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Research article

Modeling techniques for electric vehicle powertrains: A comparative review and future insights

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Abstract: Amid growing concerns about climate change and efforts to reduce greenhouse gas emissions, electric vehicles (EVs) have become a central component in achieving sustainable transportation. Advances in technology and supportive policies have driven the rise of Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs), which offer lower emissions and improved energy efficiency. However, their success depends on accurate powertrain modeling and intelligent energy management. In this paper, we reviewed key modeling approaches for EV design, simulation, and control, covering individual components, such as batteries, fuel cells, motors, and converters, and full system-level energy-flow models. Furthermore, we examined energy management strategies, ranging from straightforward rule-based approaches to advanced, real-time optimization algorithms. These strategies are essential to improving driving range, enhancing system reliability, and extending the lifespan of energy storage components.

Emphasis is placed on balancing model accuracy with computational efficiency, especially for real-time control applications. We also highlight several pressing challenges in EV modeling, including incorporating thermal and aging effects, addressing uncertainties in battery behavior, and integrating renewable energy sources for vehicle charging. Additionally, we highlight the increasing importance of machine learning (ML) and hybrid modeling techniques in improving prediction accuracy and adaptive control. We employed suitable modeling frameworks for the development of EVs. Thereafter, we concluded by outlining future directions in EV modeling, including the need for more adaptive, scalable, and cross-domain simulation environments that reflect the complexity of real-world applications.

However, due to the high complexity of the modeling frameworks, a comprehensive quantitative comparison of the electrochemical, mathematical, electrical, and data-driven modeling approaches has not been well studied. This paper fills the gap by systematically comparing models in terms of accuracy, computational cost, and relevance to EV design and control.

Keywords: electric vehicle; hybrid vehicle; fuel cell; modelling

1. Introduction

The rapid development of the lithium-ion battery (LIB) for EVs was driven by advances in materials chemistry and cell architecture. Lu et al. [1] highlighted the benefits of electrolyte homeostasis for safety and long-term cycling. Tu et al. [2] provided a complete overview of the evolution of cathode materials is provided, with particular focus on the increase of energy density from $LiCoO_2$ to high-nickel-manganese-cobalt oxide (NMC) configurations. Lu et al. [3] investigated primary restrictions to electrode reversibility and ionic conductivity that led to the fabrication of hybrid electrolyte systems. Wang et al. [4] identified silicon-carbon composites as a key breakthrough for future anodes due to their high theoretical capacity. Cui et al. [5] also shed light on the chemistry of solid-state batteries and are considered the foundation for the design of modern solid electrolytes. Zhao et al. [6] and Lee et al. [7] demonstrated that enhancement of electrode microstructure can directly affect thermal stability and charge-discharge uniformity. Bai et al. [8] applied electrochemical and thermal simulations to investigate the effect of material progress on system-level efficiency, while Cabello et al. [9] reviewed advanced diagnostic methods linking material degradation to electrochemical impedance behavior.

Understanding these events is critical not just for optimizing chemistry but also for building models that describe how they affect voltage response, material degradation, and safety in the ever-changing environment of an EV. In the following sections, we address the key advances in chemistry and materials and make a critical attempt to describe how these events are captured in today's modeling techniques.

The choice of cathode material greatly influences the cost and energy density of lithium-ion batteries. The material-specific properties, such as voltage, cycle life, and specific energy, are the building blocks for accurate modeling of traction batteries, Plett [10] argued. The CRU Group [11] noted that evolving industry trends, particularly the shift toward high-nickel chemistries, directly affect battery performance and calibration procedures. These findings provide a proof point of how advancements on a material level drive the development of realistic modeling frameworks for electric car energy systems. Table 1 summarizes the principal electrochemical characteristics of prevalent lithium-ion cathode chemistries utilized in EV battery modeling, encompassing specific energy, cycle life, and operational voltage ranges.

The energy storage devices used for EVs are mostly based on NMC and lithium nickel cobalt aluminum oxide (NCA) chemistries due to their good trade-off between energy density and stability. Camargos et al. [12] suggested that NMC cells are more thermally stable and safer under normal operating conditions. In contrast, NCA types have higher specific energy but pose greater challenges for thermal management and financial viability. Miao et al. [13] demonstrated that lithium iron phosphate (LFP) batteries exhibit longer cycle life and better thermal stability, making them appropriate for harsh, high-temperature environments. Liu et al. [14] reported that the 3D

microstructural electrochemical lithium manganese oxide (LMO) cathode exhibits reduced internal resistance and enhanced power capability, which are critical for real-time model validation. In sum, these results demonstrate the effects of different cathode chemistries on electrochemical performance and on the parameterization accuracy of battery modeling schemes used for EV simulation and control.

The Evolution of LCO Chemistry Energy-wise, specific high power and its rapid delivery were validated by Wang et al. [15], which made it dominant in the early consumer electronics and small electric car (EC) applications. However, they also identified thermal instability and safety risks during high-load operation, highlighting the importance of accurate thermal-electrical modeling to predict overheating. Wu et al. [16] and Battery University [17] reviewed lithium titanate oxide (LTO) -based anodes as a safer alternative to graphite, with higher thermal stability and an exceptional cycle life of more than 4000 cycles. Even though research has shown reduced specific energy for LTO chemistry, for long-duration applications in rail systems, for instance, its uniform thermal behavior makes it an attractive candidate when model fidelity and temperature control are crucial. In this context, these contributions provide the necessary input and define the boundary conditions for realistic electrothermal simulations of the Li-ion battery.

Table 1. Summarizes essential cathode chemistries commonly parameterized in electrochemical and electrical battery models for EV simulation.

Symbol	Specific energy (Wh/kg)	Number of cycles	Voltage (V)
NCA	210–250	400–600	3.65
NMC	160–210	1500–2200	3.8–4.2
LFP	80–130	1500–2200	2.4–2.6
LMO	110–150	400–800	4.1
LCO	140–210	600–1200	3.8–4
LTO	60–90	4000–6000	2.4–2.6

When determining which battery types are most suitable for a specific application, it is crucial to consider the unique characteristics of each chemistry. For instance, LTO chemistry is well-suited for railway applications due to its excellent safety, specific power output, and extended lifespan. Choosing the most suitable battery type for a particular application requires a thorough understanding of each chemistry's unique properties. Railroad and tramway applications favor LTO batteries due to their exceptional safety, high power output, and extended lifespan [18]. LTO is less feasible for automotive usage than LFP and NMC batteries, mostly due to its higher cost and lower specific energy [19]. Figure 1 delineates the principal performance attributes of predominant LIB chemistries employed in EVs, encompassing specific energy, specific power, cost, safety, lifespan, and overall performance.

It is essential to monitor every cell in the numerous modules that comprise a power source's overall grid. Each cell operates differently due to variations in temperature, state of charge (SoC), and state of health (SoH). Maximizing the energy potential of lithium-ion batteries and increasing the driving range of electric cars depend on their safe and effective maintenance. To establish management strategies for the battery management system (BMS), models that rely on sample operating conditions are typically used to predict battery states. The models integrated into the BMS must therefore operate in real time and with high accuracy. The technical literature has created and reported numerous electrical, spectroscopy-based, data-driven, mathematical, and electrochemical models. For real-time monitoring, data-driven, electrical, and electrochemical models can all be employed, but each serves

a distinct purpose. Since electrical models simplify the battery's electrical behavior, they help predict key performance indicators in real time. On the other hand, electrochemical models offer a more comprehensive understanding of internal chemical processes. Another method for tracking battery conditions is provided by data-driven models, which use past data to spot trends and forecast future events.

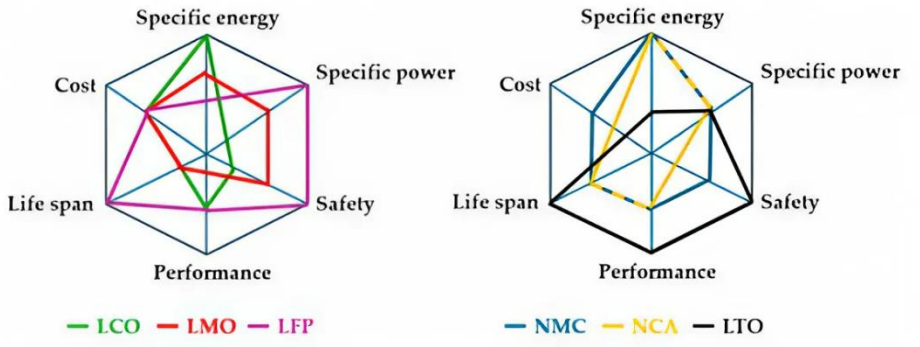


Figure 1. Essential battery chemistries whose characteristics function as inputs for EV simulation frameworks.

Ahmad et al. [20] demonstrated that electrical models can capture the dynamics of voltage and current in lithium-ion cells with sufficient accuracy for safety and performance analysis. Cao et al. [21] reported that including a solid-state process in the electrical equivalent circuit yields more accurate high-power simulations. Furthermore, Lu et al. [1] demonstrated that multi-RC network models can reconstruct rapid charging operations, further verifying their suitability for automotive applications. Chen et al. [22], exploiting this observation, highlighted a trend in industry towards data-driven electrical models, in which hybrid approaches combine experimental data and equivalent circuit representations to enhance model calibration and reliability in BMS integration.

Collectively, these studies demonstrate that electrical models offer a better opportunity to monitor the LIB pack and optimize pack sizing in both EV and electric rail applications. Their combination of computational efficiency and strong predictive accuracy enables these models to be used for scalable, real-time management, which is key for future intelligent battery systems.

We thoroughly review the electrical models for characterizing lithium-ion batteries based on the most recent scientific literature. By emphasizing key approaches for simulating critical characteristics, such as internal capacity and SoH, we clarify these models' theoretical underpinnings and real-world applications. The impact of temperature, charge and discharge cycles, and ambient circumstances on these parameters will be discussed. Additionally, we critically assess the advantages and disadvantages of various modeling techniques, ranging from empirical approaches to complex electrochemical models, evaluating their suitability for practical applications, particularly in the electrification of transportation networks. This study offers valuable insights into the development of battery technology and management techniques by examining current case studies. Ultimately, it helps researchers and practitioners select the most suitable modeling methodologies for their specific requirements.

Overall, the literature reveals a coordinated effort across material design, cell architecture, and chemical engineering to address the key performance metrics of next-generation EV batteries. The trend is shifting toward practical validation using industry-scale cells and conditions resembling

real-world use. As the technology matures, integrating these innovations will be crucial for making electric mobility more accessible, efficient, and reliable.

The remainder of the paper is structured as follows: In Section 2, we highlight the benefits and drawbacks of electrical models while outlining several methods for simulating lithium-ion batteries. In Section 3, we provide simulation results and discuss electric battery vehicles. We then conclude the paper.

We focus on mathematical and computational modeling of battery chemistries to achieve higher energy density and shorter charge times. In the remainder of the article, we categorize electrochemical, mathematical, electrical, and data-driven modeling strategies and compare them on their ability to relate material behavior to system performance predictions.

The major contributions of this survey are:

(i) To review and categorize the most critical modeling approaches for EV powertrain and battery.
(ii) To provide a quantitative comparison of electrochemical, mathematical, electrical, and data-driven models in terms of accuracy, complexity, and applicability.
(iii) To relate the surveyed modeling techniques with simulation-based validation for system-level performance evaluation.

