

Passive EIS-Based Battery State of Health Estimation Using Internal Temperature Modelling Under Dynamic Operating Conditions

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Abstract

Reliable onboard estimation of the State of Health of lithium-ion batteries remains challenging because battery impedance is simultaneously affected by ageing, temperature, and operating conditions. Although Passive Electrochemical Impedance Spectroscopy enables impedance estimation under dynamic operating conditions without dedicated excitation signals, the resulting impedance measurements must account for temperature effects before being exploited for diagnostic purposes. This work proposes a diagnostic framework combining passive impedance measurements, internal temperature estimation, and supervised learning for battery SoH estimation. The approach relies on a thermal model identified using Thermal Impedance Spectroscopy to estimate the internal cell temperature and separate temperature-induced impedance variations from ageing-related effects. The charge-transfer resistance extracted from passive impedance measurements is then combined with the estimated temperature and State of Charge to estimate battery SoH using a supervised neural network. Unlike previous studies, which generally address passive impedance estimation, thermal modelling, or data-driven diagnosis separately, the proposed methodology integrates these components into a unified framework. The methodology is experimentally validated on lithium-ion cells under representative dynamic driving conditions and different ageing levels. The results demonstrate that coupling PEIS with internal temperature estimation improves the robustness of impedance-based diagnostic indicators, enabling accurate SoH estimation under realistic onboard operating conditions.

Keywords: Passive electrochemical impedance spectroscopy, onboard battery diagnostics, state-of-health estimation, thermal impedance spectroscopy, equivalent circuit model.

Nomenclature

Symbol	Description
A_P	Amplitude of the thermal power signal
A_T	Amplitude of the temperature signal
φ_P	Phase of the thermal power signal
φ_T	Phase of the temperature signal
C_{aged}	Measured discharge capacity of the aged cell
C_{BoL}	Measured discharge capacity at beginning of life
C_{th}	Equivalent thermal capacitance
i_{cell}	Cell current
v_{cell}	Cell voltage
i_{Rdiff}	Current through the diffusion branch
P_{heat}	Heat generation inside the cell
$Q(s)$	Heat generation in the Laplace domain
Q_{dl}	Double-layer constant phase element parameter
Q_{SEI}	SEI constant phase element parameter
R_0	Ohmic resistance
R_{ct}	Charge-transfer resistance
R_{Diff}	Diffusion resistance
R_{int}	Internal electrical resistance
R_{SEI}	Solid Electrolyte Interphase resistance
α_{dl}	Double-layer CPE exponent
α_{SEI}	SEI CPE exponent
$R_{th_{in}}$	Internal thermal resistance
$R_{th_{ex}}$	External thermal resistance
T_{amb}	Ambient temperature
T_{in}	Internal cell temperature
T_{surf}	Cell surface temperature
ΔT	Temperature rise with respect to ambient temperature
Z_{ECM}	Modelled electrical impedance
Z_{meas}	Measured electrical impedance
Z_{TIS}	Thermal impedance

1. Introduction

The transportation sector remains one of the major contributors to greenhouse gas emissions and therefore plays a key role in the ongoing energy transition [1]. In recent years, the progressive replacement of internal combustion engine vehicles by electric alternatives has emerged as an effective solution to reduce CO₂ emissions during operation. Within this context, batteries have become central components, especially in mobility applications where performance, lifetime, and reliability are critical challenges [2].

Even when multiple energy sources coexist within the same powertrain architecture, the battery remains a key element. It is particularly stressed during transient operating phases, such as acceleration, load variations, or regenerative braking events [3]. A better understanding of its behaviour and an accurate monitoring of its State of Health (SoH) are therefore essential to ensure both system performance and long-term durability. In addition, temperature plays a critical role in battery operation, as it directly affects electrochemical kinetics, impedance response, and degradation mechanisms. Recent electrochemical-thermal studies have further highlighted the strong coupling between temperature evolution and battery ageing, particularly under demanding operating conditions [4].

In parallel with advances in battery chemistries and cell architectures, continuous progress in the characterisation and optimisation of functional materials also contributes to the development of future energy storage technologies [5, 6]. Recent reviews have highlighted that these technological advances must be accompanied by improved battery modelling and diagnostic methodologies in order to fully exploit their potential [7, 8].

In this context, significant research efforts are devoted to the development of reliable diagnostic methods for battery health assessment. Several approaches have been proposed for State-of-Health estimation, including capacity measurements, voltage-based methods such as incremental capacity analysis (ICA) and differential voltage analysis (DVA), model-based techniques, and impedance-based methods. Capacity- and voltage-based approaches generally require complete charge/discharge cycles or controlled operating conditions, whereas model-based methods rely on accurate battery models whose parameters evolve with ageing [9]. Among these techniques, Electrochemical Impedance Spectroscopy (EIS) has emerged as one of the most promising solutions because it provides direct access to electrochemical processes associated with battery degradation through non-destructive measurements [10, 11]. However, the practical implementation of EIS for onboard applications remains challenging.

Nevertheless, conventional EIS implementation requires a dedicated excitation signal and quasi steady-state operating conditions, which considerably complicates its use in embedded environments. Several studies have proposed to use the power converter as an excitation source [12, 13], for instance by modulating the duty cycle. Despite its relevance, this approach remains restrictive and strongly dependent on the vehicle power electronics architecture.

Although impedance-based diagnostic techniques have demonstrated their potential for battery health assessment, several limitations still hinder their practical deployment in onboard applications. Most existing approaches rely on dedicated excitation signals or quasi steady-state operating conditions, making them difficult to implement during normal vehicle operation. In addition, the influence of the internal cell temperature on the measured impedance is often neglected or approximated using surface temperature measurements, which may lead to inaccuracies under dynamic operating conditions.

These remaining limitations highlight the need for a diagnostic methodology capable of operating under realistic driving conditions while accounting for the thermal influence on the measured impedance.

The method proposed in this paper aims to overcome these limitations by performing impedance measurements directly under dynamic operating conditions, exploiting the harmonic content naturally present in the system. This Passive Electrochemical Impedance Spectroscopy (PEIS) approach enables impedance estimation without affecting vehicle availability. The main objective of this work is therefore to integrate this passive impedance

measurement strategy into a diagnostic framework dedicated to battery SoH estimation.

Unlike our previous work, which focused on the development and validation of the PEIS signal-processing algorithm under dynamic operating conditions [14], the present study addresses the integration of passive impedance measurements into a complete diagnostic framework for battery State-of-Health estimation.

The novelty of the proposed approach does not lie in the PEIS algorithm itself, but in its coupling with a thermal model identified using Thermal Impedance Spectroscopy (TIS). Rather than directly correcting the measured impedance spectrum, the proposed thermal model estimates the internal cell temperature under load. This estimated temperature enables passive impedance measurements acquired during dynamic operation to be consistently associated with the reference EIS database obtained under zero-current conditions, thereby reducing the influence of current-induced self-heating on the extracted diagnostic indicator.

To the best of the authors' knowledge, this is the first work combining Passive Electrochemical Impedance Spectroscopy, internal temperature estimation using Thermal Impedance Spectroscopy, and supervised learning within a unified framework for battery State-of-Health estimation under dynamic operating conditions.

The overall principle of the proposed diagnostic methodology is illustrated in Figure 1, which summarises the different contributions developed in this study. The approach notably requires the estimation of both the State of Charge (SoC) and the internal cell temperature. Particular attention is therefore given to internal temperature estimation through the development of a dedicated thermal model, in order to improve the robustness and accuracy of the SoH estimation. The proposed diagnostic framework is designed to exploit impedance information extracted from onboard measurements in realistic operating conditions.

