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ASSESSING THE POTENTIAL OF ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY AS A SUPPORTING TOOL FOR EQUIVALENT CIRCUIT MODELING IN BATTERY MANAGEMENT SYSTEMS

Original Scientific Article

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Abstract Accurate yet computationally efficient battery models are essential for industrial battery management systems (BMS), which operate under strict constraints on sensing and processing power, as well as certification requirements. Electrical equivalent circuit models (ECMs) are therefore adopted widely in practice, while physics-based models (PBMs) provide detailed descriptions of transport, kinetic, and degradation processes, but are not yet adopted in embedded implementation. The present work assesses the potential of electrochemical impedance spectroscopy (EIS) as a supporting tool for equivalent circuit modeling in BMS applications, with an emphasis on its ability to provide frequency-resolved, process-level indications rather than direct parameter information. By separating the ohmic, charge-transfer, and diffusion-related contributions in the frequency domain, EIS offers complementary insights that are not accessible through time-domain measurements alone. The analysis addresses how such indications can guide ECM structure selection and parameter interpretation, the limitations imposed by measurement duration, noise, and temperature gradients, and the feasibility of EIS-supported modeling approaches under typical BMS constraints. The results delineate the scope within which frequency-informed modeling can enhance physical consistency and diagnostic interpretability while preserving the computational characteristics required for BMS implementation.

Keywords
electrochemical impedance spectroscopy, battery management system, equivalent circuit models, physics-based models, lithium-ion batteries, frequency-domain analysis, parameter identification, diagnostics

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1 Introducton

Lithium-ion batteries have become a key technology in electric mobility, stationary storage, and portable electronics, combining high energy density, cyclic stability, and adaptability to various applications (Larcher & Tarascon, 2015; Shen & Gao, 2019). The increasing requirements for energy, safety, and functionality, create the need for models that can be deployed in industrial BMSs, enabling the accurate assessment of internal states, safe operation, and real-time degradation diagnostics (Xu et al., 2022; Balasingam et al., 2020). In this context, battery cell models serve as a necessary bridge between the measurable quantities (voltage, current, temperature) and the hidden internal processes that determine the performance and lifetime of battery systems significantly. Two conceptually different modeling paradigms are established in the literature and industrial practice. Electrical equivalent models (ECMs) describe the voltage–current response with resistive and capacitive elements, often in Thevenin structures, with a historical development dating back to the early empirical formulations such as the Shepherd model (Shepherd, 1965). Physics-based models (PBMs) are based on the physical processes of diffusion, charge transfer, electrolyte transport, and electrochemical reaction kinetics. The foundational work is the Doyle-Fuller-Newman model (Doyle et al., 1993), with later extensions derived from the theory of porous electrodes and including detailed descriptions of material properties, electrode topology (Mele et al., 2020), modeling EIS spectra (Mele et al., 2024), and degradation mechanisms (Newman & Thomas-Alyea, 2004; Brosa Planella et al., 2022; Al-Zubaidi R-Smith et al., 2021) as well as safety (Katrašnik et al., 2021). Between these two classes, recent research has introduced physically consistent equivalent-circuit models (PC-ECM), which retain the structure of discretized electrochemical transport equations while remaining in a circuit-based ODE representation (Zelič et al., 2021; Tibaut et al., 2024).

The gap between the two approaches remains significant: ECMs are compatible with the embedded processor platforms due to their low computational complexity, while PBMs and PC-ECMs offer significantly more information, which, traditionally, exceeds the capabilities of real-time BMS implementation (Berger et al., 2024; Lucaferri et al., 2023), whereas recent advances of authors prove the applicability of computationally optimized models on advanced microchips (Rahmani et al., 2025). Therefore, industrial battery management systems are based almost exclusively on ECMs, while PBMs are used primarily in research environments and for digital

twins. Recent comparative studies confirmed this widening divergence, showing that ECM parameterizations calibrated under controlled conditions fail to generalize across dynamic loads and temperature variations, while physics-based models maintain mechanistic consistency (Lagnoni et al., 2024).

Electrochemical impedance spectroscopy (EIS) offers frequency-resolved insights into the dynamic processes of battery cells (Geng et al., 2021). The impedance response across different frequency ranges reveals the ohmic, kinetic, and diffusion contributions, providing information that classical time-domain tests cannot (Barsoukov & Macdonald, 2018; Orazem & Tribollet, 2017; Meddings et al., 2020). EIS is an established validation tool in PBMs (Doyle et al., 1993), and a growing body of research is investigating which frequency information can be incorporated into the parametric identification of ECM (Sovljanski et al., 2025; Mathivanan et al., 2025; Belmajdoub et al., 2024).

The central research question of the article is not whether EIS can replace PBMs, but to what extent it can contribute to reducing the discrepancy between the phenomenological and physically based approaches. Therefore, the frequency ranges with the highest diagnostic value, the influence of disturbances and temperature gradients on impedance data are analyzed, and the feasibility of measurements in industrial environments, where sensor technology and time constraints are essential (Andre et al., 2011; Da Silva et al., 2024; Xu et al., 2024).

In this paper, we first discuss the conceptual foundations and the nature of the distinction between ECM and PBMs. We then present the limitations of the embedded processor architectures and sensor technology, as well as the reasons why PBMs are currently not suitable for widespread industrial implementation. We then analyze the information value of impedance measurements, the experimental requirements, and the possibilities of incorporating EIS into the identification procedures for ECMs. The conclusion summarizes opportunities to integrate EIS into future generations of BMS systems, and identifies areas where EIS can serve as a bridge between the conceptually distinct approaches (Belmajdoub et al., 2024).

