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Review article

Integration of digital twin technologies for state estimation in electric vehicle batteries: A review

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ABSTRACT

Accurate state estimation is fundamental for the safety, reliability, and performance of electric vehicle (EV) batteries. This review highlights the critical need for precise evaluation of key battery states such as state of charge (SOC), state of health (SOH), and remaining useful life (RUL). It surveys the existing modelling and estimation techniques used in lithium-ion battery (LIB) systems. It explores parameter identification methods and the challenges associated with real-time monitoring and predictive diagnostics in dynamic EV environments. The paper further investigates the transformative role of digital twin (DT) technologies in addressing these challenges. By integrating battery digital twins technologies (BDTs): Internet of Things (IoT), cloud computing, artificial intelligence (AI), and extended reality (XR), it offers a virtual replica of the battery system. That enables continuous monitoring, predictive maintenance, and performance optimization. The review delves into the architecture, functions, challenges and future perspectives of battery digital twins (BDTs). And it emphasizes their potential to enhance traditional battery management systems (BMS) through intelligent, adaptive control. Through comparative analysis and identification of research gaps, this review provides a roadmap for future advancements in state estimation and digital twin integration.

1. Introduction

The degradation of fossil resources and the pressing requirement to prevent global warming are paving the way for a transformative shift in the automotive industry from traditional fuel-powered vehicles to electric vehicles (EVs) [1]. The escalating threat of global warming has been evident from the recent investigations conducted by the International Energy Agency (IEA) on green mobility, which found that the mobility sector accounts for 24% of worldwide carbon-based emissions, with roadways contributing nearly 85% of overall transport carbon-based emissions [2]. Despite these challenges, the shift towards electric vehicles marks a huge advancement in decreasing the adverse environmental effects of transportation. The benefits of cheaper operational and servicing costs, energy efficiency, and no pollutants make EVs a desirable choice for consumers [3]. Furthermore, the surge in electric vehicle adoption is fuelled by a combination of technological advancements, increased emphasis on green power, greater convenience of home charging, intense industry competition, supportive government policies, and global trends., [4] This rapid growth is further evidenced by the Global EV Outlook 2024 sales report, which indicates that electric vehicle sales are surging and are projected to reach a staggering 17 million units in 2024 [5]. Despite significant advancements in electric vehicle (EV) technology, widespread adoption remains hindered by limitations in battery technology and battery management systems (BMS).

EVs rely on electrochemical energy storage systems, commonly referred to as batteries, to power their propulsion systems. These batteries come in various forms, including lead-acid (Pb-Acid), nickel-metal

Abbreviations: AI, Artificial Intelligence; ANN, Artificial Neural Networks; BDT, Battery Digital Twin; BMS, Battery Management Systems; CLTC, China Light-Duty Vehicle Test Cycle; CNN, Convolution Neural Network; DST, Dynamic Stress Test; ECM, Equivalent Circuit Model; EIS, Electrochemical Impedance Spectroscopy; EKF, Extended Kalman Filter; ELM, Extreme Learning Machine; EM, Electrochemical Model; EV, Electric Vehicle; FUDS, Federal Urban Driving Schedule; HWFET, Highway Fuel Economy Driving Schedule; IoT, Internet of Things; LIB, Lithium-ion battery; LSTM, Long Short-Term Memory; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MAX, Maximum Error; MSE, Mean Square Error; OCV, Open Circuit Voltage; PSO, Particle Swarm Optimisation; RMSE, Root Mean Square Error; RUL, Remaining Useful Life; SOC, State of Charge; SOH, State of Health; SPM, Single Particle Model; SSA, Sparrow Search Algorithm; SVM, Support Vector Machine; UDDS, Urban Dynamometer Driving Schedule; XR, Extended Reality.

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hydride (NiMH), nickel-cadmium (Ni-CD), and lithium-ion (Li-ion). Among these, Li-ion batteries have emerged as the most prevalent choice due to their exceptional energy density, extended cycle life, and minimal self-discharge rate [6]. While Li-ion batteries offer numerous advantages for EV applications, they also come with certain disadvantages, such as sensitivity to temperature, safety risks, and cost concerns [7]. To ensure safe and efficient operation of lithium (Li)-ion batteries, a BMS is required to mitigate these disadvantages by monitoring and controlling various battery states, namely SOC, SOH, battery temperature, and RUL [8]. Battery modelling is essential for BMS as it provides a virtual representation of the battery's behaviour, enabling accurate state estimation, performance prediction, fault diagnosis and prognosis and thermal management. Battery modelling is categorized into different ways, namely grey, white and black box modelling.