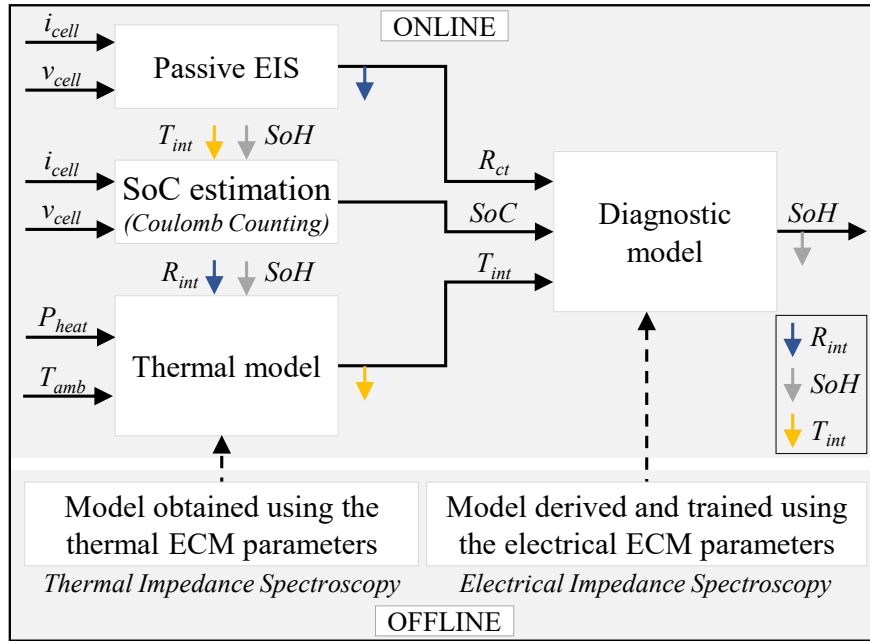


Figure 1: Overall framework of the proposed SoH diagnostic methodology

2. Onboard diagnostic approaches

2.1. Passive impedance estimation

Electrochemical Impedance Spectroscopy is widely recognised as a powerful tool for battery characterisation, as it provides access to electrochemical processes directly related to battery ageing. However, conventional EIS requires dedicated excitation signals and quasi steady-state operating conditions, which considerably limit its applicability in onboard environments.

To overcome these limitations, PEIS exploits the harmonic content naturally present in the battery current during vehicle operation, allowing impedance spectra to be estimated without dedicated excitation signals. Unlike active EIS approaches, PEIS does not require any modification of the converter control strategy, making it particularly attractive for onboard battery monitoring [15, 16, 17].

The signal-processing algorithm employed in this work was developed and experimentally validated in our previous study [14]. Since the PEIS methodology itself is not the focus of the present paper, only the resulting impedance measurements are considered hereafter and used as inputs to the proposed diagnostic framework. The reader is referred to [14] for a detailed description of the signal-processing algorithm and its experimental validation.

The PEIS signal-processing algorithm remains unchanged throughout the ageing process. Battery ageing modifies the impedance spectrum through the evolution of the equivalent circuit parameters, while the frequency-domain estimation procedure itself is independent of the battery ageing state. Consequently, the same signal-processing algorithm is applied to all measurements, and only the identified ECM parameters evolve with ageing.

To facilitate the interpretation of the estimated impedance spectra, an Equivalent Circuit Model (ECM) is employed (Figure 2). The model consists of an ohmic resistance R_Ω , a resistance associated with the solid electrolyte interphase R_{SEI} , a charge-transfer resistance R_{CT} , and constant phase elements (CPEs) represented by the parameters Q and α , which describe the non-ideal capacitive behaviour of the different electrochemical interfaces. The identified parameters vary with the operating conditions, particularly the temperature, SoC, and SoH [11, 18, 19]. These parameters therefore constitute relevant diagnostic indicators and are subsequently exploited within the proposed SoH estimation framework.

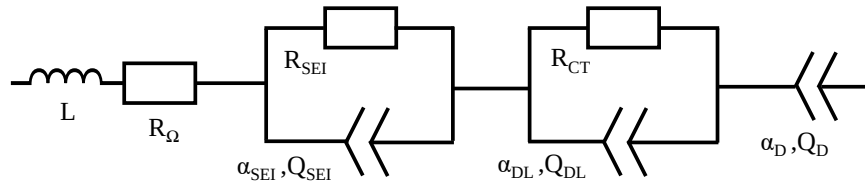


Figure 2: Equivalent electric circuit of the cell

2.2. Limitations of existing diagnostic approaches

Although significant progress has been achieved in impedance-based battery diagnostics, several challenges still hinder reliable onboard State-of-Health estimation.

First, the measured impedance is strongly influenced by operating conditions, particularly temperature, making it difficult to distinguish thermal effects from ageing-related impedance variations [4, 18].

Second, most existing studies address impedance acquisition, thermal modelling, or data-driven SoH estimation independently. Consequently, the interaction between these different components is rarely considered within a single diagnostic methodology [8, 20, 21].

Therefore, the integration of passive impedance measurements, internal temperature estimation, and data-driven SoH estimation into a unified framework suitable for onboard implementation remains scarcely investigated.

These limitations motivate the diagnostic framework proposed in this work, which is presented in the following subsection.

2.3. Diagnostic method

In general, battery diagnostic approaches aim at estimating the SoH of a cell from measurements acquired during operation in order to assess its ageing state and remaining performance [22].

In the present study, EIS is used as the main characterisation tool. It is therefore necessary to define an appropriate diagnostic methodology to exploit the information extracted from impedance measurements. In practice, a diagnostic framework relies on both the choice of a characterisation technique and the selection of a suitable data exploitation strategy. Two main families of approaches can be considered: model-based methods and data-driven methods [20, 23]. Recent reviews have shown that data-driven battery diagnostics have become increasingly important due to their ability to exploit large experimental datasets while accounting for the nonlinear behaviour of lithium-ion batteries. These approaches include both deterministic and probabilistic machine learning methods for fault diagnosis, health monitoring, and prognostics [21, 24, 25].

In this work, impedance measurements are carried out under a wide range of operating conditions, resulting in the availability of a large experimental dataset. This context naturally motivates the use of a data-driven approach. Depending on the nature of the available data, such approaches can be either supervised or unsupervised [20, 23].

In supervised learning, algorithms are trained using labelled data in order to associate specific features with a given health state or class. Commonly used techniques include k-nearest neighbours (k-NN), support vector machines (SVM), and neural networks. In contrast, unsupervised approaches rely on unlabelled data to identify underlying structures or anomalies, typically through clustering techniques. Recent reviews have also highlighted the growing interest in probabilistic learning frameworks, which explicitly account for prediction uncertainty and improve the reliability of battery health estimation, particularly under varying operating conditions [21].

Although probabilistic frameworks provide valuable information regarding prediction uncertainty, deterministic supervised learning remains well suited to the present application because a labelled experimental database covering the considered operating conditions is available.

This section does not propose a new diagnostic algorithm; instead, it reviews the main diagnostic strategies reported in the literature and justifies the selection of a supervised neural network according to the characteristics of the available experimental dataset and the

objectives of the proposed SoH estimation framework. A supervised neural network is used to exploit impedance-derived features for battery state-of-health estimation.

The PEIS-based diagnostic framework constitutes the basis of the proposed SoH estimation methodology. However, as highlighted in [18], temperature variations and ageing phenomena can induce similar impedance variations. Consequently, an internal temperature estimation model based on TIS is introduced in the following section to compensate for self-heating effects before performing the SoH estimation.

2.4. Thermal model

Temperature has a significant impact on battery impedance, making its estimation essential for reliable diagnostic purposes. However, the internal temperature of a battery cell cannot be directly measured using standard sensors. As a result, modelling approaches are required to estimate this internal thermal state. A wide range of thermal modelling strategies has been proposed in the literature. In particular, the study reported in [26] provides a comprehensive comparison of existing approaches, distinguishing between physics-based models, data-driven models, lumped parameter models, distributed models, and equivalent circuit thermal models.

Among these approaches, thermal models based on ECMs offer several advantages, including low computational complexity, good suitability for real-time implementation, and a modular structure. For these reasons, this type of model has been selected in the present work.

