implemented in practice, and provide wide frequency bandwidth for characterising both slow and fast moving electrochemical behaviours.

The method can also make use of statistical averaging by pulsing the battery with sufficiently long resting periods, to increase the signal-to-noise ratio (SNR), and accuracy of impedance estimations. Further improvements to SNR can be made by increasing the magnitude of the input signal. A trade-off between pulse length should be also be considered, as shorter pulses reduce the effects of high power dissipation, while longer pulses provide more data for identifying impedance characteristics. Shorter pulses also result in faster acquisition times and ensure that battery open circuit voltage (OCV) remains substantially unchanged. Additionally, voltage drops caused by ohmic resistance, double layer and charge transfer effects are typically of importance when measuring impedance variations due to capacity fading, degradation and faulty operation [18]. However, the battery’s impedance value is underestimated with shorter excitation signals, as slow diffusion processes, such as mass transport, cannot be characterised accurately.

Generally, the pulse length should be adjusted with SoC, such that voltage variations due to polarisation effects can be estimated with enough accuracy. Furthermore, the dependence of internal impedance with current magnitude is also neglected throughout this paper, since the excitation signal’s current magnitude remains relatively constant, and therefore the results remain valid for diagnostic and recalibration purposes [19].

Pulse widths between 40ms – 80ms (120A peak current) and 20ms – 120ms (11A peak current) were selected for the 40 Ahr and 1.5 Ahr Kokam cells respectively.

The proposed algorithm was experimentally verified on 1.5 Ahr and 40 Ahr Kokam Superior Lithium Polymer Batteries (SLPB) of similar chemistry. The 1.5 Ahr cells were tested individually, whereas the 40 Ahr cells were used to construct a 16s-1p battery pack, with a nominal voltage of 59.2V, for the Cambridge HEA project, shown in Figure 3.

The Cambridge HEA team have been researching possible energy saving solutions for promoting
cleaner and more sustainable aircraft designs. The aircraft consists of a lightweight microlight aircraft, with a high lift-to-drag ratio, powered with a parallel hybrid engine, through a combination of an 8kW internal combustion engine (ICE) and 12kW electric motor (EM) for optimising the aircraft’s overall energy efficiency [5].

### 3.1. HEA Embedded Diagnostic System

Diagnostic systems provide higher levels of reliability and improved safety standards, particularly for applications where high power batteries are used. High capacity battery systems, combined with high power capabilities, inherently carry higher levels of risk, where potential damage may arise from sudden battery failures, or avalanche effects where a single battery failure may lead to a complete and catastrophic system failure. Embedded diagnostic systems also facilitate maintenance and inspection of battery packs, for detecting weaknesses, or faults, prior to any damage incurred from actual failures.

Performing regular and accurate battery impedance measurements over its lifetime is important when designing reliable energy systems. The most common battery failures are caused by excessive temperatures, over-charging, over-discharging, short-circuiting, and manufacturing defects. Even with a good BMS, a battery’s SoH may degrade to such a point that its internal impedance may dissipate large amounts of power, increasing its probability of failure. Prior to failure, batteries usually exhibit internal impedance changes until complete failure has been reached.

The proposed diagnostic system, shown in Figure 4, evaluates a battery’s internal impedance, by implementing the previously described algorithm. Data acquisition is triggered during a short instantaneous event, where voltage and current samples are subsequently stored in $[1000 \times 5]$, 16-bit integer matrix array, requiring 10kB of RAM. A 5kHz sampling rate was selected, as it is sufficiently fast to determine the highest possible frequency in the battery’s dynamic response, according to the Nyquist sampling theorem. Once acquired, the diagnostic system may compare impedance results with other cells in a battery pack, or assess if impedance values are within an acceptable range when compared to expected baseline data obtained empirically.

The combination of all resistances (i.e. $R_0 + R_1 + R_2$) corresponds to the battery’s total DC resistance ($R_{TOT}$) for estimating overall SoH, while variations in $C_1$ and $C_2$, provide additional information for diagnosing and identifying particular failure modes. A predefined impedance increase from nominal conditions is also used as an indication for battery End-of-Life (EoL), as this is more suitable for high power applications, as opposed to capacity fading. This ensures that proper operation is consistently maintained and faulty, or weaker cells, are progressively replaced as to avoid any catastrophic failures.