2 Battery cell models

Battery cell models serve as the basis for analyzing, simulating, and managing lithium-ion systems (Larcher & Tarascon, 2015). The voltage–current response of a lithium-ion cell is nonlinearly dependent on temperature, state of charge, load history, and degradation rate; therefore, models enable understanding of the operation and development of algorithms for state assessment, diagnostics, and optimization of operation in BMS. Two main paradigms are established in the literature: equivalent electrical models (ECM) and PBMs (Doyle et al., 1993; Barsoukov & Macdonald, 2018). ECMs provide a computationally efficient description of the dynamic response, whereas PBMs are based on a physically grounded description of the transport, kinetic, and thermal processes.

2.1 Equivalent electrical circuits model ECM

ECMs are based on equivalent electrical circuits that approximate the internal electrochemical processes by using voltage sources, resistances, and capacitances. The main advantage of the approach is its simple linear structure, which enables implementation in embedded processing units and the direct application of standard control, observation, and filtering methods (Shepherd, 1965). ECMs will enable the simulation of voltage response with low computational complexity, which is why they have become the standard choice in industrial applications such as electric vehicles, energy storage, and transmission devices (Tran et al., 2021).

The historical development of ECMs began with semi-empirical voltage-driven models, among which Shepherd's approach is one of the first systematic formulations of the voltage response as a function of current and discharged capacitance (Shepherd, 1965). Over time, structural extensions were introduced, including an internal resistance to describe the ohmic drop and additional dynamic terms. This led to the Rint models, and, later, to the family of Thevenin models, with one or more RC branches, as shown in Figure 1.

The RC branches describe the polarization phenomena and stress relaxation after load changes, thereby enabling the matching of transient phenomena across different time scales.

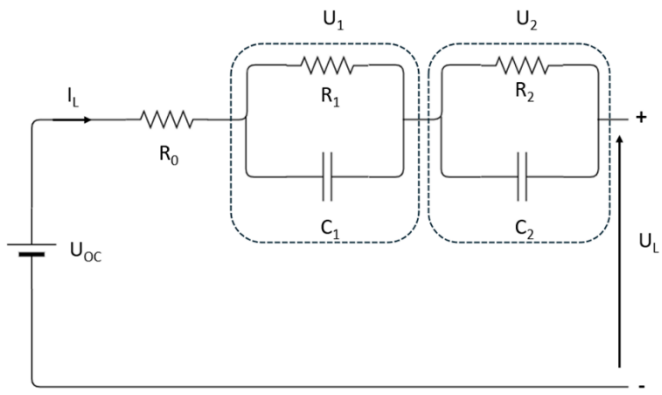

Figure 1: Second-order equivalent circuit (2nd-order RC Thevenin model) for a Li-ion cell

Over time, ECM development has progressed toward greater dynamic accuracy and flexibility. The structural extensions include multiple parallel RC branches, while the parametric extensions consider resistances and capacitances as functions of the state of charge, temperature, current, and aging. The parameters are determined from experimental data using identification methods that enable real-time adaptation of the model during operation. Such a formulation is compatible with extended and unscented Kalman filters, Luenberger observers, and online identification methods (Xu et al., 2022; Belmajdoub et al., 2024). The mathematical description of ECM is based on linear differential equations that relate the current, voltage, and voltage contributions of individual RC branches. The linear structure enables straightforward discretization and implementation in algorithms running on embedded processor platforms, ensuring real-time operation without excessive load on the processor resources.

ECMs allow for fast simulation, relatively easy parameter identification, and direct integration into BMS. Limitations arise from the aggregated nature of the parameters: the same parameter may capture contributions from multiple physical mechanisms, limiting interpretation to the phenomenological level. In addition, the model validity and predictive accuracy are typically restricted to the operating domain used for parameter identification, resulting in reduced reliability when extrapolating beyond the training conditions. Under extreme operating conditions–high currents, low temperatures, or advanced degradation–more pronounced

deviations from realistic behavior may occur, requiring additional correction structures or model extensions (Belmajdoub et al., 2024).

2.2 Physics-based models PBM

PBM describes the operation of lithium-ion cells at the level of fundamental physical processes. They include the diffusion of lithium in the active particles, the charge and mass transport in the electrolyte, the kinetics of charge transfer at the electrode–electrolyte interface, double layer phenomena and thermal dynamics. The primary purpose of such models is to understand the influence of the material properties, electrode geometry, and operating conditions on the voltage response, efficiency, and degradation (Doyle et al., 1993; Newman & Thomas-Alyea, 2004). A breakthrough development is the DFN model, which combines solid-phase diffusion, electrolyte transport, and Butler–Volmer charge-transfer kinetics into a unified mathematical framework (Doyle et al., 1993). The Doyle–Fuller–Newman (DFN) model (often referred to as the pseudo-2D, P2D model) is a physics-based porous-electrode framework that links terminal voltage to the internal electrochemical processes. It represents transport in the electrolyte across the cell thickness and diffusion of the lithium within the active-material particles, coupled with charge conservation and interfacial reaction kinetics. As a result, DFN can reproduce the key dynamic and impedance features of Li-ion cells, but it is typically too computationally demanding for direct real-time use in embedded BMS hardware. (Figure 2). The structure of PBMs includes diffusion dynamics in particles (described by radial diffusion equations), transport in the electrolyte (described by Nernst–Planck or simplified transport equations), charge transfer kinetics at the interface (Butler–Volmer expression), and a thermal sub-model. Such a structure enables the simulation of local concentrations and potentials, the calculation of local heat generation, and the investigation of degradation mechanisms, including SEI growth, loss of active material, and electrolyte degradation.