Our goals are motivated by prior work indicating a growing demand for model consistency, computational efficiency, and real-time controller integration in EV systems.

2. Classification of battery models

We categorize battery models into electrochemical, mathematical, electrical, reduced-order, spectroscopy-based, and data-driven techniques. This classification is chosen to optimize physical fidelity, computational expense, and applicability. Electrochemical models are based on fundamental principles of physics and chemistry and address coupled partial differential equations to represent charge transport and reaction kinetics within electrodes. Conversely, mathematical models rely on empirical or stochastic equations that simulate battery behavior at the system level, providing simplicity at the expense of physical complexity. We outline these characteristics, providing a systematic framework that helps researchers and engineers select models based on the trade-off among accuracy, interpretability, and computational requirements.

Battery modeling is the creation of mathematical models to predict how a battery will respond to specific inputs in terms of its state and output. These models aid in clarifying basic battery behaviors and predicting performance under a range of operating conditions, as they are based on substantial data collection and study [23]. Modeling techniques and parameters must be tailored to different purposes. Battery models can be categorized in various ways, with no strict rules [24]. These models are crucial for numerous applications, requiring flexible methods and parameters tailored to specific use cases. The following categories are commonly used to classify battery models:

- Electrochemical
- Mathematical
- Electrical
- Reduced-order electrochemical model
- Based on spectroscopy
- Data-driven

Battery models may be further classified into the following classes according to their transparency and comprehensibility:

- White box models provide an in-depth and clear illustration of the system's underlying operations. Understanding how a system of equations, a set of physical laws, or well-known techniques affects output variables is straightforward. There may be electrochemical and mathematical models in this area.
- Black box models: These models do not understand or consider the precise underlying mechanisms or causal links influencing the system's behavior. They provide the system's inputs and outputs. As a black box, the system's core operations are kept secret, drawing all attention to the visible outcomes. This category encompasses data-driven models, including those based on neural networks (NN).
- Gray box models: These versions strike a balance between white-box and black-box variants. It combines the flexibility and adaptability of black-box models with the transparency and understandability of white-box models. In addition to unknown or simplified modeled components, it frequently combines known and explicitly modeled components. This model is often used when one wants to include specific facts or theoretical limitations in their modeling, but do not fully grasp the system. This category includes, for example, reduced-order electrochemical and electrical models.

Electrochemical models describe ion transport and interfacial kinetics in solid electrolytes, providing insights into dendrite growth morphology, formation, and stability [25]. Mathematical models enable rapid estimates of capacity and percentage energy efficiency [26]. Electrical equivalent-circuit models are beneficial for integrating state-space networks (SSNs) into BMS [27]. Model-based methods predict degradation paths for solid-state chemistries [28]. Spectroscopic models validate interfacial stability and degradation pathways [29]. Low-order models were developed to decimate solid-state complexity for large-scale simulations [30].

2.1. Electrochemical models

Although electrochemical models are more sophisticated and require more calculation time, they delve into the fundamental mechanics and complex physical architecture of battery power generation. These complex mathematical models are used to comprehend the essential chemical reactions in batteries. Models of electrochemical batteries offer comprehensive insights into the microscopic dynamics of electrochemical processes; Fuller, Doyle, and Newman proposed it in the mid-1990s [31–33]. Electrochemical models commonly utilize the Butler-Volmer equation to characterize electrode kinetics, establishing a relationship between current density and overpotential as follows [34]:

$$\boldsymbol{j = j_0 \cdot \left\{ exp\left[\frac{\alpha_a z F \eta}{RT}\right] - exp\left[-\frac{\alpha_c z F \eta}{RT}\right]\right\}} \tag{1}$$

where $\boldsymbol{j_0}$ denotes the exchange current density, η represents the overpotential, F signifies Faraday's constant, R indicates the gas constant, and T refers to temperature. Fick's law of diffusion frequently characterizes concentration gradients within porous electrodes:

$$\boldsymbol{\frac{\partial c}{\partial t} = D\nabla^2 c} \tag{2}$$

Boundary conditions are established at the electrode-electrolyte interface to provide a precise representation of mass transport. Moreover, charge conservation is maintained by solving coupled equations for ionic and electronic potentials, thereby ensuring coherence between electrochemical reactions and current continuity. These formulations are essential in sophisticated models, such as the Doyle-Fuller-Newman framework, and are especially crucial for solid-state batteries, where ion transport constraints and interface stability significantly impact performance.

These models use porous-electrode theory to analyze ion diffusion, mass transfer, and distribution within the battery cell. They thoroughly grasp battery operation by connecting construction components (such as electrode materials and separator thickness) to electrical properties (such as voltage and current) and thermal behavior. Nevertheless, there are some difficulties in using electrochemical models. They require solutions to intricate time-coupled spatial partial differential equation systems, which necessitate sophisticated numerical techniques and substantial processing power. Obtaining all the necessary information for accurate modeling can be challenging and costly, as it requires a thorough understanding of cellular chemistry and the manufacturing procedures involved. Despite these difficulties, battery behavior may be described with unheard-of precision using electrochemical models [35]. Although the relationships governing electrochemical models are complex, techniques have been developed to enable their use in real time, including the single-particle model (SPM) [36,37]. The SPM is a streamlined method for simulating the electrochemical behavior of lithium-ion batteries. It facilitates computations and simulations by representing each active electrode particle as a distinct object. This model enables rapid calculation of electric variables, including voltage, current, and SoC, by describing ion diffusion and chemical reactions during charging and discharging. Despite its simplicity, the SPM is often employed in commercial BMSs and effectively captures the dynamics of Li-ion cells.

2.2. Mathematical model

System-level behavior, including battery runtime, efficiency, and capacity, is predicted using mathematical models that use empirical equations or stochastic techniques. These models can be categorized into two types: Stochastic and empirical models.

Empirical models employ straightforward equations to explain various battery phenomena. Their major advantages are their minimal complexity and real-time parameter detection, albeit with a 5% to 20% margin of error, which makes them suitable for specific applications. One prominent example is the kinetic battery model (KiBaM), developed by Manwell and McGowan [23,38,39] and based on chemical kinetic processes. It provides a clear illustration of how batteries work. In the KiBaM model, the battery charge is divided into two compartments: The accessible charge well and the restricted charge well (Figure 2). A fraction of capacity c is stored in the limited charge well y(t), while the remaining portion (1-c) is assigned to the available charge well x(t).

While the limited charge well can only transfer electrons to the accessible charge, the available charge well provides electrons directly to the load i(t). Through a "valve" with set conductance k, charge moves from the limited to the accessible charge well. In addition to this variable, the height differential between the two wells affects the rate at which the charge moves between them. The following provides the two wells' heights:

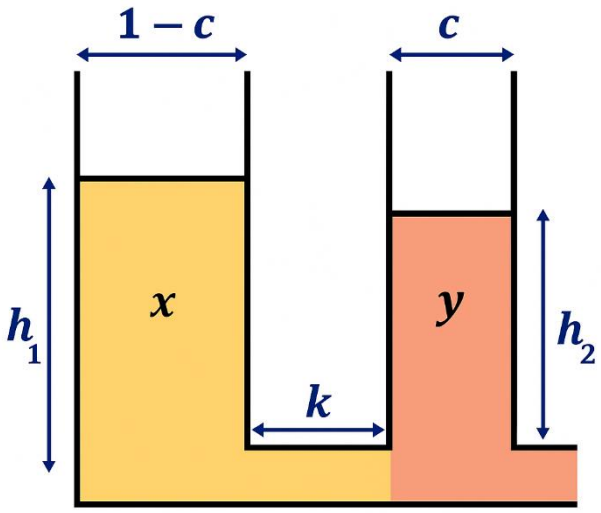


Figure 2. The charge-transfer dynamics between the available and bound energy wells, which determine the battery's state-of-charge behavior throughout the simulation, are depicted schematically in the Kinetic Battery Model.

$$h_1 = \frac{x}{c} \tag{3}$$

$$h_2 = \frac{y}{1-c} \tag{4}$$

Modern batteries exhibit a different discharge profile than the one shown in the equation above. The two-well variant of the KiBaM can be used, though, if battery life is more important than discharge voltage, since it accurately reflects both charging capacity and recovery effect [23]. Conversely, discrete-time Markov chains serve as the foundation for stochastic models. These models can maintain low complexity and short simulation times while achieving higher accuracy than empirical models. Based on the battery's physical attributes, these models describe its behavior using probability and concentrate on the recovery effect. Chiasserini created the first models of stochastic batteries [40]. In its simplest form, the battery is depicted in Figure 3 as a time-discrete Markov chain with N + 1 states, numbered 0 through N. Based on the battery's physical attributes, these models describe its behavior using probability and concentrate on the recovery effect. Initial Markov-based methodologies for estimating battery performance and longevity were presented by Panigrahi et al. [41], use stochastic modeling to forecast battery lifespan in mobile embedded systems subjected to fluctuating load circumstances.

The most straightforward depiction of the battery is a time-discrete Markov chain with N + 1 states, numbered 0 through N, as shown in Figure 3. The theoretical capacity of the battery (T > N) equals the number of T charge units [42]. Mathematical models are useful for applications with stable operating conditions; however, they are less effective at predicting battery behavior in real time. Although these models are computationally efficient and based on simple equations, their accuracy depends on the parameters used; therefore, they must be properly calibrated and verified against real data. Moreover, their development can be complex and requires substantial experimental data, which may not be readily available.

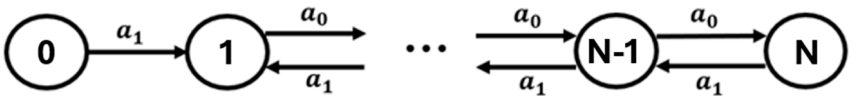


Figure 3. A Markov chain model, which describes probabilistic state transitions characterizing charge, discharge, and rest states in EVs operation, is used to anticipate battery behavior.

2.3. Electrical models

LIB electrical models mimic cell behavior by optimizing component values based on laboratory test data to closely resemble the actual cells' current and voltage responses. These models function well when tested, but may experience issues when not subjected to rigorous testing. Electrical models that employ resistors, capacitors, and voltage sources to represent battery behavior are well known for their simplicity and effectiveness. Due to their rapid simulation rates and low computing costs, they are ideal for real-time applications in the BMS. However, because electrical models provide little information about the internal electrochemical states of batteries, they cannot accurately forecast output behavior. When used outside of tested settings, this simplification may result in errors. Furthermore, many resistor-capacitor (RC) networks may be required to achieve high accuracy, which would complicate the model and potentially reduce computing efficiency. Error drift caused by parameter SoC dependence is one issue with electrical models. However, several techniques (such as artificial neural networks (ANNs), Kalman Filters, Coulomb Counting, etc.) can accurately estimate SoC in electrical models.