Two main aspects must then be defined: the structure of the thermal ECM and the parameter identification methodology. Since the objective of this study is to obtain a simple and computationally efficient estimation of the internal temperature, a reduced-order model is preferred. In this framework, the internal temperature of the cylindrical cell is assumed to be spatially uniform, and the initial temperature is considered equal to the ambient temperature.

Under these assumptions, several studies have proposed the thermal ECM structure illustrated in Figure 3, which is based on the association of a thermal resistance and a thermal capacitance [27].

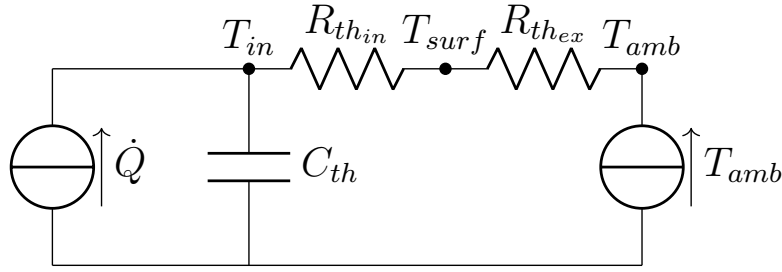


Figure 3: Equivalent thermal circuit of the cell

This model allows the thermal behaviour of the cell to be described by the transfer function given in (Eq. 1). The internal temperature is expressed as the sum of the ambient temperature T_{amb} and the temperature rise ΔT induced by internal heat generation ($T_{in} = T_{amb} + \Delta T$). Consequently, the thermal dynamics are mainly driven by heat generation within the cell, while the external temperature acts as a reference boundary condition.

$$\Delta T(s) = \frac{R_{th_{in}} + R_{th_{ex}}}{1 + s C_{th}(R_{th_{in}} + R_{th_{ex}})} Q(s) \quad (1)$$

where $\Delta T(s)$ denotes the temperature rise with respect to the ambient temperature in the Laplace domain, and $Q(s)$ represents the heat generation within the cell. The absolute internal temperature is then obtained as $T_{in} = T_{amb} + \Delta T$. The parameters $R_{th_{in}}$ and $R_{th_{ex}}$ correspond to the internal and external thermal resistances, respectively, characterising heat transfer both inside the cell and between the cell and its environment. Finally, C_{th} denotes the equivalent thermal capacitance of the battery, which reflects its ability to store thermal energy.

The next step of the study focuses on the identification of the thermal parameters. Two main approaches are commonly reported in the literature: current pulse methods and TIS [27, 28].

In this work, TIS is selected to identify the thermal parameters from the cell thermal frequency response. The method relies on injecting a periodic current excitation, which induces a modulated heat generation within the cell.

By analysing the corresponding temperature response, the thermal impedance at the considered frequency can be calculated according to (Eq. 2).

$$Z_{TIS} = \frac{A_T}{A_{P_{th}}} e^{j(\varphi_T - \varphi_{P_{th}})} \quad (2)$$

where Z_{TIS} denotes the thermal impedance spectrum, A_T and $A_{P_{th}}$ represent the amplitudes of the temperature and thermal power signals, respectively, and φ_T and $\varphi_{P_{th}}$ are the corresponding phase angles of these signals.

By repeating this procedure over a range of excitation frequencies, the thermal impedance spectrum of the cell can be obtained (Figure 4). In order to identify the thermal parameters R_{th} and C_{th} , an optimisation algorithm is then employed to determine the parameter set providing the best fit between the model and the experimental data.

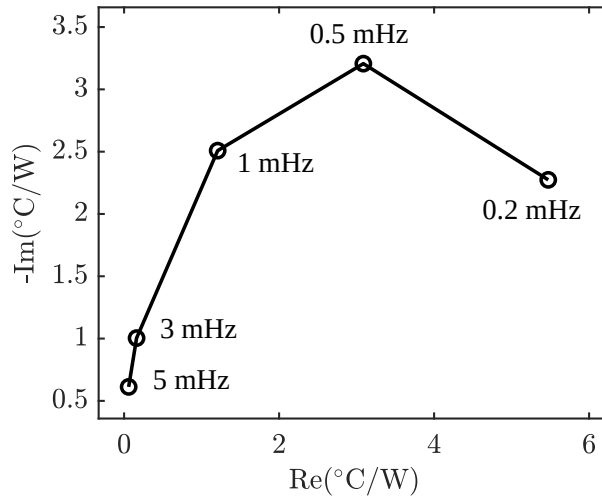


Figure 4: Thermal impedance spectrum of the cell

2.5. Relationship between the input parameters of the diagnostic method

Now that the different methods have been introduced, it is important to highlight the interactions between the various blocks involved in the proposed diagnostic framework.

- *PEIS*: No additional parameters beyond voltage and current measurements are required for ECM parameter identification. This constitutes one of the main advantages of the passive impedance measurement approach developed in this work [14].
- *Coulomb counting*: The estimation of the SoC mainly relies on current measurement together with an OCV–SoC relationship derived from a reference capacity. Alternative model-based approaches have also been proposed in the literature, including competitive SIR-based models capable of improving estimation accuracy while limiting overfitting when only a limited amount of training data is available [29]. However, numerous studies have shown that battery capacity is strongly affected by ageing and temperature [11, 30, 18]. Consequently, both the internal temperature and the actual cell capacity, which is directly related to the SoH, should be considered in this estimation process.
- *Thermal model*: The estimation of the internal temperature requires the evaluation of the heat generation within the cell, which depends on the internal resistance of the system [27]. Since this resistance is itself influenced by temperature and ageing effects, these parameters must be accounted for in order to obtain an accurate internal temperature estimation.
- *Diagnostic model*: The SoH estimation is based on the evolution of the ECM parameters, which provide information on the effective capacity of the cell and therefore on its ageing state. As a result, all input parameters indirectly influence the diagnostic performance. It should nevertheless be noted that the relationship between internal resistance and capacity is mainly valid for ageing induced by cycling conditions. Other ageing mechanisms, such as calendar ageing, may lead to different trends [31]. In this study, the proposed model is therefore considered applicable under ageing conditions predominantly driven by current cycling.

Based on these considerations, the proposed approach enables the estimation of the battery SoH from passive onboard impedance measurements combined with temperature and SoC estimations. In order to develop and validate the different models involved in the methodology, a dedicated experimental test bench was implemented to perform EIS and TIS measurements under controlled conditions.

3. Experimental test bench

A dedicated laboratory setup is used to perform both electrochemical and thermal characterisation of lithium-ion cells. The investigated cell is a commercial 2.6 Ah cylindrical NMC lithium-ion cell. The experimental platform, previously presented in [14], enables the simultaneous acquisition of current, voltage, and surface temperature measurements under controlled thermal conditions using a climatic chamber. Since the experimental setup itself is unchanged, only a brief description is provided here, while the reader is referred to the previous publication for further details.

In the present work, the experimental platform is used to perform three complementary characterisation campaigns. First, reference EIS measurements are carried out over a wide range of SoC, temperature, and ageing conditions in order to identify the ECM parameters. Second, TIS measurements are performed to identify the thermal model used for internal temperature estimation. Finally, passive impedance measurements are acquired under dynamic driving cycles to validate the complete SoH diagnostic framework.

4. Thermal Model Identification for Internal Temperature Estimation

The impedance of lithium-ion batteries is strongly influenced by temperature. Under dynamic operating conditions, the current flowing through the cell generates self-heating, leading to an increase in the internal temperature and consequently to variations in the measured impedance. Since similar impedance variations may also result from battery ageing, distinguishing between thermal and ageing effects is essential to ensure reliable State-of-Health estimation.

To address this issue, a thermal model is developed to estimate the internal cell temperature during operation. This estimated temperature is subsequently used within the diagnostic framework to account for the influence of self-heating on the impedance measurements. A surface temperature measurement is employed during the model identification stage to perform TIS and to assess the consistency of the proposed thermal model.