The model consists of a system of nonlinear partial differential equations and algebraic equations that describe the concentrations, potentials, and current densities throughout the electrodes and electrolyte (Figure 3). Due to its computational complexity, the DFN model serves as a reference framework for analysis and development, while simplified versions have been developed for faster simulations.

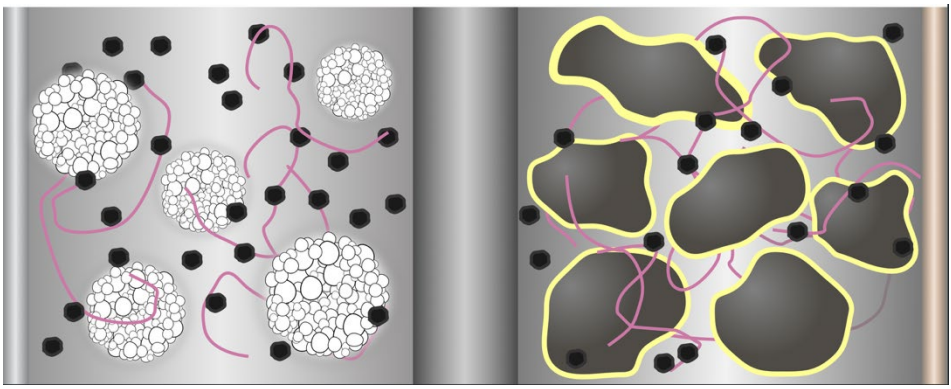

Figure 2: Conceptual DFN (P2D) porous-electrode model structure

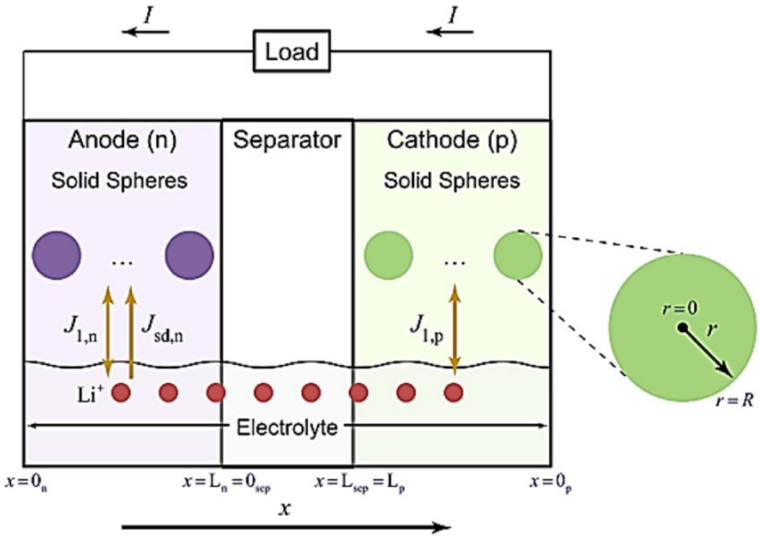

Figure 3: Diagram of the Doyle-Fuller-Newman (DFN) model (Pandey et al., 2023)

Simplifications are often based on the single-particle (SPM) approach (Rahmani et al., 2025), which preserves diffusion in the solid phase while neglecting gradients in the electrodes, and, hence, transport in the electrolyte, or replacing it with an efficient description (Newman & Thomas-Alyea, 2004; Brosa Planella et al., 2022). This reduces the number of states and equations, while retaining the crucial connection between diffusion in the active mass and the voltage response. Further

extensions include models in which selected electrolytic processes are incorporated as correction terms or additional concentration states (Chapman et al., 2019).

The advantage of PBMs is the physical interpretability of parameters and the ability to separate the effects of individual mechanisms on the cell response. The models enable the analysis of the influence of materials, electrode thickness, porosity, diffusivity, and other design parameters on performance and lifetime. The limitations comprise challenging parameter determination and/or identification, which often requires advanced experimental equipment, and the higher computational demands of solving nonlinear partial differential and algebraic equations. Therefore, PBMs are used primarily in research environments and in the design of digital twins, materials, and structures.

2.3 Physically consistent equivalent-circuit models (PC-ECM)

Physically consistent equivalent-circuit models (PC-ECM; Zelič et al., 2021; Tibaut et al., 2024) constitute a class of circuit-based representations derived from the mathematical reduction of electrochemical partial differential equations (PDEs) into systems of ordinary differential equations (ODEs), followed by their transformation into equivalent electrical structures. Their development has been motivated by the need for model formulations that retain the key physical characteristics of ionic and electronic transport, interfacial reaction kinetics, and solid- and electrolyte-phase diffusion. If models are linearized, which makes them applicable for low current simulations, e.g. simulating EIS spectra, the system of equations is simplified to the ODE framework.