Grey box models, also known as Equivalent Circuit Models (ECMs), represent the battery as an interconnected system of electrical components. Despite their simplicity, computational efficiency, and flexibility, which make them suited for real-time applications, these models have disadvantages, including a lack of physical interpretation, reduced accuracy in harsh situations, and challenges in identifying parameters [9]. White box models, generally referred to as Electrochemical Models (EMs), offer a detailed representation of battery behaviour by analysing its internal chemistry, including electrode kinetics, electrolyte transport, and solid-state diffusion [10]. While EMs provide a deep understanding of battery processes, they are computationally demanding and require extensive parameter identification. In contrast, black box models rely on statistical methods and machine learning algorithms to learn from battery data and predict its performance. Black box models can adapt to complex and nonlinear battery behaviour, such as ageing effects and temperature dependence, providing accurate state predictions and identifying patterns that physical models may overlook. However, these models have a high reliance on training data, which can result in poor generalisation and erroneous predictions. Furthermore, their inability to extrapolate outside of the training data range limits their capacity to forecast battery behaviour in a variety of extreme circumstances [11].

Given the contrasting strengths and weaknesses of grey box, white box, and black box models, researchers are exploring hybrid approaches to develop more accurate and computationally efficient battery models [12]. These hybrid models aim to combine the interpretability of grey box models with the accuracy of white box and black box models. For instance, a hybrid model might use a grey box model as a foundation and then incorporate machine learning techniques to refine its predictions based on real-world data [13]. This approach could address the limitations of each model type, leading to more reliable and robust battery management systems. Additionally, the development of Battery Digital Twins (BDTs) offers a promising avenue for overcoming the challenges faced by current BMS. By creating a virtual replica of the battery system, BDTs can provide valuable insights into battery behaviour, ageing, and degradation. These virtual models can be used to test different operating conditions, optimise charging strategies, and predict battery performance over time. As IoT, cloud computing, AI, and extended reality technologies continue to advance, BDTs are expected to play an increasingly important role in battery management and electric vehicle applications. As research in battery modelling and BDTs continues to advance, we can expect to see significant improvements in battery management systems and the overall performance and reliability of EVs.

1.1. Contribution of Existing Reviews to the Field

A multitude of review articles [14–19] have delved into the examination of research articles concentrated on conventional battery modelling strategies and estimation techniques. These investigations primarily focused on estimating battery SOC and SOH in lithium-ion batteries, specifically for EVs and energy storage systems (ESS). They discuss model-based approaches, such as equivalent circuit models (ECMs) and electrochemical models and data-driven approaches, such as support vector machines (SVMs) and neural networks. While existing review papers have made significant contributions to the field of battery SOC and SOH estimation, several areas could benefit from further exploration. These include examining research articles that leverage advanced machine learning techniques, such as deep learning, to extract patterns and correlations from large datasets. Additionally, exploring the potential of BDTs to enable real-time monitoring, predictive analytics, and optimised control strategies for battery ageing, degradation, and safety could provide valuable insights. The comparative analysis of recent review literature on EV battery estimation and Digital Twin technologies is presented in Table 1.

1.2. Contributions of this review article

This paper principally aims to conduct a critical review of various state-of-the-art techniques for battery state estimation and explore the potential of digital twins, focusing on their applications in electric vehicle battery management systems. The review comprehensively covers a wide range of state estimation techniques, including those related to deterministic and non-deterministic forms. It explores their integration with battery management systems for optimal performance.