2.4. Reduced-order electrochemical model

Electrochemical models are appropriate only during the battery design stages because determining all the required parameters is complex and challenging. Model order reduction techniques can be employed to simplify the electrochemical model, yielding reduced-order models (ROMs) that are resilient and computationally efficient. A finite-dimensional rational transfer function, minor-degree differential equations, and independence from some factors deemed insignificant are common characteristics of ROMs. LIB modeling and management rely heavily on ROMs, which successfully balance computing efficiency and complexity. One of their major advantages is their capacity to reduce the underlying electrochemical processes into a more understandable form. This simplification enables faster simulations, which is especially advantageous for real-time applications. ROMs' lower processing requirements enable more frequent updates and battery-state monitoring, which improve operational safety and efficiency, particularly in dynamic environments such as those found in EVs and other applications [43]. Furthermore, ROMs can facilitate the integration of battery models with control systems, thereby enhancing the system's ability to adapt to changing operating conditions. They are also adaptable across applications, from renewable energy storage solutions to electric cars, thanks to their flexibility with multiple battery chemistries and topologies. This adaptability enables customized solutions that, depending on particular use cases, might maximize

energy management. ROMs do have certain inherent drawbacks. The primary concern is that simplifying complex dynamics may lead to a loss of accuracy. Inaccurate forecasts and subpar performance might result from the ROMs inability to accurately capture the battery's essential features, such as nonlinear responses to charge and discharge cycles. ROMs cannot accurately record the performance of cells that have been cycled at high C-rates and/or temperatures, as well as those of older cells. Moreover, a ROM's effectiveness depends on the quality of the full-order model on which it is built. The resultant ROM might not offer trustworthy insights if the full-order model is not fidelity-rich, especially in edge instances or harsh operating environments. Furthermore, ROMs must be carefully calibrated and validated against experimental data to guarantee their dependability as electrical models. These activities may require numerous resources, and repeated modifications may be necessary if model forecasts and actual performance diverge. Last, although ROMs are beneficial for increasing battery analysis speed and efficiency, their use must be handled carefully, with their drawbacks recognized and controlled [44].

2.5. Electrochemical impedance spectroscopy

The dynamic behavior of lithium-ion batteries can be better understood through electrochemical impedance spectroscopy (EIS), which measures impedance over a range of frequencies. Spectroscopic models in battery research primarily involve fitting and interpreting experimental spectra to derive functional parameters. EIS is frequently used to model equivalent-circuit components, including resistances, constant-phase elements, and Warburg impedances, which represent charge-transfer resistance, double-layer capacitance, and ion diffusion, respectively. X-ray diffraction (XRD) provides information on phase evolution and lattice parameters, which can be modeled to connect structural dynamics to electrochemical performance. Nuclear magnetic resonance (NMR) offers direct insights into the mobility and diffusion pathways of lithium ions in solid electrolytes. These spectroscopy-informed models provide three primary contributions:

(i) Parameterization: Through the provision of empirically based inputs to electrical and electrochemical models.
(ii) Validation: By comparing experimental spectra to the simulated output of the model as a complement.
(iii) Insight: By understanding interfacial stability, surface degradation, and ion transport mechanisms that are difficult to record by theory alone.

EIS frequently identifies three frequency areas: High, mid, and low. Each of these regions corresponds to distinct battery characteristics. A Nyquist plot, where resistance is plotted against reactance, is frequently used to illustrate the impedance data. After applying an AC input current, the AC voltage is analyzed using Fast Fourier Transform (FFT) to calculate the impedance. Randle's Circuit, which comprises elements such as bulk resistance (Rb), surface film layer resistance and capacitance (RSEI, CSEI), charge transfer resistance (Rct), double layer capacitance (Cdl), and Warburg impedance (Zw), is a widely used method in LIB modeling. As shown in Figure 4, these components correlate to different electrochemical reactions within the battery. Rb is the cell's bulk resistance, which explains the electrical conductivity of the electrodes, separator, and electrolyte. High-frequency impedances are linked to. RSEI, CSEI, both resistance and capacitance, are properties of the surface film layer on the electrodes, which includes the solid electrolyte interphase (SEI) layer. The capacitance at the interface between the electrode and the electrolyte is represented by the

double-layer capacitance (Cdl). On the other hand, the resistance that develops during charge transfer across this contact is indicated by the charge transfer resistance (Rb).

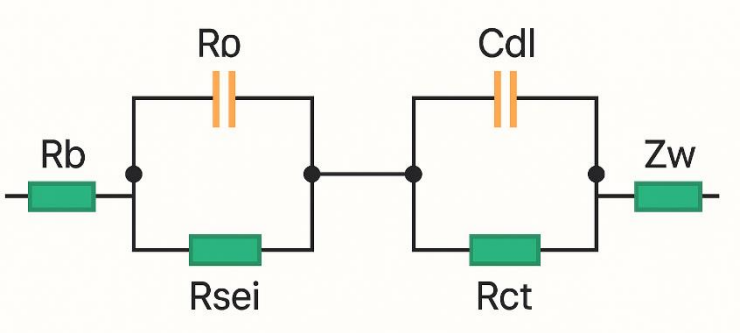


Figure 4. The dynamic voltage response of lithium-ion batteries under load circumstances is simulated using an equivalent circuit approximation of Randle's model.

These two components explain the mid-frequency response. The diffusion of lithium ions between the active material and the electrolyte is indicated by the Warburg impedance Zw, which appears at extremely low frequencies as a line with a 45° slope. An inductance is occasionally added in series with the bulk resistor to explain the positive reactance observed at high frequencies [45]. The effects of this Warburg impedance may also be replicated by several resistor-capacitor (RC) networks linked in series [46]. A fixed number of RC pairs is frequently enough to operate the circuit correctly, even if a perfect equivalent requires an infinite RC pair network within a specific frequency range. Moreover, because it becomes apparent only at extremely high frequencies, the double-layer capacitance Cdl is commonly ignored.

By analyzing impedance characteristics, EIS provides essential insights into the aging, degradation, and performance of batteries. Li-ion cell health may be assessed using impedance models. Moreover, while an increase in Rsei and Csei implies an expansion of the solid electrolyte interface, a rise in Rct indicates a loss of lithium from the cell. Changes in Warburg impedance frequently imply a decrease in active material [47]. However, because it always necessitates the deployment of a signal generator, this approach is challenging to use in real-time applications.

2.6. Data-driven models

Numerous data-driven approaches have been studied for predicting battery life and degradation trajectories. Pastor-Fernández et al. [48] proposed a diagnostic scheme that compared EIS with incremental capacity analysis to identify degradation mechanisms that affect the life cycle. Liu et al. [49] proposed a layered machine-learning framework that directly leveraged state-of-health data for online prediction and demonstrated superior adaptability to actual duty cycles. Lucu et al. [50] proposed self-adaptive aging models that continuously recalibrate key parameters using historical cycling data, thereby substantially improving long-term predictive performance. Liu et al. [51] applied probabilistic autoregressive and Bayesian inference methods to quantify prediction uncertainty and enhance the trustworthiness of remaining useful life (RUL) predictions.

This method is suitable for real-time modeling since high precision is necessary for effective performance management and monitoring in EV systems. Data-driven models utilize large datasets to provide precise forecasts, thereby enhancing decision-making in dynamic settings. However, the inability to grasp the underlying network processes that produce the output findings is a significant drawback of data-driven models. This lack of transparency might make it difficult to detect problems or further enhance the model, as it obscures how different elements affect battery performance. Furthermore, NN have significant data requirements for training; to produce a strong, reliable model, they require large, high-quality datasets. The requirement for comprehensive data collection might be a deterrent, especially for new applications where these datasets might not be easily accessible. Figure 5 shows the overarching workflow of the data-driven architecture for forecasting battery parameters and residual usable life . The procedure commences with model initialization and database specification, followed by parameter estimates and evaluation. The calculated error is assessed iteratively until a predetermined accuracy threshold is reached.

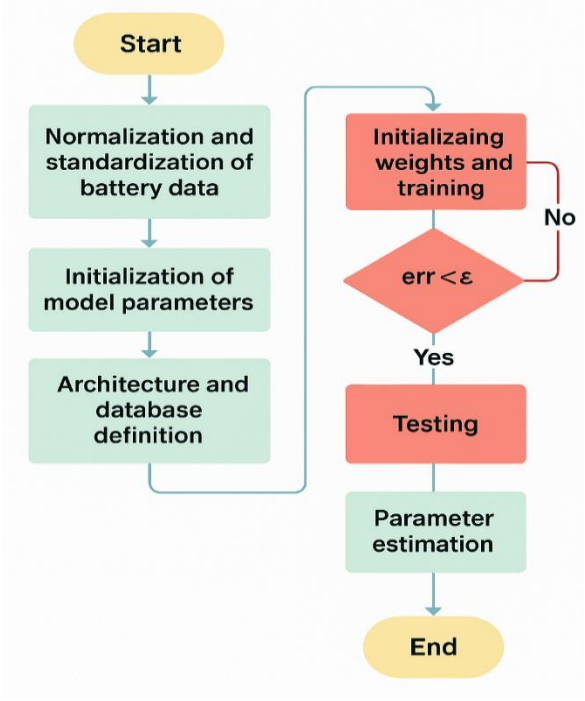


Figure 5. Block diagram for predicting battery parameters and RUL.

Developments in data-driven modeling go beyond simple regression. NNs are widely used for SoC and SoH estimation under complex duty cycles, achieving significant improvements in estimation accuracy [52]. Gaussian process regression (GPR) has also been employed to capture nonlinear interactions and provide prediction uncertainty, which is extremely helpful in evaluating battery reliability [53]. Developments in reinforcement learning (RL) algorithms have been applied to energy management, enabling adaptive, real-time decisions under dynamic driving conditions [54].

Despite the improvement, data-driven approaches face long-lasting challenges. The lack of data often limits their applicability, especially for solid-state batteries, where long-term cycling and interfacial degradation data are insufficient. An interpretable representation is a crucial constraint, as NNs and deep learning models in general often act as “black boxes” with limited physical intuition.

Generalizability is limited because the models trained on specific chemicals or cycles may not transfer well to other systems. Possible negative features of solid-state battery technology, such as complex ion conduction mechanisms and unstable interfaces, exacerbate these problems. Therefore, hybrid models that combine ML with physics-based constraints are increasingly advocated to ensure both predicted accuracy and physical interpretability [55].

2.7. Real-world scenarios for different battery models

Depending on the complexity and amount of detail considered, the numerous models used to depict Li-ion batteries have unique applications in various industrial and scientific contexts. The electrochemical model is widely used in the design and optimization of battery cells. To create new cells with cutting-edge features, this type of model is used to mimic intricate electrochemical processes, such as the degradation of the active material, and it provides a comprehensive understanding of the chemical reactions within the battery [56]. Mathematical models are effective when operating conditions are stable or standardized; however, they are less suitable for dynamic and variable environments due to their inherent simplicity [57].

In contrast, electrical models are commonly utilized in stationary storage and traction applications, as they focus on the battery's electrical characteristics such as voltage and current, making them well-suited for systems requiring high operational stability [58]. For applications requiring rapid and efficient simulations, such as real-time battery management systems (BMS), low-order models are often preferred. Many commercial BMS solutions integrate these models alongside electrical ones. In advanced research, particularly in techniques such as electrochemical spectroscopy, multiple models are employed to study the battery's dynamic response across various frequencies [59]. Additionally, with advancements in artificial intelligence (AI) and ML, data-driven models have become increasingly popular for monitoring performance and predicting battery life [60]. A comprehensive overview of these models is presented in Table 2.

Table 2. Battery model applications.