PC-ECM occupies a natural intermediary position between full PBMs and phenomenological ECM. They preserve the spatial structure of the underlying PDEs in a reduced, yet physically grounded form, which makes them suitable for resolving the contributions of individual processes, interpreting the origins of specific impedance features, and validating simplified or reduced-order models. The development of PC-ECM remains active, with a large number of variants proposed in the literature (Zelič et al., 2021; Geng et al., 2021; Von Srbik et al., 2016; Scipioni et al., 2017) that differ in the physical mechanisms captured, geometric assumptions, and numerical discretization strategies. Among these approaches, two representative examples are highlighted: a transmission line model (TLM) for porous electrodes

derived from the concentrated-solution theory (Zelič et al., 2021), and a particle-level TLM obtained from the finite-volume discretization of Fick's diffusion equation in spherical geometry (Tibaut et al., 2024). These models illustrate typical PC-ECM formulations; detailed descriptions of their structure, parametrization, and validation are provided in the cited works. Because PC-ECM retains the spatial structure of the underlying PDE, it provides several advantages:

- transparent separation of processes such as ionic transport, charge-transfer kinetics, and solid-phase diffusion;
- the ability to reproduce impedance spectra across the full electrochemical frequency range;
- compatibility with standard circuit-based identification techniques; and
- computational tractability relative to the original PDE models.

In practice, PC-ECM is used primarily for research and diagnostic purposes, including the interpretation of impedance spectra, the extraction of transport and kinetic parameters, and the analysis of degradation mechanisms under controlled laboratory conditions.

3 Discrepancy between ECM and PBM

The different conceptual starting points of ECM and PBM result in significant differences in how they describe the behavior of Li-ion batteries. ECMs describe the battery cell as a macroscopic system in which the voltage response results from the sum of simplified, physically undetermined dynamic processes, combined into RC branches. PBMs describe the distributed processes that occur at the microscopic level within the active particles and in the electrolyte. This enables the direct analysis of the influence of diffusion in the solid phase, reaction kinetics at electrode surfaces, or charge transport in the electrolyte using a physical model (Brosa Planella et al., 2022). ECMs are based on a phenomenological approach, and describe the voltage response of a cell by a combination of an ohmic resistor and one or more RC branches, where the time constant of each branch is defined as (Tran et al., 2021):

$$\tau_i = R_i C_i. \tag{1}$$

Although these processes do not have a direct physical interpretation, they provide an effective approximation of different segments of the impedance spectrum of a battery cell. Typical time intervals covered by the RC branches of the ECM include the ohmic response (from 10 -5 to 10 -3 seconds), kinetic polarization processes (10 -2 to 1 second), and slower relaxation processes (1–20 seconds) (Barsoukov & Macdonald, 2018; Choi et al., 2020). Exact ranges vary with the cell design, temperature, and SoC; the intervals above indicate typical orders of magnitude. The Nyquist response of the ECM has the form of a sum of semicircular arcs:

$$Z_{ECM}(j\omega) = R_0 + \sum_{i=1}^{n} \frac{R_i}{1+j\omega\tau_i}, \quad (2)$$

which means that ECMs can describe the arc fairly accurately in the mid-frequency range, but cannot generate the diffusion tail resulting from transport limitations inherently (Tran et al., 2021; Ali et al., 2024), as shown in Figure 4 (Lazanas & Prodromidis, 2023).

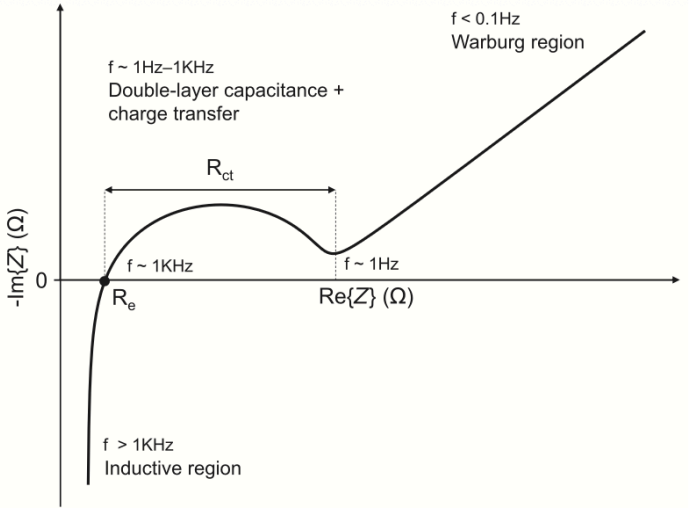

Figure 4: Idealized Nyquist diagram of a Li-ion cell with the ohmic, kinetic, and diffusion contributions (Lazanas & Prodromidis, 2023)

PBMs are derived by describing the processes at electrodes and in the electrolyte, where the cell behavior depends on a set of nonlinear transport and kinetic phenomena. For example, the Doyle–Fuller–Newman (DFN) model is derived by

solving partial differential equations that describe the charge transport, ion diffusion in the solid phase, electrolyte diffusion, and reaction kinetics. A porous electrode model of the DFN type involves solving diffusion in the solid phase, concentration and potential transport in the electrolyte, double layer phenomena, and charge transfer kinetics simultaneously. The model does not generate a single time constant, but a continuum of eigentimes ranging from microseconds to several thousand seconds, leading to a dispersed frequency response (Drummond & Duncan, 2019). The slowest segment of the spectrum arises from the diffusion of lithium in the solid phase, which is determined by the time constant

$$\tau_{diff} = \frac{R_s^2}{D_s}, \tag{3}$$

where $R_s$is the radius of the active particle, $D_s$and is the diffusion coefficient in the solid phase. The mentioned time constant determines the rate of concentration equalization within the particles and in the graphite anodes, which occurs over approximately 10 to several hundred seconds. The faster part of the response is determined by the charge transfer kinetic processes, which are characterized by a time constant of

$$\tau_{\mathrm{ct}} = \frac{RT}{F j_0}. \tag{4}$$

The equation includes the gas constant R and the Faraday constant F, $j_0$which is the exchange current density that describes the intensity of the electrochemical reaction at zero overpotential. Higher values of $j_0$mean shorter time constants, while the growth of interfacial layers and changes in the surface morphology reduce j_0, and thus prolong the kinetic response. Typical values of τ_{ct}range from a few milliseconds to about a tenth of a second. Diffusion in the electrolyte is described by the time constant

$$\tau_{\mathrm{elyte}} = \frac{L_e^2}{D_e}, \tag{5}$$

where L_e defines the characteristic transport length in the electrolyte, D_e, and is the diffusion coefficient of the lithium ions in the liquid phase. The time constant, which ranges from tenths of a second to a few seconds, has a significant impact on the system's behavior at medium frequencies.