The primary contributions of this paper are

1. To provide a solid foundation for this review, a detailed study of the current battery landscape, BMS functionalities, battery modelling techniques (grey box, white box, and black box), and SOC estimation techniques (deterministic, non-deterministic, and hybrid approaches) is conducted.
2. This paper comprehensively analyses deterministic SOC estimation methods, considering their key approaches(filters/observers), influencing factors (test profiles/drive cycles, battery type, battery model, parameter extraction, temperature), performance evaluation metrics and their suitability for BDTs.
3. A thorough examination of non-deterministic SOC estimation methods focusing on their network model, influencing factors (test profiles/drive cycles, battery dataset, input variables, temperature), and performance evaluation metrics are conducted.
4. A systematic analysis of SOH/RUL estimation methods, including descriptions, battery/dataset usage, methods employed, temperature considerations, tools/software used, estimation techniques, and performance metrics are presented.
5. The potential of digital twin technologies for electric vehicle battery management, including predictive maintenance, optimized charging strategies and virtual testing, is explored.

1.3. Organization of the paper

This paper is organised as follows: Section 2 provides a comprehensive overview of battery types, BMS architectures, and their suitability for EVs. Section 3 delves into battery modelling techniques and parameter identification. Section 4 explores various SOC estimation methods, including traditional and state-of-the-art approaches. Section 5 discusses recent advancements in SOH and RUL prediction, highlighting the latest techniques and their applications. Section 6 presents a detailed review of digital twin-based battery state estimation, BDT framework, challenges, emphasising its potential to enhance BMS functionality. A detailed discussion is provided in Section 7. Finally, Section 8 concludes and presents future perspectives on the paper by summarising key findings and discussing future research directions.

2. Batteries and BMS

The performance and success of EVs are heavily reliant on the efficiency and reliability of their battery systems. Batteries not only store energy for propulsion but also contribute significantly to the overall cost, weight, and range of EVs. Therefore, advancements in battery

Table 1
Comparative Analysis of Recent Review Literature on EV Battery Estimation and Digital Twin technologies.

Reference	Year	Battery Technology	BMS	Battery Modelling	Battery Parameter Estimation			Digital Twin Technology	Limitations
					SOC	SOH	RUL		
[20]	2022	×	×	×	✓	×	×	×	Discusses SOC algorithms only; does not compare or classify advanced or hybrid methods; no contextual validation.
[21]	2023	✓	✓	✓	✓	✓	×	×	Provides broad scope on SOC, SOH, charge/discharge behaviours; lacks technological integration such as in digital twin (DT), battery estimation frameworks.
[22]	2024	×	×	✓	✓	✓	×	×	Focused on estimation methods; no detailed modelling, no treatment of full BMS architecture or digital twin integration.
[23]	2024	×	✓	×	✓	×	×	×	Focused solely on SOC methods; lacks SOH/RUL and no exploration of real-time BMS frameworks or digital twin concepts.
[24]	2024	×	×	✓	✓	✓	×	×	Lacks modelling or parameter extraction discussion; not holistic across battery lifecycle or digital twin readiness.
[25]	2025	×	×	✓	✓	×	×	×	Primarily SOC estimation-focused; no insight into other battery states, nor digital twin-enabled approaches.
[26]	2025	✓	×	✓	✓	×	×	☑	Includes DT but lacks architectural frameworks or implementation strategy, challenges; doesn't cover hybrid estimation methods
[27]	2025	×	✓	✓	✓	✓	×	☑	Provides minimal digital twin analysis; lacks BDT architectural frameworks or implementation strategy, challenges.
This Review	-	✓	✓	✓	✓	✓	✓	✓	**This review covers entire battery state estimation landscape along with in-depth analysis of BDT technologies, Challenges and Future perspectives.**

× - not discussed; ☑ - partially discussed; ✓ - well discussed

technology and battery management systems (BMS) are crucial for the widespread adoption of electric vehicles. Rechargeable batteries, a key component of electric vehicles, not only contribute to a significant portion of their cost (25% to 50%) but also play a vital role in determining their efficiency, performance, and overall lifespan [28]. To address these critical factors, advancements in battery technology and management systems have focused on enhancing key performance metrics. The advancements in batteries and their management technology primarily aim to enhance batteries' energy density, specific energy, and ability to charge rapidly [29]. Electric vehicles (EVs) utilize various kinds of battery technologies, such as lithium-ion, lead-acid, nickel-cadmium, and nickel-metal hydride.