4.1. Thermal characterisation of the cell

The objective of the proposed method is to identify the thermal parameters R_{th} and C_{th} using TIS (Figure 3). To achieve this, the previously described experimental test bench is used to generate a controlled thermal power within the cell, inducing temperature variations that can be exploited to determine the thermal impedance.

This thermal power is produced by injecting a current through the cell. Similarly to conventional EIS measurements, the acquisition must be performed under operating conditions that are as stable as possible. However, TIS involves relatively slow thermal dynamics, leading to measurement durations that may extend over several hours. Under such conditions, cell discharge and the resulting SoC evolution represent the main sources of measurement non-stationarity.

To mitigate this effect, the current is alternated between charge and discharge phases with periods of 10 seconds, allowing heat generation while maintaining the SoC close to the target value. In this study, TIS measurements are therefore conducted only for a SoC close to 100 %.

Several assumptions are required to enable the calculation of the thermal impedance, particularly regarding the estimation of the dissipated thermal power. Different modelling approaches are available in the literature [27], involving varying levels of model complexity and parameterisation.

In the present work, the heat generation within the cell is assumed to be mainly caused by Joule losses associated with the different internal resistive contributions. The thermal power can thus be expressed as

$$P_{\text{heat}} = R_{\text{int}} i_{\text{cell}}^2 + R_{\text{Diff,cell}} i_{\text{Rdiff,cell}}^2, \quad (3)$$

where P_{heat} denotes the heat generation power, $R_{\text{Diff,cell}}$ is the diffusion resistance, i_{cell} is the applied current, $i_{\text{Rdiff,cell}}$ is the current flowing through the diffusion branch, and R_{int} is the internal resistance of the cell.

In the proposed equivalent circuit model, the internal resistance is expressed as

$$R_{\text{int}} = R_0 + R_{\text{SEI}} + R_{\text{ct}}, \quad (4)$$

where R_0 denotes the ohmic resistance, R_{SEI} is the resistance associated with the solid electrolyte interphase, and R_{ct} is the charge-transfer resistance.

Within a simplified framework, the diffusion contribution is neglected, and the thermal power is approximated using the internal resistance only. This choice is motivated by the fact that the internal resistance R_{int} can be more readily and reliably estimated than the diffusion resistance, which is more difficult to isolate and quantify accurately. The dissipated thermal power can thus be expressed as $P_{\text{heat}} = R_{\text{int}} i_{\text{cell}}^2$. During the online diagnostic procedure, R_{int} is directly obtained from the passive impedance spectrum using the impedance measured at the lowest available frequency. This value is then used to estimate the dissipated thermal power.

The experimental procedure detailed in Table 1 is used to perform TIS measurements over a range of excitation frequencies and ambient temperatures.

Table 1: TIS experimental procedure

#	Process	Units
1	Set the temperature of the cell in the thermal chamber	2 h before test
2	TIS test at $SoC_{\text{initial}} = 100\%$	$\text{Discharge current} = 0.3\text{ C}$, $f_{\text{inj}} = [5, 3, 1, 0.5, 0.2]\text{ mHz}$
3	Repeat the procedure for all temperatures	$T_{\text{amb}} = [5, 25]^\circ\text{C}$

Thus, Figure 5.a shows the thermal power calculated from the measured current at a given excitation frequency, together with the corresponding measured surface temperature (Figure 5.b). This procedure is repeated for several excitation frequencies and ambient temperature levels, making it possible to obtain the thermal impedance spectra presented in Figure 5.c.

These thermal impedance measurements are then used to identify the thermal model parameters, which are summarised in Table 2.

Table 2: Identified thermal ECM parameters at different ambient temperatures

$T_{\text{amb}} (^\circ\text{C})$	$R_{\text{thex}} (^\circ\text{C/W})$	$R_{\text{thin}} (^\circ\text{C/W})$	$C_{\text{th}} (\text{J}/^\circ\text{C})$
5	0.7	6.2	54.3
25	0.4	6.2	58.8

As reported in Table 2, the identified thermal parameters remain relatively close over the investigated temperature range. Consequently, a single parameter set identified at 25°C is selected for the thermal model in order to limit model complexity while ensuring a representative description of the cell thermal dynamics under nominal operating conditions.

The proposed thermal model is intended to estimate the internal cell temperature with a computationally efficient formulation suitable for onboard implementation rather than to

describe the dependence of the thermal parameters on SoC, temperature, or ageing. Consequently, the thermal parameters identified by TIS are assumed to remain constant over the investigated operating range. The influence of operating conditions and battery ageing is instead taken into account through the dissipated thermal power, whose calculation relies on the battery current and on the internal resistance identified as a function of SoC, temperature, and SoH in the following section. This simplified modelling strategy was adopted as a proof of concept and provides a suitable compromise between model accuracy and computational complexity. Identifying ageing-dependent thermal parameters would require repeating the complete TIS characterisation at each ageing state, resulting in a substantial increase in the experimental duration. This aspect will therefore be investigated in future work.