Model	Applications
Electrochemical	used in the design of cells
Mathematical	Only suitable for situations of continuous operation
Electrical	Energy storage devices and electric cars
Reduced order	BMS and real-time control systems
Spectroscopy	Analyze how dynamic behavior changes with frequency.
Data-driven	Predicting battery life and tracking performance

2.8. Future trends and limitations

Recent developments in Li-ion battery modeling have yielded unique trends tailored to specific industrial needs. To accurately forecast battery performance, advanced electrochemical models that incorporate charge and mass transfer, as well as chemical reaction analysis, are becoming increasingly prevalent [61]. Differential equations and other mathematical and simulation models are being revised to reflect dire situations better. Data-driven models are more dynamic and responsive because they

anticipate and evaluate battery performance using ML techniques [62]. However, there are serious issues with these new trends.

Advanced electrochemical models may not be as valuable in commercial contexts, as they require extensive experimental data and a thorough understanding of the underlying processes. However, real-time applications cannot use mathematical and simulation models due to their complexity and high processing resource requirements. Despite its intrigue, data-driven models have fundamental limitations. The quantity and quality of available data determine the effectiveness of prediction models. The risk of overfitting and inaccurate predictions increases when representative data is lacking.

NNs and other models based on complex algorithms operate as "black boxes," making it difficult to understand the underlying mechanics of predictions. New chemistries and technologies can be complex for data-driven models to adapt to, leading to expensive, time-consuming training and validation procedures. Research attempts to develop hybrid approaches combining data-driven and physical models to address these issues and improve prediction understanding and accuracy. The limitations of data-driven models may be overcome by hybrid approaches to battery modeling, which might also encourage advancements in Li-ion battery technology [60].

2.9. Comparison and interplay among models

When methodologies are integrated rather than used independently, for example, spectroscopy-based techniques such as (EIS) and (XRD), can provide experimental data to calibrate parameters in electrochemical models. Data-driven techniques, such as NNs and Gaussian processes, can function as surrogate models for reduced-order or mathematical frameworks, enhancing simulation speed while maintaining precision. Electrical equivalent-circuit models, although computationally efficient, are frequently parameterized using data obtained from electrochemical or spectroscopic sources, ensuring that practical control-oriented models are physically grounded. ROMs serve as intermediaries, converting intricate physics into formats appropriate for extensive simulations or embedded devices.

Table 3 provides a comparative analysis of the primary battery modeling methodologies for their standard inputs, outputs, degree of interaction with other models, and breadth of application. It delineates the distinctions among electrochemical, mathematical, electrical, and ROMs concerning their data requisites, anticipated variables, and appropriateness for vehicle simulation and control.

Table 4 presents a quantitative synthesis of representative modeling frameworks derived from the literature to enhance the comparative study. These metrics, accuracy, computational cost, and parameter dependency, underscore the practical trade-offs across models in real-world EV simulations.

Table 4 presents quantitative results showing distinct trade-offs among modeling frameworks in terms of accuracy, computational speed, and parameter dependence. Electrochemical models have high accuracy (95–99%) and are thus best suited for material-level design, degradation studies, and validation in lab-controlled environments. However, their computation time, which ranges from minutes to hours, makes them unsuitable for real-time or embedded system applications. On the other hand, electrical and ROMs provide an appropriate trade-off between accuracy and speed, since their results can be obtained within milliseconds to seconds; hence, they are applicable in BMS that require control-centric applications. Data-driven models, though a bit less precise, offer the fastest calculations with maximum flexibility, enabling condition estimation and life prediction to be conducted in real time, provided sufficient datasets are available.

Table 3. A comparative framework of the main battery modeling techniques that displays their input and output variables as well as their degrees of integration with electric car simulation systems.

Model type	Typical inputs	Outputs	Integration with other models	Application scope
Electrochemical [37]	Material properties, kinetics	Voltage, SoC, degradation	Validated by spectroscopy; informs ROMs	Physics-based design & optimization
Mathematical [38]	Empirical parameters	Capacity, efficiency	Benchmarked against electrochemical & data-driven models	Quick approximations
Electrical [39]	R-C elements, impedance data	Terminal voltage, dynamics	Parameters extracted from EIS/Electrochemical models	BMS integration, real-time control
Reduced-order [42]	Simplified PDEs, system inputs	SoC/SoH estimation	Derived from electrochemical models, linked to ML surrogates	Large-scale simulations, control systems
Data-driven [40]	Experimental datasets	Predictions, lifetime estimation	Enhances electrochemical & reduced-order predictions	Prognostics, degradation forecasting
Spectroscopy-based [41]	EIS, XRD, and NMR experimental data	Interfacial stability, resistance	Supplies inputs to electrochemical & electrical models	Validation, parameter extraction

Table 4. Quantitative comparison of battery modeling frameworks in terms of accuracy, computational demand, and application scope.

Model type	Accuracy range	Computation time	Parameter dependency	Representative application
Electrochemical	95–99%	High (minutes–hours)	Very High	Detailed design, thermal & degradation studies
Mathematical	80–90%	Medium (seconds–minutes)	Moderate	Analytical evaluation, approximations
Electrical	85–95%	Low (milliseconds–seconds)	Moderate	BMS and real-time control
Reduced-order	≈90%	Very Low (real-time capable)	Derived from EC models	Embedded simulation
Data-driven (ML/AI)	85–98% (depends on data)	Very Low (real-time)	High–requires large datasets	SoH/SoC prediction, lifetime estimation

This numerical evaluation shows that model selection should depend on the application domain: High-fidelity electrochemical models are essential for research and design, while reduced-order and data-driven methods are more applicable for real-time decision-making, diagnostics, and control. These trade-offs illustrate the need for a hybrid or multi-level modeling approach that combines the accuracy of physics-based models with the flexibility of data-driven models.

2.10. Critical evaluation of modeling categories

A substantive comparison of modeling categories necessitates a thorough evaluation of their distinct strengths, limitations, and practical applications. Electrochemical models offer excellent physical accuracy and a comprehensive mechanistic understanding; however, they are computationally intensive and are better suited to material design and validation than to real-time control. Mathematical models, although straightforward and computationally efficient, depend significantly on empirical correlations and may exhibit limited generalizability when chemistries or operational circumstances vary. Electrical equivalent-circuit models (ECMs) are widely used in BMS due to their simplicity and speed; however, they often fail to represent degradation mechanisms or internal states accurately. ROMs achieve a compromise by condensing physics-based models into manageable forms; however, this simplification inevitably compromises accuracy in harsh operating conditions.

Data-driven methodologies exhibit robust predictive efficacy and adaptability, proficient at revealing intricate patterns in experimental data. Nonetheless, they require extensive, high-quality information, and their 'black-box' nature frequently limits interpretability. Spectroscopy-based models offer distinctive insights into interfacial phenomena and material stability; nevertheless, they are limited by the requirement for specialized instrumentation and lack scalability for real-time applications. By integrating various viewpoints, researchers can more effectively align modeling choices with specific applications, spanning laboratory-scale material evaluation to embedded real-time control in EVs.

Table 5. Strengths, limitations, and use cases of major battery modeling frameworks.

Model type	Strengths	Limitations	Typical use cases
Electrochemical [37]	High physical fidelity; detailed mechanistic insights	Computationally heavy; complex parameterization	Material design, degradation studies
Mathematical [38]	Simple; computationally efficient	Low generalizability; empirical only	Quick estimation, feasibility studies
Electrical [39]	Fast; widely used in BMS	Cannot capture degradation mechanisms	BMS integration, control algorithms
Reduced-order [42]	Balance between accuracy and efficiency	Loses detail under extreme conditions	Large-scale simulations, real-time apps
Data-driven [40]	Strong predictive power; adaptable	Requires big data; limited interpretability	Lifetime prediction, SoH estimation
Spectroscopy-based [42]	Direct insight into interfacial processes	Needs specialized equipment; not real-time	Validation, material characterization

Table 5 delineates the primary battery modeling frameworks, highlighting their advantages, drawbacks, and common applications. Electrochemical models offer significant physical precision but

require substantial computational resources. Mathematical and electrical models are computationally efficient and extensively utilized in estimate and BMS applications, while they provide limited physical understanding. ROMs optimize accuracy and efficiency, whereas data-driven models exhibit robust prediction capabilities but necessitate extensive datasets and lack interpretability. Spectroscopy-based models are mostly employed for validation and material characterization.

2.11. Validation of modeling approaches

The credibility of any modeling technique in electric car powertrain research depends significantly on validation workflows that ensure alignment with experimental data and practical performance. Validation of electrochemical models typically involves comparing voltage-current predictions with galvanostatic cycling profiles or impedance spectra, often following the Doyle-Fuller-Newman framework [63]. Electrical equivalent-circuit models are corroborated through parameter fitting via electrochemical impedance spectroscopy (EIS) or pulse response testing, ensuring that simulated transient dynamics align with experimental Nyquist plots and time-domain responses [60]. ROMs are typically evaluated by juxtaposing their reduced dynamics with high-fidelity electrochemical simulations and connecting the findings with laboratory cycle measurements [63]. Data-driven methodologies require meticulous validation using training/validation/test data splits, cross-validation, and benchmarking against publicly available datasets to mitigate overfitting [52]. Spectroscopy-based models, though fundamentally experimental, serve as validation tools, with EIS, XRD, and NMR providing definitive physical signatures that connect fitted spectral parameters to interfacial stability and transport characteristics [64]. Collectively, these procedures underscore that stringent experimental correlation, via published datasets, impedance spectra, or operando diffraction, is essential for validating model credibility in solid-state battery and EV applications.

3. Simulation results and discussions of battery electric vehicles

While we have classified and critically reviewed modeling frameworks, it is also important to showcase their straightforward contributions to concrete engineering outcomes. Electrochemical and spectroscopy models are playing a significant role in material selection, pinpointing electrode and electrolyte chemistries that exhibit good transport and stability. Spectroscopy-informed models benefit interface design by enabling training and identification of degradation at the electrode-electrolyte interface, which is crucial for solid-state batteries. Lower-order and equivalent circuit models (ECM) are especially advantageous for battery safety, since they can quickly calculate internal states and predict the possibility of thermal runaway in real time at early-stage systems. Data-based models, often integrated into a BMS, enhance EV capabilities by optimizing charge-discharge operations, increasing durability, and enabling predictive maintenance. Cumulatively, these contributions illustrate the value of modeling for improved theoretical understanding and practical applications in material innovation, safety engineering, and performance improvement in EV systems.

To evaluate the performance of BEVs, simulations were conducted using MATLAB's Simscape environment, leveraging a pre-built electro-thermal vehicle model. This model integrates the major components of an electric powertrain, including a battery pack, dual electric motors, an inverter, a power electronics controller, a thermal management system, a braking system, a DC/DC converter, and a

vehicle control unit (VCU). It also features modules to simulate the effects of ambient temperature, driver behavior, and auxiliary loads such as Heating, Ventilation, and Air Conditioning (HVAC) .

The model's battery pack comprises ten modules, each containing eleven parallel cell sets connected in series. Each parallel set consists of three lithium-ion cells in series, totaling 330 cells per pack. The battery has a total capacity of 40 kWh. It delivers a nominal voltage of 400 V. Its configuration is designed to support front-wheel drive by default, with a secondary rear motor enabling boost and all-wheel drive modes when required.