![Figure 4: CAD prototype of HEA’s BMS modular circuit](image)

### 3.2. BMS Firmware & Hardware

The impedance algorithm, and associated BMS functionalities, were implemented using a low power PIC32MZ microcontroller, with custom firmware code, written in ANSI C standard, for minimising program space and optimising calculations for rapid battery impedance estimation.
The microcontroller includes 5 separate 12-bit analog-to-digital (ADC) channels, capable of acquiring up to 5 individual analogue signals simultaneously. The system can therefore estimate up to 4 individual battery impedances, with a single current pulse, when cells are connected in series. With a total of 5000 samples (4 voltages and 1 current signal), the microcontroller’s computational time for estimating battery impedance for each of the four cells, was approximately 350ms.

The final BMS for the HEA project is composed of 4 identical circuit modules, which communicate to a central unit in a master/slave configuration, allowing for simultaneous battery impedance estimations on all 16 cells. Power consumption for each module varies between 350mW and 1W depending on CPU clock speeds, and is taken directly from the terminals of 8 cells connected in series, via a DC-DC converter.

### 4. Results & Discussion

The following battery impedance results were obtained from the 1.5 Ahr cell across its entire operating SoC range (3.0V and 4.2V cutoff voltages), to better understand impedance variations caused by battery ageing and operating temperature.

#### 4.1. Impedance Parameter Extraction

To validate the proposed algorithm, regular impedance values were extracted from records of battery voltage variations caused by short duration, current pulse excitation signals, during a 1C charge. The battery’s voltage response, and subsequent recovery, is primarily dependent on SoC, with voltage reaching equilibrium more rapidly at higher SoC than at lower values, as shown in Figure 5. Ideally, the battery’s voltage response should provide the maximum amount of information on the system being measured; and while a constant pulse width of 20ms can be used, the system is no longer well defined beyond 30% SoC.

By varying the signal’s pulse length with SoC, a more accurate impedance estimation is possible. As shown in Figure 5, impedance values extracted onboard the PIC32MZ microcontroller match experimental data very well, where high $R^2$ coefficients (> 0.97) are obtained over the battery’s entire SoC and temperature range.

#### 4.2. Impedance & Ageing

Battery ageing, and resulting impedance increase, must be considered in applications where the available energy or power are limiting factors, as power capabilities and associated battery efficiencies decrease with increasing impedance. However, a detailed examination of dependencies of battery impedance over a wide range of conditions and lifetime is essential for designing a robust energy storage system in high power applications.

Battery degradation and ageing mechanisms are often caused by an association or combination of complex electrochemical processes. These are usually associated with a change in internal impedance, resulting in battery capacity loss and decrease in energy efficiency.
In contrast, impedance dependency on SoC changes significantly for impedance parameters \( R_1 \) and \( C_1 \), but remains relatively constant for all others. An exponential increase in \( R_1 \) is also observed for SoC values below 50%. Results from Table 1 demonstrate that \( R_0 \) increases linearly with cycle number. This can be explained with a lower electric conductivity of the electrolyte and gradual decrease in lithium concentration, resulting from surface film growth at the solid electrolyte interface (SEI) on the surface of the anode and occurrence of irreversible side reactions. This is supported with results in Table 1, where a linear relationship between battery capacity loss and increase in series resistance \( R_0 \) is also observed.

Variations in \( R_1 \), \( C_1 \) and \( R_2 \), \( C_2 \) with cycle number, result in altered \( RC \) time constants and changes in battery dynamic responses to a load. In Figure 6, \( R_0 \) represents the highest resistance for SoC values greater than 15%. Though this may not actually be the case, as the analysis does not account for mass transport on battery polarisation. Nonetheless, impedance variations demonstrate linear variations with degradation, which is in agreement with data obtained from Electro-Impedance Spectroscopy (EIS) in other works [19, 20, 9, 21].

Figures 6 and 7 illustrate how individual impedance parameters change with SoC and lifetime. Each cycle consists of a 1C charge and 4C discharge between 3.0V and 4.2V, at 25°C. Results show that both \( R_0 \) and \( R_1 \), are mainly responsible for increases in \( R_{TOT} \) and overall degradation, whereas the contribution of \( R_2 \) to \( R_{TOT} \) is very marginal. Additionally, capacitance \( C_1 \) and \( C_2 \), show opposite variations with ageing, where values in \( C_1 \) decrease and values in \( C_2 \) increase with cycle number.