The diffusion nature is captured by the Warburg impedance, which, in the case of semi-infinite diffusion, takes the form

$$Z_W = \sigma(1 - j)\,\omega^{-1/2}. \tag{6}$$

The coefficient σ represents the Warburg diffusion resistance, and determines the amplitude of the diffusion impedance. It is a function of the diffusion coefficients, concentrations, active surface area, and geometry of the porous structure. A larger value σ indicates slower diffusion and a longer a 45-degree segment in the Nyquist plane.

For systems with finite diffusion, the Warburg impedance takes the form

$$Z_W = R_W \frac{\tanh(j\omega\tau_W)}{j\omega\tau_W}, \tag{7}$$

where R_W represents the diffusion resistance to equilibrium, τ_W and the corresponding diffusion time constant. At high frequencies, the expression reproduces a 45-degree segment, while, at low frequencies, it transitions into a vertical, distinctly capacitive-like response.

The presented physical model enables direct analysis of the influence of solid-state diffusion, reaction kinetics at the electrode surfaces, or charge transport in the electrolyte. In contrast, ECMs capture these processes indirectly through the time constants of physically undefined processes. The difference leads to situations in which ECMs cannot capture the behavior of a battery cell when nonlinear interactions between the diffusion, kinetic, and thermal processes occur, especially at high currents, low temperatures, or advanced degradation (Ali et al., 2024; Drummond & Duncan, 2019).

The discrepancy continues at the temporal and spatial scales. Electrochemical processes co-occur in the active particles, electrolyte, porous electrodes, and interfacial layers, creating multi-layered dynamics distributed over a wide range of time constants, from a few milliseconds to a few hours. The ECMs combine these processes into a limited number of effective RC branches, meaning that several different physical processes contribute to the exact equivalent time constant. As a result, ECMs often fit the real response well in a limited frequency range, but deviate where separate physical mechanisms affect the voltage on different time scales. The gap between the two models is expressed most clearly when considering the degradation processes. PBMs enable the description of various aging mechanisms, including the growth of an interfacial solid layer, loss of active material, lithium plating, and the formation of microscopic cracks within the electrode structure. Each process can be represented in the model as a separate equation, or as an additional physical mechanism, enabling understanding of the impact of degradation on performance and lifetime. ECMs do not allow such differentiation; the degradation is reflected only as changes in the parameters, such as an increase in internal resistance or changes in the time constants. This limits the interpretation of long-term changes in ECMs, as it is impossible to separate the impact of the different aging mechanisms.

The discrepancy between the two approaches stems from the absence of a direct correlation between their parameters. As shown by Lagnoni et al. (2024), even when the ECM and PBMs are calibrated using identical datasets, the ECM structure collapses under dynamic load or thermal variation, confirming that the phenomenological model cannot preserve mechanistic fidelity. The ECM can be extended with additional RC branches or distributed elements to produce a very accurate fit of the impedance response. However, this does not improve the model's explanatory value, since the ECM parameters capture the aggregated consequences of multiple processes. The key methodological problem is that there is no mapping operator:

$$\mathcal{T}: \Theta_{\mathrm{ECM}} \rightarrow \Theta_{\mathrm{phys}}, \tag{8}$$

where Θ_{ECM} represents the space of resistances, capacitances, CPE parameters, and their derived time constants, while Θ_{phys}encompasses the diffusion coefficients, kinetic constants, porosities, and other physical quantities.

The discrepancy between the ECM parameters and physical processes becomes clearer when examining specific examples. First, different physical mechanisms can cause precisely the same changes in the ECM parameters. For example, an increase in the thickness of the SEI layer, a decrease in the electrolyte's ionic conductivity, an increase in electrode polarity, or an increase in contact resistance is reflected almost identically as an increase in the ohmic resistance R_0. Although these are four completely different physical causes, the ECM detects only the joint effect, so it is not possible to determine reliably from the change in R_0 which mechanism is responsible. The ECM thus describes the effect, not the cause, leading to inherent non-uniformity in interpretation.

Second, a single physical mechanism can affect multiple ECM parameters simultaneously. Diffusion limitation at the anode is a good example: the slowed diffusion of Li ions not only causes an increase in the resistance of a single RC branch, but also changes the CPE–α parameter, widens the Warburg segment, affects the phase angle, and changes the effective capacitance of the second RC branch. This means that a single physical process affects the entire set of ECM parameters, making it impossible to attribute the change to a single "electrical component." Again, we see that the ECM parameters represent aggregated indicators of multiple simultaneous processes, rather than direct physical quantities.