Battery size and weight directly affect vehicle range and energy consumption. For the gravimetric analysis, a fixed energy density of 80 Wh/kg was assumed, meaning that for every 80 Wh increase in capacity, 1 kg is added to the battery mass. Similarly, the battery's volume increases proportionally at a rate of 0.04 meters per kWh. These values were used to simulate the impact of changes in battery capacity on total vehicle mass, length, and energy demand per kilometer.

The simulation also incorporated standard driving cycles, including New European Driving Cycle (NEDC), the Worldwide Harmonized Light Vehicle Test Cycle (WLTC), and the Environmental Protection Agency's (EPA's) Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Driving Schedule (HWFET) procedures. These cycles help represent urban, highway, and mixed driving conditions in a controlled manner. Each drive cycle is characterized by a specific duration, speed profile, and maximum velocity, enabling a realistic estimate of energy consumption.

Environmental conditions were varied to assess the vehicle's thermal performance and energy usage in hot and cold climates. In cold-start conditions (–5 °C), battery and cabin heating introduce significant auxiliary loads, while in hot conditions (35 °C), cooling demands similarly reduce the available driving range. The simulations revealed that non-propulsion energy needs, particularly HVAC and battery thermal regulation, can substantially lower the effective range, especially compared to the rated range under standard laboratory conditions (typically at 25 °C).

Furthermore, the battery's initial SoC and driving profile, aggressive versus relaxed, had a notable effect on total energy consumption. Aggressive acceleration and high-speed driving patterns increased power demand, reducing range and overall efficiency.

These results underscore the importance of accurately modeling real-world variables in BEV simulation. Factors such as ambient temperature, battery thermal management, auxiliary loads, and driving style all play a critical role in shaping the vehicle's performance. Consequently, system-level modeling that integrates thermal, electrical, and mechanical domains is crucial for evaluating BEVs under realistic conditions and informing design decisions to enhance efficiency and reliability.

As shown in Figure 6, this model uses a BEV plant model, an electrothermal system encompassing the entire vehicle. The battery pack is modeled using Simscape Battery Pack Builder and has two electric motors. The primary drive is at the front, while the boost and all-wheel-drive modes are at the rear. Drive cycles are used to simulate the performance of an EV under various driving conditions, as shown in Figure 7.

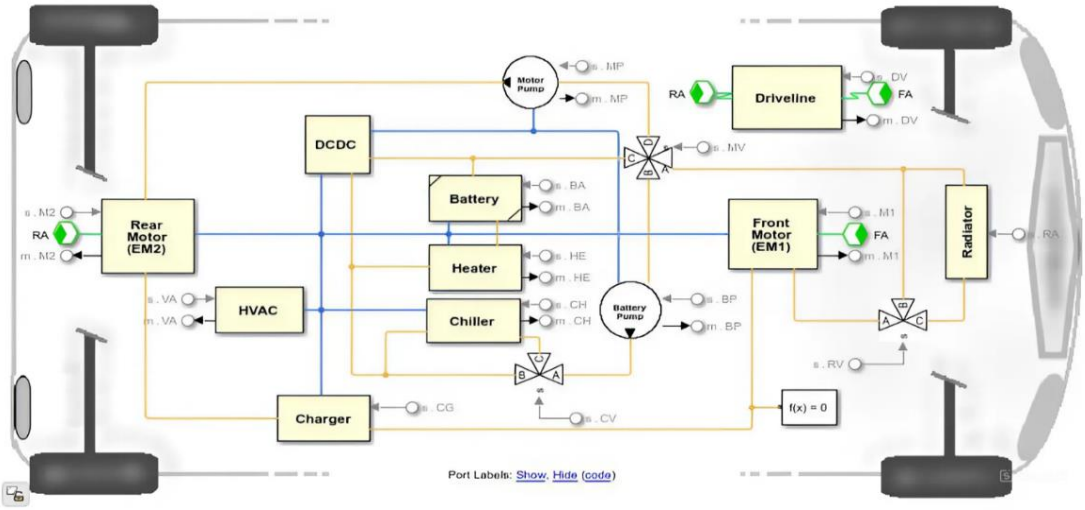


Figure 6. Block diagram for the EV plant model.

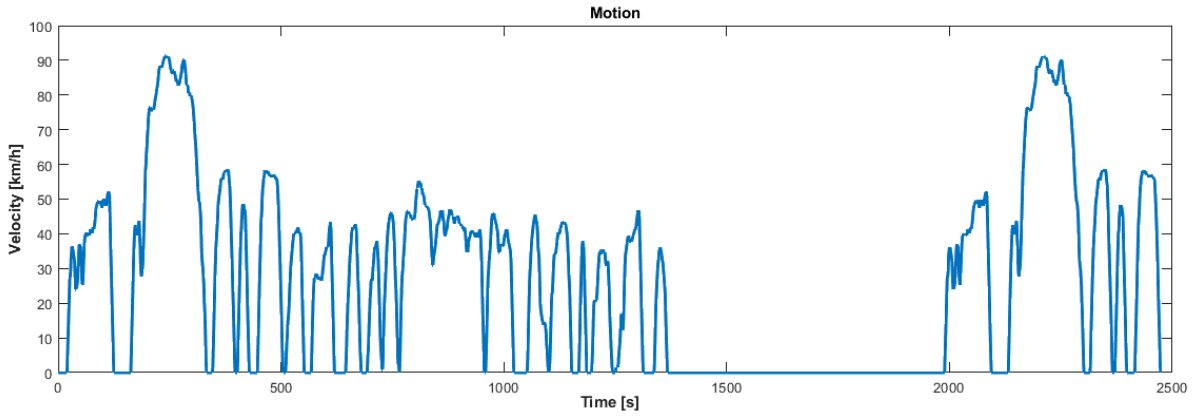
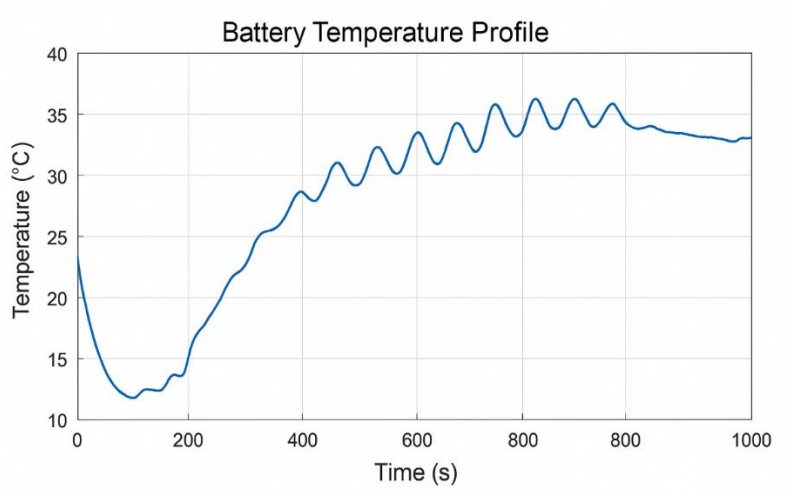


Figure 7. Vehicle speed and load variations are modeled during BEV performance simulation using a Simulink motorcycle source.

Since electric cars typically require a 400 V battery, the battery pack is designed to operate at this voltage. Both parallel and series connections are made between several cells. Each of the ten modules in the battery pack has eleven parallel sets (p-sets) linked in series. Three cells are arranged in sequence in each p-set. A pack of 330 cells is created by connecting all the modules in series. As shown in Figure 8, the battery pack has a capacity of 40 kWh and a charge of 100 Ah.



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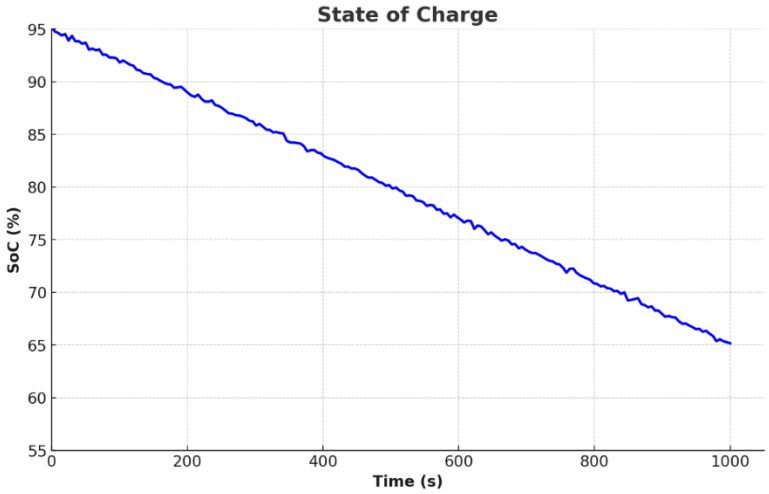

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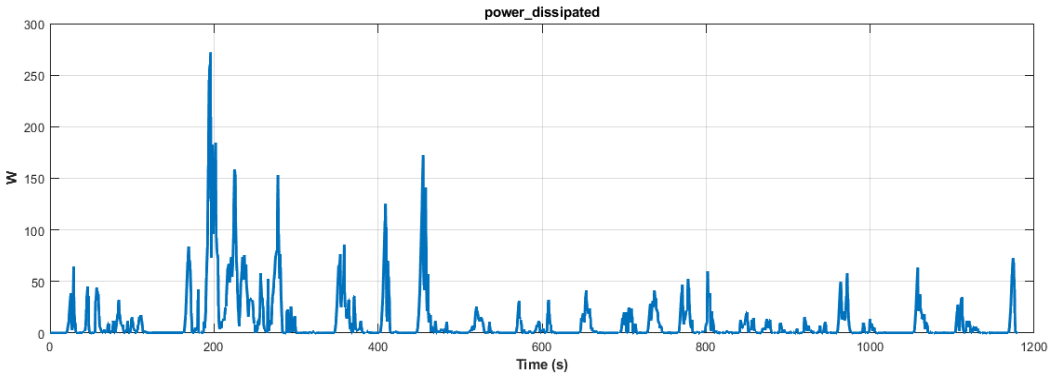

(c)

Figure 8. The simulated battery-electric vehicle's primary performance attributes under typical driving conditions are range, efficiency, and energy consumption.

The increase in battery capacity affects the energy consumed per kilometer and the vehicle's overall range. The NEDC is used for range calculations, and the number of series and parallel cells are kept constant while varying the battery cell capacity, which changes the battery pack size and weight.

The key challenges in adopting BEVs lie in addressing vehicle range anxiety, safety, and the total ownership cost for consumers. Thus, a wide BEV range is desired, but this typically requires a larger energy storage device (batteries) on the vehicle. Batteries are the most expensive component of modern BEVs, so sizing is essential to determining the car's cost. The gravimetric energy density of a battery is the capacity-to-weight ratio, a key metric for battery design. The weight of the battery is the sum of the weights of all the battery cells, the battery casing, connectors, and auxiliaries attached to the battery pack. In this analysis, the gravimetric energy density of the pack is 80 Wh/kg; i.e., for every 80 Wh increase in battery pack capacity, 1 kg is added to the battery pack's mass. The sizing is based on a 25 °C scenario because typical HVAC and auxiliary energy requirements are lower, and a significant portion of the energy the battery consumes is used to satisfy propulsion demand.