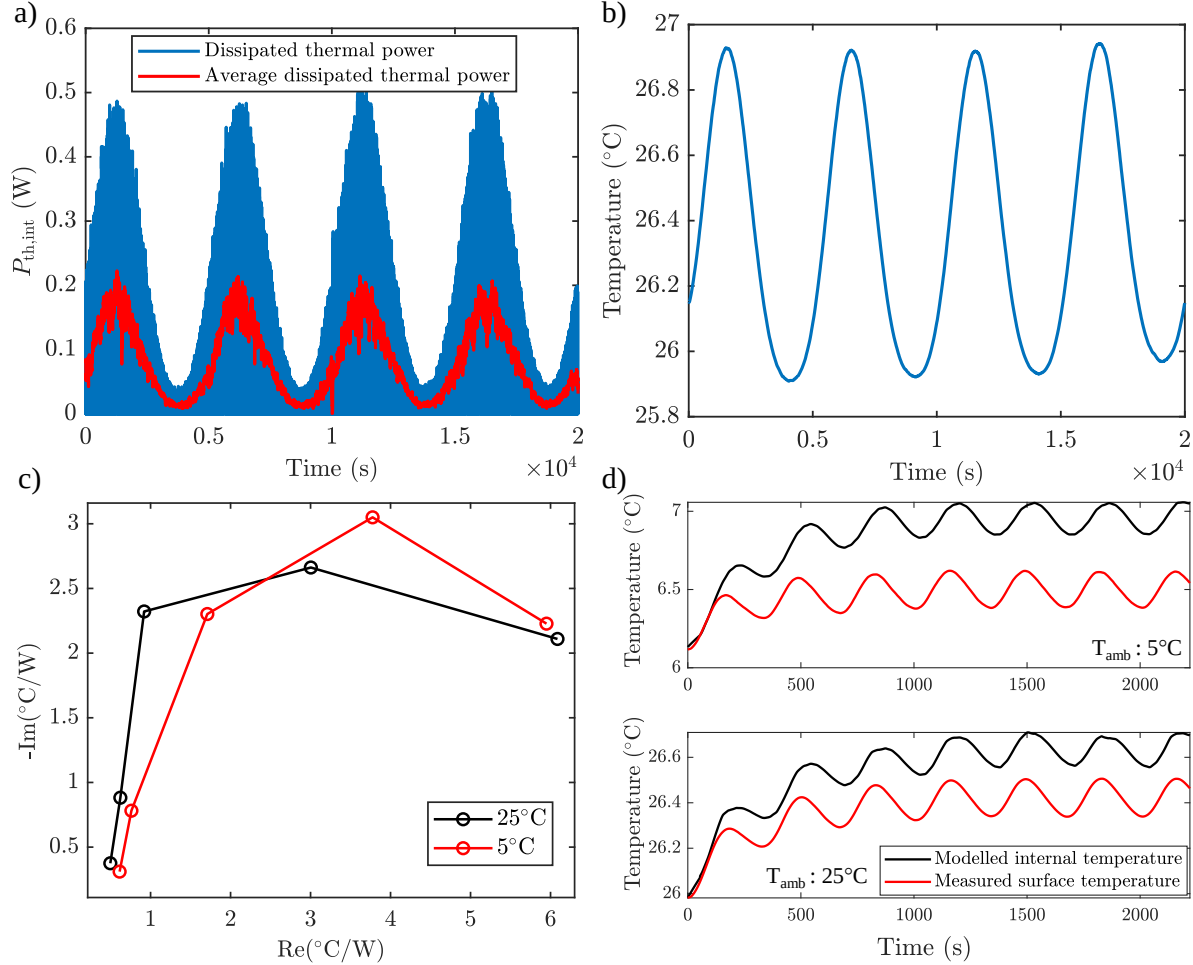


Figure 5: a) Dissipated thermal power for a current with an amplitude of 0.5C, 0.2 mHz, 25 $^{\circ}$, SoC = 100% b) measured surface temperature response, c) measured thermal impedance spectrum at two ambient temperatures, b) Internal cell temperature for an ambient temperature of 5 $^{\circ}\text{C}$ and 25 $^{\circ}\text{C}$

4.2. Model implementation

All the thermal parameters have been identified in the previous section. A validation step is then carried out by implementing the thermal model in *Matlab/Simulink*. For this

purpose, the transfer function given in (Eq. 1), together with the identified parameter set, is used.

The model behaviour is assessed by comparing the estimated internal temperature with the measured surface temperature. Experimental data obtained during the TIS measurements are therefore reused, providing the dissipated thermal power, the ambient temperature, and the surface temperature measurement.

Although the proposed model estimates the internal cell temperature, only the surface temperature can be directly measured experimentally. Consequently, the comparison presented here is intended to assess the consistency of the predicted thermal dynamics rather than to provide a direct quantitative validation of the internal temperature itself. The estimated internal temperature is expected to remain higher than the measured surface temperature because of the thermal gradient within the cell.

Figure 5 presents the modelled internal temperature compared with the measured surface temperature for two different ambient temperature conditions. It can be observed that at low temperature, the temperature difference between the internal and surface measurements is more pronounced than at higher temperature (Figure 5.d). This behaviour can be explained by the variation of the internal resistance of the cell with temperature, which directly influences heat generation [32].

The proposed thermal model can now be integrated into the diagnostic framework in order to estimate the internal cell temperature and thereby enable a clearer separation between temperature effects and ageing-related variations in the measured impedance. Once the thermal parameters have been identified by TIS, the measured surface temperature is no longer used during the diagnostic phase. During the diagnostic phase, the internal temperature is estimated solely from the ambient temperature and the dissipated thermal power using the identified thermal transfer function.

5. Diagnostic Model Identification for State-of-Health Estimation

The development of the diagnostic model constitutes a key step in the estimation of the battery state of health. The relationship linking the ECM parameters, temperature, and SoC to the SoH is established from reference EIS measurements performed on a healthy battery cell.

5.1. Electrical characterisation of the cell

Battery characterisation represents a crucial step in understanding the evolution of impedance as a function of current, SoC, temperature, and SoH. An experimental campaign was therefore carried out in order to obtain reference EIS measurements over the frequency range from 10 kHz to 0.1 Hz under various operating conditions.

The EIS measurements were first performed under zero-current conditions to minimise variations in both temperature and SoC. One of the main advantages of operating in such conditions is the reduction of the thermal power dissipated within the cell. This makes it possible to accurately characterise the impedance behaviour at the imposed ambient temperature and, subsequently, to better distinguish temperature-related effects from ageing-induced variations.

In addition, EIS measurements were conducted at different current levels, as reported in [14]. When current flows through the cell, ohmic losses occur and lead to internal heat generation, mainly associated with the battery internal resistance [30, 33]. At low temperatures, this heat generation can result in a local increase in the internal cell temperature, which affects the electrochemical processes and consequently modifies the measured impedance spectrum. In this study, it is therefore assumed that the variation of the impedance with current is predominantly driven by the dissipated thermal power, while the contribution of charge-transfer kinetics is considered secondary and neglected in a first approximation [34].

For this reason, the reference EIS measurements acquired under zero-current conditions are used to establish the diagnostic database. During the online diagnostic phase, the thermal model estimates the internal cell temperature under load, allowing the passive EIS measurements acquired under current to be interpreted consistently with the reference EIS database despite the current-induced self-heating.

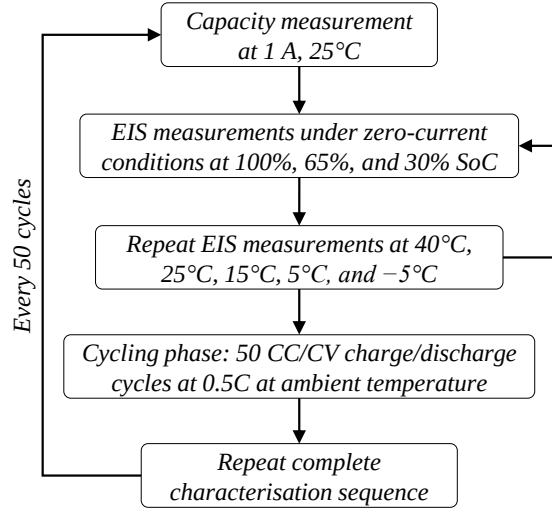


Figure 6: Experimental protocol used for the ageing and EIS characterisation campaign

To build the reference EIS database required for the diagnostic model, a dedicated ageing and characterisation campaign was carried out using the supervision system of the experimental test bench (Figure 6). Current cycling was selected as it provides a suitable compromise between accelerated degradation and ageing conditions representative of real operating scenarios. The characterisation campaign was repeated every 50 ageing cycles. This interval was selected as a compromise between the resolution of the ageing evolution and the overall experimental duration while ensuring a sufficient number of intermediate SoH levels for model development.

The reference SoH associated with each characterisation campaign was determined from the measured discharge capacity obtained by Coulomb counting. The measured beginning-of-life (BoL) capacity was used as the reference value, leading to:

$$SoH(\%) = \frac{C_{\text{aged}}}{C_{\text{BoL}}} \times 100 \quad (5)$$

where C_{aged} is the measured discharge capacity at the considered ageing state and C_{BoL} is

the discharge capacity measured before the ageing campaign.

Selected examples of the resulting Nyquist diagrams are presented in Figure 7.a and Figure 7.b.

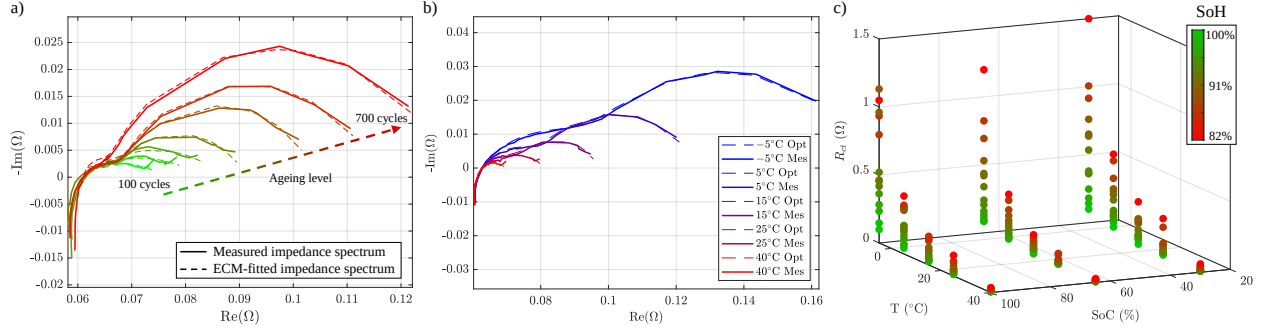


Figure 7: a) Reference spectra at 25 °C, 0C, and 65% SoC for different SoH levels, b) reference spectra at the 200th cycle, 0C, and 65% SoC for different temperatures, c) variation of R_{ct} as a function of temperature, SoC, and SoH.