Both examples emphasize that the mapping between PBM and ECM parameters is neither unique, nor vice versa. Different physical mechanisms can cause identical changes in the ECM parameters, and a single physical mechanism can affect multiple ECM parameters simultaneously. Therefore, changes in the ECM parameters cannot be interpreted without additional physical context, while PBMs allow for a physical interpretation of the internal processes (Brosa Planella et al., 2022; Drummond & Duncan, 2019).

A PC-ECM does not alter the fundamental conclusions drawn in the preceding comparison between PBMs and classical ECM. PC-ECMs are aligned with PBMs conceptually and structurally, as its states, parameters, and topology arise from

spatially resolved transport, interfacial kinetics, and diffusion processes, rather than from phenomenological aggregation (Zelič et al., 2021; Tibaut et al., 2024). Consequently, the relationship between PC-ECM and ECM exhibits the same structural limitations as the relationship between PBMs and ECM. When a PC-ECM is projected onto a low-order ECM structure–typically by collapsing the distributed resistive–capacitive pathways into a limited number of lumped time constants–the distinct contributions of transport and kinetic processes merge into aggregated parameters. This implies that different PC-ECM configurations, corresponding to distinct sets of physical properties and spatial distributions, can yield ECM parameter sets that are essentially identical. Similarly, a given ECM parameterization may be compatible with multiple, physically inequivalent PC-ECM configurations. The mapping remains inherently many-to-one.

As such, a PC-ECM does not provide a unique interpretative bridge between the ECM parameters and underlying physical mechanisms. Their primary contribution lies in offering a physically transparent intermediate representation, in which the individual processes remain separable and quantifiable, before they are ultimately collapsed into the simplified ECM structures required by embedded battery-management applications.

4 Industrial constraints on model-based BMS and SoX estimation

Battery management systems operate in an environment with limited processing power, a limited number of measurable quantities, and incomplete information about the cells' internal structure. Algorithms must operate within time frames defined by protection functions, communication protocols, and condition assessment procedures. Due to these limitations, electrical circuit models (ECMs) have been introduced in industrial practice to enable real-time implementation and parametric identification from the measurements available in service (Shen & Gao, 2019; Balasingam et al., 2020; Belmajdoub et al., 2024).

Three constraints determine the applicability of model approaches in BMS: the processor architecture, the set of available measurements, and the accessibility of the battery cell parameters. The combined impact of these constraints drives the development toward models with a limited number of states and low computational complexity (Berger et al., 2024).

4.1 Processor limitations and real-time execution

The embedded processing units in the BMS operate with a limited number of processing cycles and low power consumption. The calculations are performed at sampling rates between 1 and 10 kHz (Barsoukov & Macdonald, 2018), allowing sub-millisecond intervals to complete all the functions. PBMs comprise nonlinear differential equations that describe the transport, diffusion, and kinetic processes occurring at the electrodes and in the electrolyte (Lucaferri et al., 2023). Solving such equations requires iterative numerical methods, spatial discretization of distributed systems, and stable integration schemes, which increases the computational complexity of these models significantly compared to ECMs. Resultantly, ECMs allow for deterministic execution times and fewer arithmetic operations, making them more suitable for real-time BMS algorithms (Shen & Gao, 2019).

4.2 Limited sensors and the unavailability of parameters

BMSs have a limited set of measurements, such as cell voltage, current, and temperature. PBMs require information on electrode topology and material parameters, including the diffusion coefficients, kinetic constants, electrolyte transport properties, and maximum concentrations in the active materials, as well as the geometric parameters and electrode porosities. These data are not part of commercial data sheets, and experimental determination requires specialized equipment or destructive procedures (Balasingam et al., 2020). These parameters are determined most credibly using detailed analytical methods, such as microscopy, measurements of the open circuit potentials of electro materials… In-situ determination requires observable structures with a large number of states, which increases the sensitivity to errors, nonlinearity, and computational burden (Balasingam et al., 2020).

ECMs enable the identification of parameters from voltage, current, and impedance measurements, which are feasible under industrial conditions and do not require access to material data (Belmajdoub et al., 2024).

4.3 Industry consistency, safety requirements, and certification

The modeling approaches used in BMS must comply with Standards such as IEC, UL, ISO, and SAE. The Standards require deterministic responses, explainable deviations, repeatable diagnostic results, and numerical stability (Berger et al., 2024). PBMs exhibit a wide range of dynamics, due to their sensitivity to parameters and the variability of responses under different operating conditions, which increases the complexity of the validation. A comprehensive validation process is often beyond the capabilities of an industrial environment, due primarily to the large number of parameters and the need to validate across various operating scenarios (Balasingam et al., 2020; Lucaferri et al., 2023; Xu et al., 2024).

ECMs allow validation in a smaller number of test scenarios and have stable numerical properties. Due to their simpler verification and shorter certification time, they are suitable for environments where compliance with Standards and the predictability of performance meet the requirements for model accuracy (Shen & Gao, 2019; Berger et al., 2024).

4.4 Model-informed SoX estimation

Different battery models offer access to internal states with varying depth and fidelity, which determines the achievable accuracy and robustness of SoX estimators directly. Modern BMS implementations use a combination of sensing, data-driven, and physics-based approaches for state estimation and diagnostics (Rahmani et al., 2025). Simple ECMs offer a compact representation suitable for real-time SoC estimation; however, their empirical structure limits the identifiability of the transport and kinetic processes (Rahmani et al., 2025). PC-ECM, by preserving the spatial structure of the electrochemical transport, enables a more transparent mapping between the impedance features, time constants, and underlying mechanisms, supporting more reliable SoH and SoE estimation and physics-informed virtual sensing. High-fidelity PBMs (e.g., P2D) provide the richest set of internal variables, and are deployed increasingly as cloud-level digital twins for supervisory SoH and RUL estimation (Rahmani et al., 2025; Nguyen Van & Quang, 2023; Li et al., 2021). Together, these model families establish a hierarchy of achievable SoX capabilities, forming the basis for next-generation physics-enhanced BMS diagnostics (Rahmani et al., 2025).