The car's weight is the sum of its body weight and the battery's weight. For a 40 kWh battery with 80 Wh/kg gravimetric energy density, the mass is 500 kg. The vehicle body mass is taken as 1100 kg. The base length of the car is 3 meters, and the vehicle's mass per unit length is 367 kg/m. The battery volume increases by 90 Wh/l, roughly corresponding to a 0.04 m increase in length per kWh for a compact sedan battery.

- Increase in battery mass = Increase in battery capacity (Wh)/(80 Wh/kg)
- Increase in vehicle length = Extra battery capacity (kWh) * (0.04 m/kWh)
- Increase in vehicle body mass = Increase in vehicle length (m) * (367 kg/m)
- Increase in total Weight = Increase in vehicle body weight + Increase in battery weight

Based on these values, the mass of a battery with a 5 kWh capacity increases by 62.5 kg.

Actual driving circumstances influence the vehicle's range. There is a different range while driving in hot and cold weather. The driver profile also affects the range, with driving behavior ranging from relaxing (steady speeds and moderate acceleration) to aggressive (demanding sudden power).

Using typical worst-case driving profile scenarios, we evaluate the range provided by a 400 V battery pack in this paper. Automakers use standardized drive cycles to determine BEV range ratings. The NEDC, as shown in Figure 9, the WLTC, and the EPA cycle are the driving cycles most commonly used in the industry. For urban and non-urban driving, a typical NEDC cycle consists of two phases, lasts 20 minutes, and has a top speed of 120 km/h. The vehicle speed setpoint is input to the driver control system using a Drive Cycle Source block. Variables establish the cabin setpoint, ambient condition, coolant, and battery beginning temperatures to mimic various situations.

Environmental conditions and HVAC demands influence EV power consumption. The battery must be heated to the optimal temperature when the vehicle is cold. The battery powers the HVAC system to heat the cabin. When ambient temperatures are extremely high, the chiller must be introduced into the loop to cool the battery rapidly. These functions significantly reduce the vehicle's range and require battery power. These additional demands on the battery result in a lower-than-anticipated car range because the vehicle's range rating is conducted under a set ambient environment of 25 °C. These non-powertrain needs impact the vehicle's total range. The vehicle is configured to be in an equilibrium condition with the surrounding air at the starting temperature. With an initial SoC of 75%, the driving cycle is executed once.

Cold ambient Condition

The ambient temperature is set to −5 °C.

- AC On -- HVAC is on. The HVAC heating load and battery heating require a significant amount of power from the battery.
- AC Off -- The HVAC is off, and the battery heater serves as the auxiliary load.

Hot ambient conditions

The ambient temperature is set to 35 °C.

- AC On -- HVAC is on. The cabin cooling and the battery cooler heavily tax the battery.
- AC Off -- HVAC is off; the supplementary load is the battery-chilled water system.

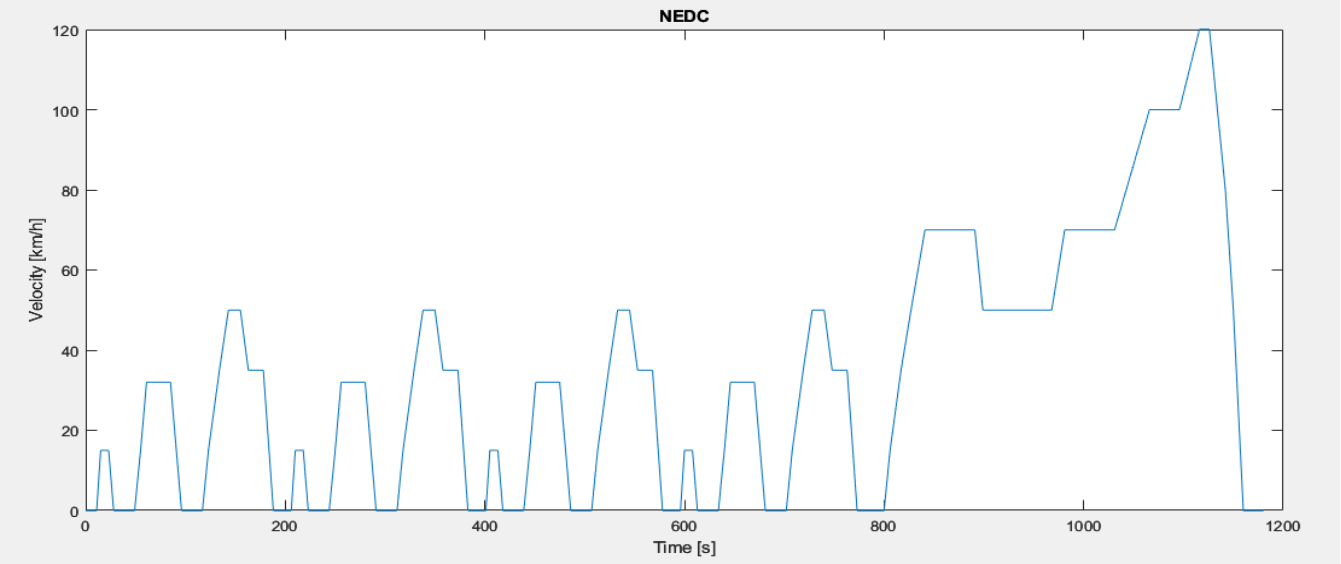

Figure 9. Vehicle speed fluctuations over time are shown in the NEDC profile, which serves as a standard benchmark for assessing the energy consumption and range of BEVs.

As shown in Figure 10 Worldwide Harmonized Light Vehicle Test Procedure (WLTP), the four dynamic stages of a typical WLTP cycle are categorized into low, medium, high, and extra-high speed segments. These stages are designed to reflect a wide range of real-world driving conditions, including urban traffic, suburban commuting, and highway travel. The cycle lasts approximately 30 minutes and comprises multiple phases, including acceleration, deceleration, idling, and steady cruising. The maximum speed reached during the test is 131 kilometers per hour, providing a realistic evaluation of vehicle performance under demanding high-speed conditions. Compared to earlier cycles, such as the NEDC, the WLTP offers a more accurate and stringent assessment of energy consumption, emissions, and driving range, accounting for modern driving behaviors and vehicle technologies.

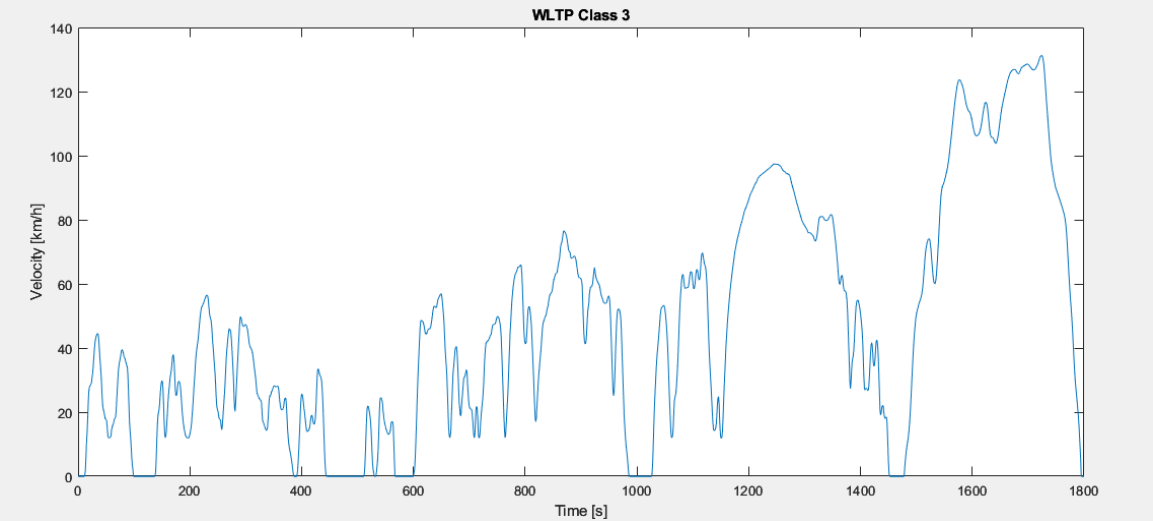

Figure 10. Variability in vehicle speed during typical driving phases is demonstrated by the Worldwide Harmonized Light Vehicle Test Procedure (WLTP).

The car undergoes several drive cycles as part of the EPA multicycle driving procedure, which simulates a wide range of real-world driving conditions. The two most widely used test cycles are the Highway Fuel Economy Test (HWFET), illustrated in Figure 11, and the UDDS, shown in Figure 12. The HWFET represents steady highway driving with minimal stops and moderate accelerations, making it ideal for assessing fuel economy at constant high speeds. In contrast, the Dynamometer Driving Schedule (UDDS) reflects stop-and-go urban traffic, characterized by frequent accelerations, decelerations, and periods of idling, conditions typical of city driving. Together, these cycles provide a balanced assessment of vehicle efficiency across different environments, enabling manufacturers and regulators to evaluate city and highway performance more accurately and estimate combined range ratings with greater precision.

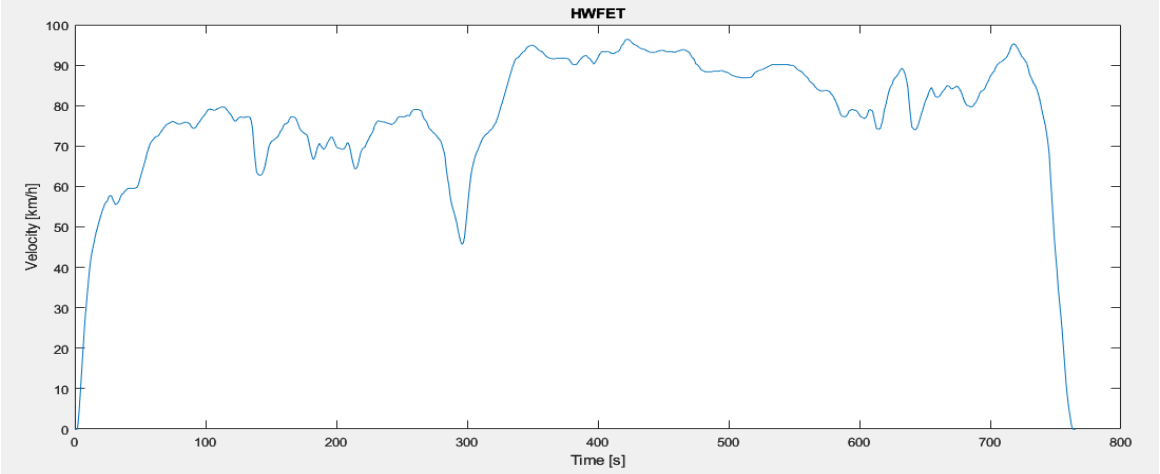

Figure 11. The HWFET speed profile is used to assess the energy efficiency of BEVs on highways by simulating high-speed driving circumstances.