2.1. Lead-Acid batteries

Lead-acid batteries, a mature rechargeable battery technology, are renowned for their affordability, ease of manufacturing, and reliability. Commonly used as starter batteries in gasoline vehicles, they offer high specific power, making them suitable for the demanding starting requirements of electric vehicle motors [30]. However, their limitations, including weight, bulk, shorter lifespan, and maintenance requirements, have hindered their widespread adoption in EVs. Despite these drawbacks, lead-acid batteries remain a cost-effective option for certain applications, particularly smaller vehicles. While environmental concerns and corrosion issues exist, ongoing research and development efforts aim to address these limitations and maintain lead-acid batteries as a viable option within the battery landscape.

2.1.1. Nickel-based batteries

In contrast to lead-acid batteries, nickel-based batteries (Ni-Cd and NiMH) are preferred in various applications due to their unique characteristics, including temperature adaptability, extended cycle life, and effectiveness. However, it encounters elevated self-discharge rates, environmental risks, and the memory effect. NiMH batteries, characterized by superior energy density and efficiency, find application in hybrid electric vehicles [31].

2.1.2. Lithium based Batteries

Lithium-ion batteries have emerged as the preferred choice for EVs due to their superior energy density, extended cycle life, and minimal self-discharge rates compared to traditional lead-acid and nickel-based batteries, as evidenced by the data presented in Table 2. However, they can deteriorate under extreme temperatures and improper charging conditions, potentially resulting in safety problems [32]. Scientists are studying lithium-sulphur batteries, offering higher power density, reliability, and smaller size. They function via the bidirectional motion of lithium ions between two electrodes, allowing for efficient energy storage and release. The total lifespan determines lithium-ion batteries' duration and degradation behaviour, along with the cost-effectiveness of EVs [33]. Despite their advantages, LIBs confront issues such as high cost, safety issues, thermal runaway, ageing, deterioration, and environmental implications [34].

2.1.3. Beyond Lithium

Researchers are examining alternative battery technologies for large-scale energy storage and EV applications, shifting beyond lithium-ion batteries. Metal/air batteries such as zinc/air, aluminium/air, and lithium/air exhibit high energy densities but are restricted by anode capacity and handling procedures [35]. Sodium-beta batteries, notably sodium/sulphur (Na/S) and sodium/metal chloride (Na/MCl2) batteries, function at elevated temperatures to enhance ionic conductivity. Na/S batteries utilize beta-alumina ceramic electrolytes, boasting a high theoretical energy density; however, they encounter performance deterioration due to heightened internal resistance [36]. Despite the obstacles faced, Na/S batteries show promise due to their extended cycle life, low cost, high efficacy, and capability to provide pulse power. Ongoing research is concentrated on the advancement of room-temperature Na/S batteries to enhance stability [37]. Table 3 shows that the recent electric vehicles come with lithium-based battery technology and are found in different geometries, such as cylindrical, pouch, and prismatic/Blade.

Understanding the mechanical and thermal responses of lithium-ion batteries under abuse conditions is crucial for ensuring their safety and performance in electric vehicles. One study [38] analyses the mechanical and thermal reactions of cylinder-shaped, pouch-shaped, and prismatic-shaped lithium-ion batteries under mechanical abuse. It identifies relationships between peak force, Open Circuit Voltage (OCV) decline, and temperature increase.

Each cell type exhibits a variety of fracture patterns, with pouch cells suffering in-plane fractures from biaxial stretching and inter-layer fractures from shearing. In contrast cylindrical cells show regular deformation stages with predictable force and OCV responses. Shear

Table 2
Characteristics of EV battery technologies [32].