5 Electrochemical impedance spectroscopy as an approach for connecting model structures

Electrochemical impedance spectroscopy (EIS) enables the measurement of complex impedance over a wide frequency range, revealing the dynamics arising from the ohmic, kinetic, and diffusion mechanisms. The frequency resolution of the processes allows the method to be used for model validation and for the synthesis of structures by ECM (Barsoukov & Macdonald, 2018; Orazem & Tribollet, 2017). The EIS data serve as the basis for identifying the transport properties, estimating time constants, and characterizing the degradation phenomena under various operating conditions (Belmajdoub et al., 2024; Andre et al., 2011).

5.1 Basic concept of electrochemical impedance spectroscopy

The method is based on the linear response of a cell to a small-amplitude sinusoidal excitation. Complex impedance

$$Z(j\omega) = Re[Z(j\omega)] + Im[Z(j\omega)], \tag{9}$$

describes the contributions of the resistive, capacitive, and diffusion processes. The interpretation of the spectrum is based on the separation of the frequency ranges, which is the fundamental starting point of electrochemical analysis (Barsoukov & Macdonald, 2018). The high-frequency part of the spectrum contains contributions from electrolyte conductivity and contact resistance. The mid-frequency part reflects the charge-transfer kinetics and double-layer response, while the low-frequency part reveals the diffusion mechanisms (Choi et al., 2020). This separation enables a comparison of the ECM paradigm with the physical parameters that are integral to PBMs (Sovljanski et al., 2025; Andre et al., 2011).

5.2 Connecting EIS, ECM, and PBMs

EIS provides an information link between the descriptive nature of the ECM and the physical design of PBMs. The electrochemical structures determine the spectral properties through diffusion coefficients, kinetic parameters, and electrolyte transport properties, which can be observed in the form of semicircular responses,

Warburg impedance slopes, and characteristic high-frequency resistive segments (Barsoukov & Macdonald, 2018; Orazem & Tribollet, 2017).

The ECM parameters describe the aggregated effects of the same processes, but without a mapping operator that would relate the parameters to the physical properties directly (Andre et al., 2011). The frequency data allow the identification of the characteristic time constants, enabling a partial correspondence between the two model representations. Such an approach supports the development of model structures that combine the computational efficiency of the ECM with an aim to the information richness of PBMs (Geng et al., 2021; Belmajdoub et al., 2024).

5.3 Integrated EIS solutions for use in BMS

Embedded diagnostic platforms incorporate integrated circuits that enable EIS measurements during battery operation (Cicioni et al., 2023; Analog Devices, 2020). The integrated systems combine current injection blocks, precision voltage measurement circuits, and digital signal processors, enabling the generation of excitation signals and the calculation of real-time complex impedance. Such architectures reduce the need for external function generators and extensive analog filters (Xu et al., 2024).

The measurements are performed at low amplitudes, so they do not impact the cell's operation significantly. The typical frequency range spans from a few mHz to several tens of kHz, enabling the identification of resistive, kinetic, and diffusion processes. Integrated digital functions enable noise filtering and compensation for parasitic elements in the conductors (Belmajdoub et al., 2024). Such an approach opens the possibility of using EIS as a diagnostic tool for embedded BMS systems, where frequency information complements the ECM parameters, thereby enabling more reliable monitoring of the degradation processes (Xu et al., 2022; Xu et al., 2024).

6 Methodology for obtaining impedance data

The methodology provides a data basis for EIS-supported parametric synthesis of ECM structures and for the identification of the transport and kinetic properties. The impedance response of a lithium-ion cell depends on the temperature, state of charge, current history, and degradation rate. Therefore, the measurements must be

designed to ensure repeatability, traceability, and data stability over the entire frequency range (Barsoukov & Macdonald, 2018; Meddings et al., 2020). Reliable data are a prerequisite for procedures that relate frequency characteristics to ECM parameters and LPV expansion, allowing the identification of time constants sensitive to the operating conditions (Belmajdoub et al., 2024).

The experimental framework comprises three interrelated components: measurement system design, calibration procedures, and data acquisition protocols in both laboratory and industrial environments. The consistency of these components determines the quality of the frequency information used in subsequent modeling.

6.1 Measurement system for impedance data acquisition

The measurement system must be capable of generating sinusoidal signals or pseudo-random excitations and measuring current and voltage simultaneously with the required resolution. Accuracy in the high-frequency range depends on controlling the parasitic wiring components, while low-frequency measurements require a stable measurement system and limiting the effects of temperature drift (Barsoukov & Macdonald, 2018). Amplifier blocks, reference sources, and isolation elements are standard building blocks that enable reliable data acquisition over an extended frequency range (Sovljanski et al., 2025).

EIS acquisition during battery cell operation requires amplitude-limited excitation to avoid influencing the voltage-stoichiometric state and thus the measurements. In industrial applications, the range of measurable quantities is limited, which requires the use of compact, energy-efficient, and BMS-compatible measurement modules. Embedded EIS platforms enable real-time measurements and complement standard diagnostics without the need for bulky external instruments (Mathivanan et al., 2025; Xu et al., 2024).