In particular, the impedance spectra obtained as a function of temperature and SoH clearly highlight a significant impact of both operating conditions and ageing on the battery impedance. In both cases, as illustrated in Figure 7, the double-layer capacitance and the charge-transfer resistance appear to be the most affected parameters. Such variations are widely reported in the literature and are generally attributed to mechanisms such as lithium plating, loss of active surface area, or dissolution of active species [35].

Having characterised the impedance behaviour under these different operating conditions, the parameters of the ECM can now be identified in order to monitor their evolution over ageing.

5.2. ECM parameters as functions of SoC, temperature, and SoH

Based on the assumption introduced in this study, the applied current generates dissipated thermal power, which induces a temperature increase and consequently affects the measured impedance. The thermal parameters identified in Section 4 are therefore used together with the ambient temperature and the dissipated thermal power to estimate the internal cell temperature. During this stage, no surface temperature measurement is required. The estimated internal temperature is subsequently used to ensure consistency between the passive EIS measurements acquired under load and the reference EIS database established from measurements performed under zero-current conditions.

For this reason, the reference dataset acquired at 0C was preferred over that obtained at 0.5C, as it is less affected by self-heating effects and therefore provides a more reliable relationship between impedance and temperature (Fig. 7.c).

Based on the electrical equivalent circuit model previously introduced (Figure 2), the ECM parameters are identified from the reference EIS measurements as functions of SoC, temperature, and SoH. To this end, a nonlinear least-squares optimisation is performed to determine the parameter set providing the best fit to the experimental impedance spectra [36].

The optimisation procedure is implemented in Matlab using the *fmincon* function with the Sequential Quadratic Programming (SQP) algorithm. Predefined lower bounds, upper

bounds, and initial parameter values are used to ensure physically meaningful solutions and improve convergence. The optimisation settings, together with the initial parameter values and parameter bounds, are summarised in Table 3.

Table 3: Optimisation settings for the ECM parameter identification

Parameter / Setting	Initial value	Lower bound	Upper bound
R_0 (Ω)	0.055	0.050	0.070
R_{SEI} (Ω)	0.100	0.002	0.150
Q_{SEI}	0.700	0.010	10.000
α_{SEI}	0.500	0.000	1.000
R_{ct} (Ω)	0.080	0.004	1.500
Q_{dl}	1.500	0.010	15.000
α_{dl}	0.500	0.000	1.000
Optimisation algorithm	<i>fmincon</i> (SQP)		
Objective function	$\min \sum_{k=1}^N Z_{\text{meas}}(\omega_k) - Z_{\text{ECM}}(\omega_k) ^2$		
Maximum iterations	1500		
Step tolerance	10^{-6}		
Constraint tolerance	10^{-6}		
Optimality tolerance	10^{-6}		

where $Z_{\text{meas}}(\omega_k)$ and $Z_{\text{ECM}}(\omega_k)$ denote the measured and modelled impedances at the angular frequency ω_k , respectively, and N is the total number of frequency samples considered during the optimisation.

The green markers correspond to the R_{ct} values measured at the beginning of life, whereas the red markers represent the values obtained after 750 ageing cycles. The variation of this parameter can thus be clearly observed under the different operating conditions investigated (Fig. 7.c).

The quality of the ECM parameter identification was assessed by comparing the measured and fitted impedance spectra. Representative examples of the corresponding Nyquist diagrams are shown in Fig. 7.a, while the associated Root Mean Square Errors (RMSE) are reported in Table 4.

Table 4: RMSE between the measured and ECM-fitted impedance spectra shown in Fig. 7.a

Ageing level (cycles)	RMSE (Ω)
100	0.0040
200	0.0049
300	0.0060
400	0.0076
500	0.0114
600	0.0144
700	0.0192

The low RMSE values confirm that the selected equivalent circuit model provides a satisfactory representation of the experimental impedance spectra over the different ageing states

considered. The diffusion impedance was intentionally not included in the selected ECM, since the proposed diagnostic approach focuses on the frequency range above approximately 0.1 Hz, where the impedance response is predominantly governed by the ohmic, SEI, and charge-transfer contributions. Including a diffusion element would therefore increase the model complexity without providing a significant improvement for the frequency range of interest.

To quantitatively justify the selection of the charge-transfer resistance as the diagnostic indicator, a sensitivity analysis was performed using the ECM parameters identified at 65% SoC and 25 °C. These operating conditions were selected to minimise the influence of temperature and SoC variations and therefore isolate the effect of ageing.

For each parameter, the relative variation between the beginning and end of life was calculated together with its Pearson correlation coefficient with SoH. The results are summarised in Table 5.

Table 5: Sensitivity analysis of ECM parameters with respect to SoH at 65% SoC and 25 °C

Parameter	Relative variation (%)	Correlation with SoH
R_0	-7.71	0.220
R_{SEI}	20.75	-0.031
Q_{SEI}	8.61	0.397
R_{ct}	470.85	-0.897
Q_{dl}	-18.45	0.714

Among all identified parameters, R_{ct} exhibits both the largest ageing-induced variation and the strongest correlation with SoH. The charge-transfer resistance increases by approximately 471% between the beginning and end of life, whereas the variations observed for the remaining parameters remain below 21% in absolute value. In addition, R_{ct} presents the strongest correlation with SoH ($|r| = 0.897$), indicating a strong monotonic relationship with battery ageing. These results justify the selection of R_{ct} as the main diagnostic indicator for the proposed SoH estimation framework.

5.3. Model implementation

The objective of this model is to estimate the cell state of health from input variables measured or estimated under onboard operating conditions, such as temperature, state of charge, and impedance. The model is constructed using one of the parameters obtained from the previously identified equivalent circuit model. The selected parameter must therefore exhibit a significant variation with respect to the state of health.

The charge transfer resistance is particularly relevant in this context, as it shows a marked evolution with ageing. For this reason, the modelling approach is intentionally limited to this single parameter in order to reduce model complexity while preserving a strong correlation with the state of health. The proposed approach is thus based on a parameter extracted from the equivalent circuit model rather than on a full electrochemical model.

The parameters extracted from the impedance spectra, combined with the state of charge and temperature, are then used as inputs to a supervised neural network to estimate the

Table 6: Main characteristics of the neural network used for SoH estimation

Model type	MLP regressor
Inputs	$\log(R_{ct})$, SoC, temperature
Output	SoH
Dataset size	210 samples
Training samples	168
Test samples	42
Architecture	128 – 64 – 32 neurons
Activation function	ReLU
Optimizer	Adam
Learning rate	3×10^{-4}
Loss function	MSE
Maximum epochs	2000
Train/Test split	80% / 20%
MAE (train)	0.00640
MAE (test)	0.01146

cell state of health. The main characteristics of the implemented model are summarised in Table 6.

A multilayer perceptron (MLP) was selected because it provides a good compromise between modelling capability and computational cost for nonlinear regression problems involving a limited number of input variables. In the present study, only three input features are considered, making a fully connected feed-forward neural network particularly well suited to establish the relationship between the operating conditions, the impedance-derived parameter, and the battery SoH.

The neural network was trained using a database composed of 210 samples generated from a single NMC cell characterised throughout its ageing process. The database includes measurements acquired every 50 ageing cycles up to 750 cycles, at different SoC levels and ambient temperatures. Prior to training, the input variables were standardised using z-score normalisation, while the target SoH was normalised between 0 and 1 using min-max scaling.

The dataset was randomly divided into a training set (168 samples, 80%) and a test set (42 samples, 20%) using the `train_test_split` function from the **Scikit-Learn** library. No independent validation dataset was available. Since all samples originate from the same cell, spectra from different ageing states of this cell may appear in both the training and test subsets. The objective of this procedure was to establish the relationship between impedance-derived parameters, operating conditions, and SoH using the available experimental database.