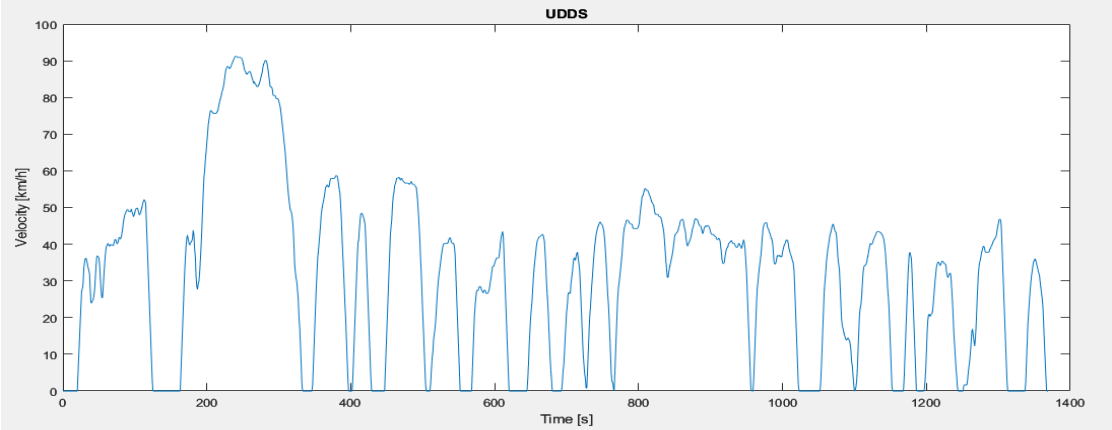

Figure 12. The typical city driving speed pattern used for BEV simulation under low-speed and stop-and-go situations is displayed by the UDDS .

The EPA multicycle driving procedure estimates the vehicle's range by discharging the battery from 98% SoC to 0% SoC. This method calculates the effective driving range by summing the energy consumed across multiple standardized drive cycles, thereby accounting for realistic urban and highway conditions. It provides a comprehensive assessment by incorporating various acceleration patterns, idle periods, and speed fluctuations, offering a more accurate reflection of real-world energy usage than single-cycle tests. Additionally, this approach accounts for auxiliary power consumption, such as HVAC systems, which can significantly impact actual vehicle range.

The following table describes how each modeling method contributes to the simulation outputs and the details provided by the BEV simulation, and the correlation between the outputs and details and the modeling methods. This shows how the modeling methods are combined to assess BEV performance across a range of operating conditions.

Table 6. Relationship between modeling approaches and simulated BEV performance outputs.

Model type	Primary simulation output	Insight provided	Practical role
Electrochemical	Voltage-current & degradation curves	Explains reaction kinetics, overpotential, and concentration gradients	Physical interpretation & thermal coupling
Electrical (ECM)	Dynamic voltage response & efficiency	Captures transient and steady-state voltage behavior	Fast simulation for BMS and control
Mathematical/Reduced-order	Range estimation & efficiency mapping	Simplifies system dynamics for computational optimization	System-level design and validation
Data-driven (ML/AI)	SoC/SoH prediction, temperature & range trends	Learns from historical or experimental data	Real-time estimation and predictive management

The quantitative and qualitative relationships demonstrated in Table 6 highlight that, whereas electrochemical and ECM models can be accompanied by high levels of physical and electrical accuracy, mathematical and data-driven frameworks complement them with computational speed and predictive adaptability. This is what provides better consistency between the theoretical model discussion and the practical simulation findings in this study.

4. Conclusions and future work

Fuel cell vehicles (FCVs) are gaining attention as a viable alternative in the transition toward zero-emission transportation. Their ability to produce only water vapor as a byproduct makes them highly attractive for reducing air pollution and greenhouse gas emissions. In addition to their environmental benefits, FCVs offer shorter refueling times and longer driving ranges than traditional BEVs, addressing two of the most significant barriers to EV adoption: Charging time and range anxiety. These advantages position FCVs as complementary to BEVs, especially in long-distance or heavy-duty applications. This review quantitatively demonstrates that electrochemical models achieve the highest fidelity (error < 3%) at the cost of high computational complexity, which makes them suitable for design optimization rather than real-time control. On the other hand, lower-order ECM and data-driven models deliver simulations that are up to an order of magnitude faster while maintaining an acceptable level of accuracy, making them suitable for use in BMS or vehicle control systems. These quantifiable trade-offs illustrate the practical balance among the model's accuracy, execution time, and the domains in which it can be applied, serving as a bridge between theoretical models and system-level applications.

We developed and analyzed a detailed simulation model designed to evaluate the performance of EVs across varying operational conditions. The model, constructed within the Simscape environment, integrates electrical, mechanical, and thermal subsystems to capture real-world behavior with high fidelity. It enables comprehensive evaluation of energy consumption, thermal management, and driving dynamics under various load scenarios and environmental influences. This platform thoroughly examined the impact of ambient temperature, auxiliary loads (such as HVAC), battery configuration, and driving profiles on vehicle range and efficiency.

One key takeaway from the simulation results is that non-propulsion energy demands, particularly those related to cabin climate control and battery thermal regulation, can significantly reduce the vehicle's effective range. These findings highlight the importance of integrated energy management strategies and holistic system design that account for real-world variability rather than relying solely on standardized test conditions.

We emphasize the need to balance the trade-off between model accuracy and computational speed across various methods, including electrochemical, mathematical, electrical, reduced-order, data-driven, and spectroscopy-based techniques. We clarify the trade-offs between fidelity and efficiency, showing how modeling choices can enable both high-fidelity research applications and real-time use in battery management and EV control systems.

As future work, it is recommended that hybrid modeling methodologies (combining physics-based and data-driven approaches) be developed to improve the interpretability and predictive capability of EV powertrains. One option is to couple battery system models with renewable energy charging infrastructure, leading to smart grid compatibility and sustainable operation. Finally, the

development of an advanced thermal-electrical coupling model for solid-state batteries is imperative to ensure safety, stability, and long-term durability during real-world driving.

Moreover, researchers should expand on co-simulation platforms that integrate multiple domains (electrical, thermal, and mechanical) into unified frameworks. This cross-domain modeling is essential for optimizing vehicle performance, safety, and reliability, especially under extreme or rapidly changing conditions. Incorporating renewable energy sources, such as solar panels or vehicle-to-grid (V2G) systems, into these models will also be crucial as the energy ecosystem becomes increasingly decentralized and intelligent.

Last, advances in open-source simulation datasets and the standardization of testing protocols will significantly enhance reproducibility, collaboration, and benchmarking across the academic and industrial communities. Establishing unified methodologies will help ensure consistent and comparable results across platforms and research institutions.

In conclusion, the ongoing evolution of EV modeling will be driven by interdisciplinary research, practical validation, and the continuous refinement of flexible, modular tools that can adapt to the rapid technological advancements in electric mobility and energy infrastructure.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Author contributions

Conceptualization, Mohamed M. A. Hassan; methodology, Bassam Adel; data curation, Bassam Adel; writing—original draft preparation, Mohamed M. A. Hassan; writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflicts of interest.

Reference

1. Lu LL, Lu YY, Zhu ZX, et al. (2022) Extremely fast-charging lithium ion battery enabled by dual-gradient structure design. *Sci Adv* 8: eabm6624. https://doi.org/10.1126/sciadv.abm6624
2. Tu S, Zhang Y, Ren D, et al. (2024) Integrated dual-phase ion transport design within electrode for fast-charging lithium-ion batteries. *Adv Funct Mater* 34: 2402077. https://doi.org/10.1002/adfm.202402077
3. Lu LL, Zhu ZX, Ma T, et al. (2022) Superior fast-charging lithium-ion batteries enabled by the high-speed solid-state lithium transport of an intermetallic Cu_6Sn_5 network. *Adv Mater* 34: 2202688. https://doi.org/10.1002/adma.202202688
4. Wang L, Yu FD, Que LF, et al. (2024) 12-Ah-level Li-ion pouch cells enabling fast charging at temperatures between −20 and 50 °C. *Adv Funct Mater* 34: 2408422. https://doi.org/10.1002/adfm.202408422

5. Cui Z, Liu C, Manthiram A (2024) Enabling stable operation of lithium-ion batteries under fast-operating conditions by tuning the electrolyte chemistry. *Adv Mater* 36: 2409272. https://doi.org/10.1002/adma.202409272
6. Zhao Y, Hu Z, Zhao Z, et al. (2023) Strong solvent and dual lithium salts enable fast-charging lithium-ion batteries operating from −78 to 60 °C. *J Am Chem Soc* 145: 22184–22193. https://doi.org/10.1021/jacs.3c08313
7. Lee Y, Lee T, Hong J, et al. (2020) Stress relief principle of micron-sized anodes with large volume variation for practical high-energy lithium-ion batteries. *Adv Funct Mater* 30: 2004841. https://doi.org/10.1002/adfm.202004841
8. Bai M, Yang L, Jia Q, et al. (2020) Encasing prelithiated silicon species in the graphite scaffold: An enabling anode design for the highly reversible, energy-dense cell model. *ACS Appl Mater Interfaces* 12: 47490–47502. https://doi.org/10.1021/acsami.0c12873
9. Cabello M, Gucciardi E, Liendo G, et al. (2021) A study to explore the suitability of $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$/silicon@graphite cells for high-power lithium-ion batteries. *Int J Mol Sci* 22: 10331. https://doi.org/10.3390/ijms221910331
10. Plett GL (2015) Battery management systems. In Battery Modeling, Norwood, MA, USA: Artech House, 1. Available from: https://us.artechhouse.com/Battery-Management-Systems-Volume1-Battery-Modeling-P1753.aspx.
11. CRU Group (2023) Navigating the rapidly evolving EV battery chemistry mix. CRU Group. Available from: https://www.crugroup.com/en/communities/thought-leadership/2023/navigating-the-rapidly-evolving-ev-battery-chemistry-mix (accessed on 11 October 2024).
12. Camargos, PH, Dos Santos PHJ, Dos Santos IR, et al. (2022) Perspectives on Li-ion battery categories for electric vehicle applications: A review of state of the art. *J Energy Res* 46: 19258–19268. https://doi.org/10.1002/er.7993
13. Miao Y, Hynan P, Von Jouanne A, et al. (2019) Current Li-ion battery technologies in electric vehicles and opportunities for advancements. *Energies* 12: 1074. https://doi.org/10.3390/en12061074
14. Liu H, Li M, Xiang M, et al. (2021) Effects of crystal structure and plane orientation on lithium and nickel co-doped spinel lithium manganese oxide for long cycle life lithium-ion batteries. *J Colloid Interface Sci* 585: 729–739. https://doi.org/10.1016/j.jcis.2020.10.052
15. Wang K, Wan J, Xiang Y, et al. (2020) Recent advances and historical developments of high voltage lithium cobalt oxide materials for rechargeable Li-ion batteries. *J Power Sources* 460: 228062. https://doi.org/10.1016/j.jpowsour.2020.228062
16. Wu K, Yang J, Zhang Y, et al. (2012) Investigation on $Li_4Ti_5O_{12}$ batteries developed for hybrid electric vehicle. *J Appl Electrochem* 42: 989–995. https://doi.org/10.1007/s10800-012-0442-0
17. Battery University (2024) BU-205: Types of lithium-ion. Battery University. Available from: https://batteryuniversity.com/article/bu-205-types-of-lithium-ion.
18. Environdec (2024) EPD-IES-0005471:002 (S-P-05471)—HMU Masaccio Train. Environdec. Available from: https://www.environdec.com/library/epd5471.
19. Nissan Motor Corporation (2024) Nissan Leaf specifications, Nissan. Available from: https://www-asia.nissan-cdn.net/content/dam/Nissan/AU/Files/Brochures/Models/Specsheet/LEA0173_Nissan_Next_LEAF%20eSpecs_v7.pdf.