6.2 Calibration, verification, and quality assurance of measurements

The calibration of a measurement system determines the accuracy of the impedance data, and, thus, the reliability of further parameter identification. The procedures include the use of reference resistors, capacitances, and parallel combinations of

elements, which allows verification of the linear response, phase accuracy, and amplitude stability over the entire frequency range (Barsoukov & Macdonald, 2018; Da Silva et al., 2024).

The reliability of the measurements is verified by repeating them at different temperatures, state-of-charge levels, and after selected loading sequences. This approach reveals the measurement system's variability and the influence of environmental conditions, enabling the identification of areas suitable for parametric synthesis and LPV identification. Special attention is paid to the low-frequency range, where the measurement time increases and the meter's stability becomes a limiting factor (Meddings et al., 2020; Sovljanski et al., 2025; Belmajdoub et al., 2024).

Impedance measurements performed at multiple state-of-charge levels improve the interpretability of frequency-dependent parameters further, and support the identification of SoC-dependent trends in ECM parameters (Wu et al., 2023).

6.3 Data acquisition under industrial conditions

Impedance data acquisition in an industrial environment requires adaptations that enable measurements under real operating conditions and with limited sensor resources. Frequency analyses are time-limited, so multifrequency excitations or pseudo-random signals are used when continuous sinusoidal excitations are not feasible (Mathivanan et al., 2025).

Environmental influences, temperature gradients, and dynamic load changes require additional procedures to filter out disturbances and verify the consistency of multiple consecutive measurements. The data obtained under these conditions allow for modeling that reflects operating conditions better, and therefore meets the diagnostic requirements in BMS systems better. Industrially oriented protocols thus contribute to the development of ECM structures and LPV models that are validated under conditions comparable to real-world applications.

7 Discussion and conclusions

The research examined the role of EIS in battery modeling for industrial BMS, with a focus on the conceptual and practical distinction between ECMs and PBMs. The analysis confirms that the discrepancy between these modeling paradigms is structural rather than parametric: ECM parameters capture the aggregated effects of multiple physical mechanisms, whereas PBMs describe the distributed transport and kinetic processes that cannot be mapped uniquely to low-order circuit elements. EIS does not eliminate this discrepancy, nor does it provide a direct mapping between the phenomenological and physical model parameters. Its primary contribution lies in offering frequency-resolved information that enables partial separation of the ohmic, kinetic, and diffusion-related dynamics, which are otherwise entangled in the time-domain responses. Integrating selected parts of the impedance spectrum into identification procedures enhances the precision with which the internal process contributions are separated. It enhances the diagnostic value of model structures, paving the way for advanced models with frequency-supported parameters (Sovljanski et al., 2025; Belmajdoub et al., 2024; Xu et al., 2024).

The effectiveness of the methodology depends on the reliability of the measurements, the repeatability of the EIS data, and the robustness of the measurement protocols. The industrial environment requires specially adapted procedures, due to limited sensors, interference, and time constraints. The advanced approaches can improve the assessment of SoC, SoH, and SoP significantly, as well as degradation mechanisms, but require well-defined parametric dependencies and validation across a wide range of operating conditions (Nguyen Van & Quang, 2023; Li et al., 2021).

The research efforts are focused on identifying the frequency ranges with the most significant diagnostic value, developing methods for processing EIS data under disturbances and temperature gradients, and designing models compatible with the processing limitations of BMS. By incorporating frequency information into linear model structures, the possibility of developing robust and computationally efficient models that capture the electrochemical dynamics of cells better is enhanced. EIS thus represents a relevant opportunity for further advancements in battery system modeling, and an essential step towards more advanced BMSs.

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Povzetek v slovenskem jeziku

Ocena potenciala elektrokemijske impedančne spektroskopije kot podpornega orodja pri modeliranju z nadomestnimi vezji v sistemih za upravljanje baterij. Sistemi za upravljanje litij-ionskih baterij (BMS) temeljijo na modelih, ki povezujejo merljive električne količine z notranjim stanjem baterijske celice. Zaradi omejene procesne moči, omejenega nabora tipal in zahtev po determinističnem delovanju se v industrijski praksi večinoma uporabljajo električni nadomestni modeli (ECM), ki opisujejo napetostno-tokovni odziv z združenimi parametri (Larcher & Tarascon, 2015; Shen & Gao, 2019). Uporaba ECM omogoča implementacijo v realnem času, vendar le omejeno interpretacijo notranjih elektrokemijskih procesov in degradacijskih pojavov. Fizikalno utemeljeni modeli (PBM) temeljijo na opisih difuzije, prenosa naboja in reakcijske kinetike ter omogočajo neposredno obravnavo notranjih stanj, vendar numerična zahtevnost in zapletena identifikacija parametrov omejujeta uporabo v industrijskih sistemih. Članek obravnava vlogo elektrokemične impedančne spektroskopije (EIS) kot vira frekvenčno ločenih informacij o procesih v baterijski celici. Poudarek je na analizi informacij, ki jih je mogoče iz impedančnih meritev prenesti v strukturo in 107arameter ECM, ter na omejitvah, povezanih s trajanjem meritev, šumom in temperaturnimi nehomogenostmi. Obravnavani so tudi pristopi k razvoju hibridnih modelov, ki združujejo časovno in

frekvenčno domeno ter so združljivi z omejitvami industrijskih BMS. Članek prispeva k razumevanju možnosti in omejitev uporabe EIS pri modeliranju baterijskih sistemov v realnih obratovalnih pogojih.