The network architecture and training hyperparameters were selected empirically based on preliminary tests aimed at obtaining a suitable compromise between prediction accuracy and model complexity. Several network architectures and learning rates were evaluated, and the final configuration was retained because it provided the best performance on the available experimental dataset. No systematic hyperparameter optimisation procedure, such as grid search or Bayesian optimisation, was performed, as the objective of this work was to demonstrate the feasibility of the proposed diagnostic framework rather than to optimise the

neural network architecture.

The network was implemented using the Adam optimiser with a learning rate of 3×10^{-4} . Training was performed for a maximum of 2000 epochs using the mean squared error (MSE) loss function.

The mean absolute error (MAE) values obtained for the training and test datasets are 0.00640 and 0.01146, respectively. The higher error observed on the test dataset may indicate a limited degree of overfitting, which is not unexpected given the relatively small experimental database (210 samples). Nevertheless, the absolute difference between the training and test MAE remains limited (0.00506), indicating a satisfactory prediction accuracy over the available experimental dataset. It should nevertheless be noted that both the training and test datasets were generated from different operating conditions and ageing states of the same cell. Consequently, the reported performance assesses the consistency of the proposed diagnostic model on the available experimental database rather than its ability to generalise across different cells.

Once all the models have been developed and trained, the diagnostic method can be evaluated using real driving cycles.

6. SoH monitoring under dynamic operating conditions

Once the diagnostic model has been developed and enables the estimation of the state of health, the different input parameters must be measured or estimated under onboard operating conditions, including temperature, state of charge, and impedance (through the parameter R_{ct}).

The objective of this study is to investigate battery behaviour under dynamic conditions. A representative driving cycle was therefore selected. The DC bus power measured during a real heavy-duty vehicle trip on the Lyon–Milan route is used as the basis for this analysis. From the measured DC bus power, the battery current profile was reconstructed using a simplified energy management strategy representative of a hybrid fuel cell/battery powertrain. The fuel cell power was obtained by applying a first-order low-pass filter to the DC bus power demand, allowing the fuel cell to supply the average power while the battery absorbed the fast power transients. The battery power was then calculated as the difference between the DC bus power and the fuel cell power, and the corresponding battery current was obtained from the DC bus voltage. Finally, the current profile was scaled to match the rated characteristics of the cell used in this study. This cycle was then reproduced experimentally in order to generate realistic dynamic conditions, including temperature variations integrated into the test protocol and state-of-charge dynamics resulting directly from the applied current profile (Figure 8.a).

The harmonic content naturally present in this driving cycle was analysed under these operating conditions [37, 38, 39]. Various excitation signals were considered to reproduce this natural harmonic content, including sinusoidal, multisine, and random signals, over a frequency range from 100 Hz down to 0.01 Hz. A sampling frequency of 1000 Hz was selected as a compromise between the accessible frequency bandwidth and the long observation duration required for PEIS analysis. Unlike our previous work, which relied on short acquisition windows of approximately 10 s, the present study analyses driving cycles lasting 1000 s. Increasing the sampling frequency would therefore considerably increase the amount of recorded

data without significantly extending the useful frequency range for the proposed SoH estimation framework. The selected sampling frequency provides a Nyquist frequency of 500 Hz, which remains well above the frequency range investigated in this study while maintaining a manageable data volume for long-duration acquisitions.

Table 7: Test protocol for impedance measurement under dynamic conditions

#	Procedure	Values
1	Set the climatic chamber temperature	30 min before the test at 30 °C
2	OCV measurement and SoC estimation	Immediately before the test
3	Change the climatic chamber setpoint	From 30 °C to 5 °C
4	Apply the driving cycle	1000 s, $F_s = 1$ kHz
5	Repeat the driving cycle while the cell cools down toward thermal equilibrium	Until the cell reaches the chamber temperature

The test protocol described in Table 7 was implemented on the previously presented experimental bench using the same lithium-ion cell characterised at three representative ageing states corresponding to SoH values of 98.08%, 92.10%, and 82.05%. Prior to each experiment, the cell was stabilised at 30,°C for 30 min. The climatic chamber setpoint was then changed to 5,°C while the driving cycle was repeatedly applied. Consequently, the cell progressively cooled down from its initial equilibrium temperature toward the new ambient temperature, creating the thermal transient required to evaluate the proposed diagnostic framework under varying thermal conditions. During this transient phase, the current, voltage, and surface temperature measurements (Figure 8.a) were continuously recorded and stored in data files, which were subsequently processed using the developed signal-processing algorithm [14]. This algorithm makes it possible to estimate the impedance under dynamic operating conditions by exploiting the natural harmonic content of the driving cycle.

Figure 8.b presents the impedance measurements obtained under dynamic operating conditions for three representative ageing states of the same cell. In order to ensure a consistent monitoring over the relevant thermal and electrochemical time scales, an averaging process over a 100 s window was applied. The nine resulting impedance spectra were then optimised to extract the corresponding R_{ct} values and track their evolution.

According to the hypothesis proposed in this study, the current generates dissipated thermal power, which leads to an increase in impedance due to the resulting temperature rise. The thermal model developed previously therefore makes it possible to estimate the internal temperature of the cell as a function of the dissipated thermal power and the external temperature.

The thermal model estimates the internal cell temperature from the dissipated thermal power and the ambient temperature. This estimated temperature is then used together with the charge-transfer resistance extracted from passive EIS and the estimated SoC as the inputs of the diagnostic model. Since the neural network was trained using reference EIS measurements acquired under zero-current conditions, the estimated internal temperature enables the passive measurements performed under load to be interpreted consistently with the reference database despite the current-induced self-heating.

For each 100 s time interval, the average state of charge and the average internal temper-