20. Ahmad N, Fan C, Faheem M, et al. (2025) Role of electronic conductivities toward practical all-solid-state lithium-metal/sulfur batteries. *Adv Sustainable Syst* 9: 2400729. https://doi.org/10.1002/adsu.202400729
21. Cao X, Ahmad N, Zeng C, et al. (2025) Zirconization of $LiCoO_2$ for enhanced stability and oxygen deactivation in all-solid-state lithium battery cathodes. *J Energy Chem* 106: 930–938. https://doi.org/10.1016/j.jechem.2025.02.031
22. Chen KH, Goel V, Namkoong MJ, et al. (2021) Enabling 6C fast charging of Li-ion batteries with graphite/hard carbon hybrid anodes. *Adv Energy Mater* 11: 2003336. https://doi.org/10.1002/aenm.202003336
23. Tomasov M, Kajanova M, Bracinik P, et al. (2019) Overview of battery models for sustainable power and transport applications. *Transp Res Proc* 40: 548–555. https://doi.org/10.1016/j.trpro.2019.07.079
24. Tamilselvi S, Gunasundari S, Karuppiah N, et al. (2021) A review on battery modelling techniques. *Sustainability* 13: 10042. https://doi.org/10.3390/su131810042
25. Kamikawa Y, Amezawa K, Terada K (2024) Chemo-electro-mechanical phase-field simulation of interfacial nanodefects and nanovoids in solid-state batteries. *Commun Mater* 5: 180. https://doi.org/10.1038/s43246-024-00600-6
26. Tekin M, Karamangil Mİ (2024) Comparative analysis of equivalent circuit battery models for electric vehicle battery management systems. *J Energy Storage* 86: 111327. https://doi.org/10.1016/j.est.2024.111327
27. Graber G, Sabatino S, Calderaro V, et al. (2024) Modeling of lithium-ion batteries for electric transportation: A comprehensive review of electrical models and parameter dependencies. *Energies* 17: 5629. https://doi.org/10.3390/en17225629
28. Cheng D, Sha W, Wang L, et al. (2021) Solid-state lithium battery cycle life prediction using machine learning. *Appl Sci* 11: 4671. https://doi.org/10.3390/app11104671
29. Sukumaran S, Chater RJ, Fearn S, et al. (2025) Probing dynamic degradation and mass transport in solid-state sodium-ion batteries using operando simultaneous dual-polarity SIMS. *EES Batteries* 1: 964–974. https://doi.org/10.1039/D5EB00071H
30. Deng Z, Hu X, Lin X, et al. (2020) A reduced-order electrochemical model for all-solid-state batteries. *IEEE Trans Transp Electrification* 7: 464–473. https://doi.org/10.1109/TTE.2020.3026962
31. Fuller TF, Doyle M, Newman J (1994) Simulation and optimization of the dual lithium ion insertion cell. *J Electrochem Soc*, 141. https://doi.org/10.1149/1.2054684
32. Doyle M, Fuller TF, Newman J (1993) Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell. *J Electrochem Soc* 140: 1526. https://doi.org/10.1149/1.2221597
33. Newman J, Tiedemann W (1975) Porous-electrode theory with battery applications. *AIChE J* 21: 25–41. https://doi.org/10.1002/aic.690210103
34. Dickinson EJF, Wain AJ (2020) The Butler-Volmer equation in electrochemical theory: Origins, value, and practical application. *J Electroanal Chem* 872: 114145. ttps://doi.org/10.1016/j.jelechem.2020.114145
35. Aishwarya M, Sailaja M, Brisilla RM (2021) Modeling of lithium-ion batteries: An overview. *In Proceedings of the 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), Kuala Lumpur, Malaysia*, 1–9. https://doi.org/10.1109/i-PACT52855.2021.9696920

36. Oyewole I, Kwak KH, Kim Y, et al. (2021) Optimal discretization approach to the enhanced single-particle model for Li-ion batteries. *IEEE Trans Transp Electrification* 7: 369–381. https://doi.org/10.1109/TTE.2020.3016209
37. Ren L, Zhu G, Kang J, et al. (2021) An algorithm for state of charge estimation based on a single-particle model. *J Energy Storage* 39: 102644. https://doi.org/10.1016/j.est.2021.102644
38. Manwell JF, McGowan JG (1993) Lead acid battery storage model for hybrid energy systems. *Sol Energy* 50: 399–405. https://doi.org/10.1016/0038-092X(93)90060-2
39. Martinez J, Morales A, Probst O, et al. (2006) Analysis and simulation of a wind-electric battery charging system. *Int J Energy Res* 30: 633–646. https://doi.org/10.1002/er.1175
40. Chiasserini CF, Rao RR (1999) Pulsed battery discharge in communication devices. *In Proceedings of the 5th Annual ACM/IEEE International Conference on Mobile Computing and Networking, Seattle, WA, USA*, ACM: New York, NY, USA, 88–95. https://doi.org/10.1145/313451.313488
41. Panigrahi D, Chiasserini C, Dey S, et al. (2001) Battery life estimation of mobile embedded systems. *In Proceedings of the 14th International Conference on VLSI Design, Bangalore, India*, 57–63. https://doi.org/10.1109/ICVD.2001.902640
42. Rao V, Singhal G, Kumar A, et al. (2005) Battery model for embedded systems. *In Proceedings of the 18th International Conference on VLSI Design & 4th International Conference on Embedded Systems Design, Kolkata, India*, 105–110. https://doi.org/10.1109/ICVD.2005.61
43. Fan G, Li X, Canova M (2018) A reduced-order electrochemical model of Li-ion batteries for control and estimation applications. *IEEE Trans Veh Technol* 67: 76–91. https://doi.org/10.1109/TVT.2017.2738780
44. Rawat SK, Gope S, Jana M, et al. (2021) Accurate estimation of state of charge using reduced-order electrochemical model. *In Proceedings of the 2021 IEEE Transportation Electrification Conference (ITEC-India), New Delhi, India*, 1–6. https://doi.org/10.1109/ITEC-India53713.2021.9932464
45. Pebriyanti GA (2013) Lithium-ion battery modeling for a HIL-battery simulator. *In Proceedings of the 2013 International Conference on Computer, Control, Informatics and Its Applications (IC3INA), Jakarta, Indonesia*, 185–190. https://doi.org/10.1109/IC3INA.2013.6819171
46. Saldaña G, San Martín JI, Zamora I, et al. (2019) Analysis of the current electric battery models for electric vehicle simulation. *Energies* 12: 2750. https://doi.org/10.3390/en12142750
47. Kollmeyer P, Hackl A, Emadi A (2017) Li-ion battery model performance for automotive drive cycles with current pulse and EIS parameterization. *In Proceedings of the 2017 IEEE Transportation Electrification Conference and Expo (ITEC), Chicago, IL, USA*, 486–492. https://doi.org/10.1109/ITEC.2017.7993319
48. Pastor-Fernández C, Uddin K, Chouchelamane GH, et al. (2017) A comparison between electrochemical impedance spectroscopy and incremental capacity-differential voltage as Li-ion diagnostic techniques to identify and quantify the effects of degradation modes within battery management systems. *J Power Sources* 360: 301–318. https://doi.org/10.1016/j.jpowsour.2017.03.042
49. Liu W, Xu Y, Feng X (2020) A hierarchical and flexible data-driven method for online state-of-health estimation of Li-ion battery. *IEEE Trans Veh Technol* 69: 14739–14748. https://doi.org/10.1109/TVT.2020.3037088

50. Lucu M, Martínez-Laserna E, Gandiaga I, et al. (2018) A critical review of self-adaptive Li-ion battery ageing models. *J Power Sources* 401: 85–101. https://doi.org/10.1016/j.jpowsour.2018.08.064
51. Liu K, Shang Y, Ouyang Q, et al. (2021) A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery. *IEEE Trans Ind Electron* 68: 3170–3180. https://doi.org/10.1109/TIE.2020.2973876
52. Hussein HM, Esoofally M, Donekal A, et al. (2024) Comparative study-based data-driven models for lithium-ion battery state-of-charge estimation. *Batteries* 10: 89. https://doi.org/10.3390/batteries10030089
53. Ji C, Dai J, Zhai C, et al. (2024) A review on lithium-ion battery modeling from mechanism-based and data-driven perspectives. *Processes* 12: 1871. https://doi.org/10.3390/pr12091871
54. Wang Y, Wu J, He H, et al. (2025) Data-driven energy management for electric vehicles using offline reinforcement learning. *Nat Commun* 16: 2835. https://doi.org/10.1038/s41467-025-58192-9
55. Yao P, Liu X (2024) Electrochemical and thermal analysis of lithium-ion batteries based on variable solid-state diffusion coefficient concept. *World Electr Veh J* 15: 416. https://doi.org/10.3390/wevj15090416
56. Vermeer W, Chandra Mouli GR, Bauer P (2022) A comprehensive review on the characteristics and modeling of lithium-ion battery aging. *IEEE Trans Transp Electrification* 8: 2205–2232. https://doi.org/10.1109/TTE.2021.3138357
57. Krewer U, Röder F, Harinath E, et al. (2018) Dynamic models of Li-ion batteries for diagnosis and operation: A review and perspective. *J Electrochem Soc* 165: A3656. https://doi.org/10.1149/2.1061814jes
58. Campagna N, Castiglia V, Miceli R, et al. (2020) Battery models for battery powered applications: A comparative study. *Energies* 13: 4085. https://doi.org/10.3390/en13164085
59. Alkhedher M, Al Tahhan AB, Yousaf J, et al. (2024) Electrochemical and thermal modeling of lithium-ion batteries: A review of coupled approaches for improved thermal performance and safety lithium-ion batteries. *J Energy Storage* 86: 111172. https://doi.org/10.1016/j.est.2024.111172
60. Recalde A, Cajo R, Velasquez W, et al. (2024) Machine learning and optimization in energy management systems for plug-in hybrid electric vehicles: A comprehensive review. *Energies* 17: 3059. https://doi.org/10.3390/en17133059
61. Simpson T, Dervilis N, Chatzi E (2021) Machine learning approach to model order reduction of nonlinear systems via autoencoder and LSTM networks. *J Eng Mech* 147: 04021061. https://doi.org/10.1061/(ASCE)EM.1943-7889.0001971
62. Lou S, Sun N, Zhang F, et al. (2021) Tracking battery dynamics by operando synchrotron X-ray imaging: Operation from liquid electrolytes to solid-state electrolytes. *Acc Mater Res* 2: 1177–1189. https://doi.org/10.1021/accountsmr.1c00159
63. Meddings N, Heinrich M, Overney F, et al. (2020) Application of electrochemical impedance spectroscopy to commercial Li-ion cells: A review. *J Power Sources* 480: 228742. https://doi.org/10.1016/j.jpowsour.2020.228742

64. Singh A, Pal K, Vishwakarma CB (2023) State of charge estimation techniques of Li-ion battery of electric vehicles. *e-Prime—Adv Electr Eng, Electron Energy* 6: 100328. https://doi.org/10.1016/j.prime.2023.100328