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Variations in \( R_1 \), \( C_1 \) and \( R_2 \), \( C_2 \) with cycle number, result in altered \( RC \) time constants and changes in battery dynamic responses to a load. In Figure 6, \( R_0 \) represents the highest resistance for SoC values greater than 15%. Though this may not actually be the case, as the analysis does not account for mass transport on battery polarisation. Nonetheless, impedance variations demonstrate linear variations with degradation, which is in agreement with data obtained from Electro-Impedance Spectroscopy (EIS) in other works [19, 20, 9, 21].

<table>
<thead>
<tr>
<th>Cycle Number</th>
<th>Capacity (%)</th>
<th>( R_0 ) (mΩ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>100.0</td>
<td>9.39</td>
</tr>
<tr>
<td>1050</td>
<td>92.5</td>
<td>10.8</td>
</tr>
<tr>
<td>1750</td>
<td>86.8</td>
<td>11.8</td>
</tr>
</tbody>
</table>

### 4.3. Impedance & Temperature

Temperature variations of \( R_{TOT} \) (i.e. total resistance), \( R_0 \) (i.e. bulk resistance), \( R_1 \) (i.e. charge-transfer resistance), \( R_2 \) (i.e. solid electrolyte interface resistance), \( C_1 \) (i.e. double-layer capacitance), and \( C_2 \) (i.e. solid electrolyte interface capacitance) for the 1.5 Ahr LiPo battery are presented.

It is observed that \( R_1 \) and \( R_2 \) vary similarly with temperature variations, while \( R_0 \) shows little temperature dependence. This is because \( R_1 \) and \( R_2 \)
are largely determined by ionic conductivity of the liquid electrolyte and cell reactions between the electrolyte-electrode interface, which are strongly temperature dependent, as slower kinetic reactions occur [22]. At lower temperatures, the charge transfer resistance \( R_1 \) significantly contributes to \( R_{TOT} \), as opposed to \( R_0 \) at higher temperatures. Therefore, the battery’s cycling performance is mainly limited by slow kinetics of the cell’s reaction with higher values of \( R_1 \) at lower temperatures [22].

Dependency of the real-part impedance characteristics with temperature follows an exponential increase as temperature decreases, particularly below freezing temperatures \((< 0°C)\). Conversely, decreases in temperature leads to a decrease in both \( C_1 \) and \( C_2 \) values, which are comparable to results presented in other works [21, 19]. Therefore, low temperature causes high power losses and lower power availability, limiting the useful energy which may be extracted from the battery.

The exponential increase in \( R_1 \) at low temperatures and low SoC, observed in Figure 9, will result in a very difficult and slow charging process if the battery is discharged below 15% SoC. This is mainly caused by high IR voltage drops across \( R_{TOT} \), where battery cutoff voltages are reached prematurely and lower currents must be used to ensure safe operation. From the results in Figure 8, it is suggested that battery SoC is maintained above 20% when operating below freezing temperatures \((< 0°C)\).

Temperature has significantly larger influence on battery impedance variations than actual degradation, as illustrated in Figures 6 – 10. Therefore, it is necessary to compensate influences of temperature on impedance measurements if comparisons are to be made at other temperatures for diagnostic and recalibration purposes. Consequently, both accurate impedance and temperature measurements, are required in order to assess a battery’s present power availability and SoH.
4.4. RC Time Constants

The battery’s RC time constant $\tau$ is defined as $\tau_1 = R_1C_1$ and $\tau_2 = R_2C_2$ with $[\tau]$ = seconds. Its value reflects on the dynamic rate of change of battery voltage after applying an excitation signal. Larger time constants indicate slower exponential voltage variations, while lower values indicate faster exponential changes.

Results in Figure 11 show that $\tau_1$ and $\tau_2$ exhibit a linear increase with decreasing temperatures, whereas $R_1$ and $R_2$ demonstrate an exponential increase with respect to temperature. Both time constant $\tau_1$ and $\tau_2$, also exhibit similar temperature dependence when compared to real parts of impedance values ($R_0$, $R_1$, $R_2$), while they show marginal changes with ageing, as illustrated in Figure 6 and 7. These results are comparable to EIS data in other works [21, 19].