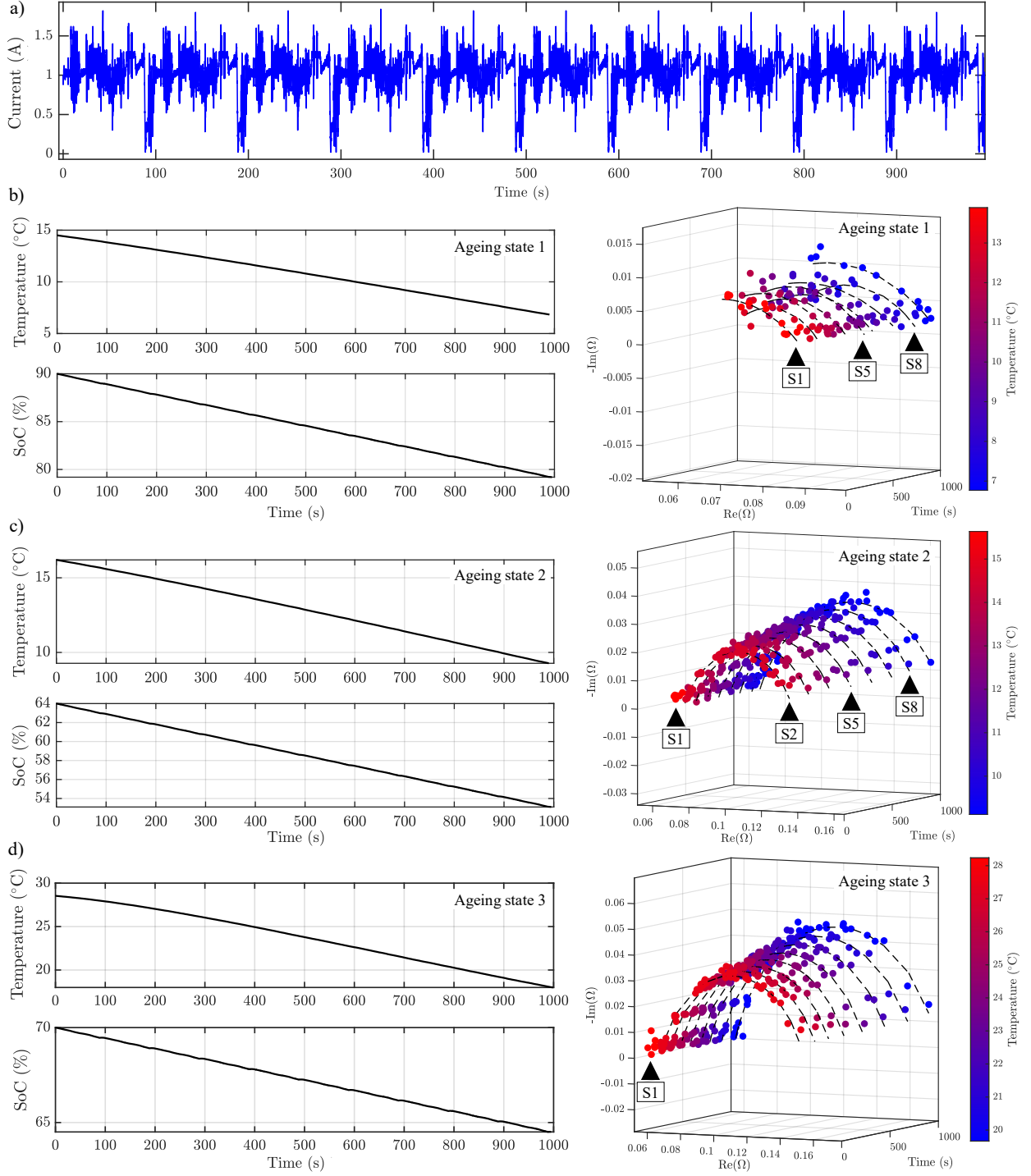


Figure 8: a) Measured dynamic current profile and corresponding estimated temperature and SoC evolution for three representative ageing states (SoH = 98.08%, 92.10%, and 82.05%), b) Passive EIS obtained under dynamic operating conditions for the same ageing states

ature were also calculated, allowing all the required inputs to be obtained for the subsequent SoH estimation. The identified parameters are summarised in Table 8 for the three representative ageing states investigated.

Table 8: Estimated SoH for three different cells

Ageing state 1 (Reference SoH: 98.08%)				
Spectrum	R_{ct} (Ω)	SoC (%)	Temperature ($^{\circ}\text{C}$)	SoH (%)
1	0.0374	99.44	13.89	96.51
2	0.0242	98.35	13.47	98.26
3	0.0339	97.27	12.74	97.14
4	0.0302	96.18	11.98	97.76
5	0.0355	95.10	11.20	97.29
6	0.0355	94.01	10.41	97.47
7	0.0469	92.93	9.61	96.59
8	0.0349	91.84	8.80	97.86
9	0.0521	90.75	7.98	96.51
Average estimated SoH (%)				97.27
Standard deviation (%)				0.64
Absolute error (%)				0.81
Ageing state 2 (Reference SoH: 92.10%)				
Spectrum	R_{ct} (Ω)	SoC (%)	Temperature ($^{\circ}\text{C}$)	SoH (%)
1	Insufficient detected frequency content			
2	0.0603	63.34	15.27	92.34
3	0.0654	62.25	14.61	92.13
4	0.0716	61.15	13.93	92.01
5	0.0774	60.06	13.22	91.97
6	0.0835	58.96	12.51	91.95
7	0.0897	57.87	11.78	91.87
8	0.0936	56.77	11.05	91.88
9	0.1034	55.68	10.31	91.51
Average estimated SoH (%)				91.96
Standard deviation (%)				0.24
Absolute error (%)				0.14
Ageing state 3 (Reference SoH: 82.05%)				
Spectrum	R_{ct} (Ω)	SoC (%)	Temperature ($^{\circ}\text{C}$)	SoH (%)
1	Insufficient detected frequency content			
2	0.0863	69.16	27.27	83.21
3	0.0902	68.61	26.55	83.54
4	0.0925	68.06	25.74	83.30
5	0.0959	67.51	24.93	83.35
6	0.1007	66.96	24.12	83.34
7	0.1097	66.40	23.31	83.09
8	0.1170	65.85	22.40	82.90
9	0.1229	65.30	21.59	82.65
Average estimated SoH (%)				83.17
Standard deviation (%)				0.28
Absolute error (%)				1.12

It should be noted that the impedance spectra obtained at the first ageing state (SoH = 98.08%) exhibit lower impedance values than those obtained at the two more degraded ageing states because of the higher State of Health. Consequently, the identified impedance parameters are more sensitive to the limited harmonic content available in the driving cycle.

In particular, considering the R_{ct} values reported for the first ageing state (Table 8), spectra 7, 8, and 9 show a slight decrease in R_{ct} for spectrum 8, whereas a more monotonic evolution with temperature would be expected. This behaviour is attributed to the limited amount of high-frequency information contained in the driving cycle, together with the selected sampling frequency of 1 kHz.

This limitation results from the compromise adopted between the sampling frequency and the long acquisition duration required to analyse representative driving cycles. Nevertheless, the selected sampling frequency remains sufficient to capture the frequency range required for the proposed diagnostic methodology while keeping the recorded datasets compatible with long-duration experiments. As the battery ages, the increase in impedance improves the robustness of the parameter identification. Consequently, this effect becomes less pronounced for the two more degraded ageing states.

Despite these limitations, the proposed diagnostic model provides accurate SoH estimates for the three representative ageing states investigated (Table 8). The reference SoH values obtained by Coulomb counting for the three representative ageing states are 98.08%, 92.10%, and 82.05%, respectively. The corresponding average estimated SoH values are 97.27%, 91.96%, and 83.17%, leading to absolute estimation errors of 0.81%, 0.14%, and 1.12%, respectively.

These results demonstrate that reliable SoH estimation can be achieved under dynamic operating conditions using passive EIS, provided that the excitation signal contains sufficient harmonic content. Increasing the amount of high-frequency information would nevertheless improve the robustness of the impedance identification and, consequently, the overall SoH estimation accuracy.

7. Conclusion

This paper presented a unified diagnostic framework for lithium-ion battery State-of-Health estimation under dynamic operating conditions. The proposed methodology combines Passive Electrochemical Impedance Spectroscopy, internal temperature estimation, and supervised learning in order to perform onboard SoH estimation without requiring dedicated excitation hardware.

A thermal model identified using Thermal Impedance Spectroscopy was introduced to estimate the internal cell temperature from the ambient temperature and the dissipated thermal power. By accounting for the self-heating induced by the operating current, the proposed model makes it possible to distinguish temperature-induced impedance variations from ageing-related effects, thereby improving the robustness of the extracted diagnostic indicators.

The resulting impedance features, together with the estimated internal temperature and the State of Charge, were used as inputs to a supervised neural network trained from an experimental database covering different ageing states, temperatures, and SoC levels. The proposed framework was successfully validated under representative driving conditions, leading to absolute SoH estimation errors below 1.2% for the investigated ageing states. These results demonstrate the feasibility of combining passive impedance measurements, internal temperature estimation, and data-driven diagnosis within a unified framework for accurate onboard SoH estimation under realistic operating conditions.

Future work will focus on extending the methodology to a larger population of cells in order to evaluate cell-to-cell variability, as well as investigating the evolution of the thermal model parameters with ageing. Another perspective will consist in relaxing the assumption that the current only affects the impedance through self-heating by explicitly modelling its influence on the charge-transfer processes, thereby further improving the accuracy of the proposed SoH estimation framework.

Acknowledgments

This work has been supported by the EIPHI Graduate school (contract "ANR-17-EURE-0002" and the Region of Bourgogne Franche-Comté).

The HYSySPEM project was funded by the "France 2030" government investment plan managed by the French National Research Agency, under the reference ANR-22-PEHY-0018.

This work was supported by a grant from the French State, managed by the National Research Agency under the Investments for the Future program, reference ANR-21-ESRE-0033.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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