The increase in $\tau_1$ and $\tau_2$, at lower temperatures may be advantageous in applications where high frequency signals (e.g. 100Hz – 5kHz) are used for supplying or storing energy. Sinusoidal charging, or pulsing, circuits have already been proposed [13]. Since the voltage response is slower at higher $\tau$ values, high frequency charging, or discharging, techniques may prove advantageous in terms of increasing a battery’s total energy efficiency, while decreasing charging times [13]. However, the presence of series resistance $R_0$ still remains the main source of energy losses and factor limiting the battery’s power capability under typical operating conditions.

4.5. HEA Battery Pack Impedance

Results for battery impedance extraction on-board the PIC32MZ microcontroller are presented in Table 2. Data was acquired for 4 cells connected in series at 95% SoC in the 16s-1p HEA battery pack, with a 70ms current pulse and 5kHz sampling frequency. Statistical averaging was implemented by using a total of 5 separate current pulses with a 500ms resting period to ensure voltage reaches equilibrium prior to each pulse. After summing the data from each pulse into the pre-allocated $[1000 \times 5]$ matrix array, impedance parameter extraction for each cell was executed.

The coefficient of variation (CV), shown in parentheses in Table 2, was calculated from 4 separate impedance acquisitions at the same SoC and temperature. Results show very low CV for all individual impedance parameters, suggesting low variability and consistency in the acquired data. Impedance parameters $C_1$ and $C_2$, show higher variability, since large variations in respective values cause small differences in the time-domain representation of the battery voltage response.

Table 2: Simultaneous extracted impedance results for a string of 4 cells in the 40 Ah battery pack at 25°C and 95% SoC

<table>
<thead>
<tr>
<th></th>
<th>Cell 1</th>
<th>Cell 2</th>
<th>Cell 3</th>
<th>Cell 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_0$ (mΩ)</td>
<td>0.58 (1.6%)</td>
<td>0.51 (1.9%)</td>
<td>0.52 (1.9%)</td>
<td>0.54 (1.8%)</td>
</tr>
<tr>
<td>$R_1$ (mΩ)</td>
<td>0.28 (2.1%)</td>
<td>0.34 (3.8%)</td>
<td>0.35 (2.7%)</td>
<td>0.33 (3.5%)</td>
</tr>
<tr>
<td>$R_2$ (mΩ)</td>
<td>0.63 (2.2%)</td>
<td>0.63 (3.1%)</td>
<td>0.61 (2.9%)</td>
<td>0.60 (2.8%)</td>
</tr>
<tr>
<td>$C_1$ (F)</td>
<td>60 (6.1%)</td>
<td>57 (5.3%)</td>
<td>55 (4.9%)</td>
<td>48 (5.0%)</td>
</tr>
<tr>
<td>$C_2$ (F)</td>
<td>4.9 (4.9%)</td>
<td>4.3 (4.5%)</td>
<td>4.5 (5.2%)</td>
<td>4.4 (4.8%)</td>
</tr>
</tbody>
</table>

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5. Conclusions

A practical battery diagnostic system and robust complex impedance measurement algorithm is presented in this paper. Results have shown that accurate battery impedance estimations are possible from variations in voltage and current samples with short duration pulsed signals. With appropriate initial conditions and removal of input-output signals’ DC offsets, the proposed algorithm provides stable and consistent results with low variance and high $R^2$ coefficients.

The impedance algorithm was successfully implemented on-board a low power PIC32MZ microcontroller, for extracting impedance characteristics on a 1.5 Ahr cell and 16s-1p 40 Ahr battery pack. The computational and acquisition times for estimating battery impedance benefit from low memory requirements and fast execution. Data extracted from this technique was presented for impedance variations caused by ageing and temperature.

Additionally, results presented in this paper have demonstrated that correlations between a battery’s SoH, degradation and subsequent capacity loss, can be established with accurate impedance measurements. With appropriate empirical data, increases in $R_0$ can be linearly correlated to capacity loss with cycling, suggesting that accurate battery capacity estimations are possible without having to completely cycle the cell in order to measure it.

Further work with the technique includes the development of a sophisticated battery diagnostic system for identifying faulty cells from distinctive variations in impedance with particular failure modes, such as short-circuiting, over-charging, over-discharging, and over-heating. An investigation on the technique’s effectiveness with other excitation signals should also be carried out.

6. Acknowledgements

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References


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