Battery type		Trade-offs	Specific Energy (Wh/kg)	Cycle life	Charge time (Hours)	Self-discharge/ month at 25 °C (% SOC)	Over charge tolerance	Safety requirements
Lead Acid		Available in various sizes and designs with high-rate recyclability, but can suffer from irreversible polarization and hydrogen evolution and maintenance is high.	30-50	200-300	8-16	5	High	Thermally Stable
Nickel	Ni-Cd	Resistant to electrical and physical abuse with low maintenance, though comparatively expensive, contains toxic cadmium, and utilises caustic alkaline electrolyte.	50-80	1000	1-2	20	Moderate	Thermally Stable, Fuse Protection
	Ni-MH	High-temperature and high-rate capable with long shelf life and good charge retention, but at a higher cost and reduced performance in low temperatures.	60-120	300-500	2-4	30	Low	
Lithium	Cobalt	Requires less maintenance, charges quickly, is free of memory effects, can be designed with various chemical compositions, but is more expensive and requires protective circuitry.	150-190	500-1000	3-4	>5% Protection Circuit consumes 3% per month	Low, No trickle charge	Protection circuit mandatory
	Phosphate		90-120	1000-2000	≤1 h			
	Manganese		100-135	500-1000	≤1 h			

Table 3
Comparative Overview of Battery Specifications Across Electric Vehicle Models (source: https://ev-database.org/) (accessed 10 May 2025).

Vehicle Segment	Vehicle Model	Average Range (Km)	Battery information			
			Type/ Cathode material	Nominal/Usable Capacity (kWh)	Nominal Voltage (Volts)	Pack Configuration s-Series, p-Parallel
Mini/Small	Dacia Spring Electric 45	167	Lithium-ion	26.8/25.0	240	72s1p
	Kia e-Soul 39.2 kWh	235	Lithium-ion	42.0/39.2	372	90s2p
	Renault Zoe ZE50 R110	320	Lithium-ion/NCM712	54.7/52	350	96s2p
Medium	Volkswagen ID.3 GTX	464	Lithium-ion/NCM	84.0/79.0	352	96s3p
	Volkswagen ID.3 Pro S - 4 Seats	459	Lithium-ion **(Pouch)**/ NCM712	84.0/77.0	352	96s3p
	BYD ATTO 3	336	Lithium-ion **(Prismatic)**/LFP	62.0/60.5	403	126s1p
Large	Tesla Model 3	421	Lithium-ion **(Prismatic)**/LFP	60.0/57.5	340	106s1p
	Tesla Model 3 Long Range Dual Motor	504	Lithium-ion **(Cylindrical-LG M50)**/NCM	78.1/75.0	357	96s46p
	BYD SEAL 61.4 kWh RWD Comfort	372	Lithium-ion **(BYD BLADE)**/ LFP	63.0/61.4	410	128s1p
Executive	BYD HAN	478	Lithium-ion **(Prismatic)**/LFP	88.0/85.4	569	178s1p
Luxury	Tesla Model S Plaid	563	Lithium-ion (Panasonic 18650)/NCM	100.0/95.0	407	110s72p
Passenger	Volkswagen ID. Buzz Pro	345	Lithium-ion/NCM	82.0/77.0	352	96s3p

fractures lead to larger OCV dips, influencing heat generation and temperature distribution. Because of their flexibility, pouch cells experience rapid OCV dips and temperature increases. Cylindrical batteries provide stable performance and solid mechanical integrity because of their stiff shell, while prismatic batteries have excellent energy density but less charge/discharge power [39]. Understanding these mechanical responses is critical for increasing battery safety and performance. Another study [40] examined several battery designs for electric vehicles, revealing that blade batteries outperform others for both economic and performance vehicles.

The Blade Battery from BYD, which comes with a lithium iron phosphate (LFP) battery characterized by its elongated, flat configuration, which improves volumetric energy density & structural integrity. It stresses safety, passing harsh tests without fire or explosion, and delivers long cycle life, fast charging, and environmental benefits thanks to its cobalt-free chemistry. While it significantly lags in gravimetric energy density and cold-weather performance, its reasonable price and durability make it a preferred alternative for modern EV applications.

Finally, this section outlines the dependence of EVs on various battery technologies along with their geometries, each with its own strengths and limitations. Lead-acid batteries, while cost-effective and reliable, are heavy, bulky, and have a shorter lifespan [41]. Nickel-based batteries offer better energy density and efficiency, but they also suffer from issues such as high self-discharge rates, memory effects, and environmental risks [42]. Lithium-ion batteries are the preferred choice for EVs due to their high energy density and long lifespan, but they come with challenges such as high cost and safety concerns [43]. As researchers explore alternatives like lithium-sulphur and metal/air batteries, the focus is on improving energy density, safety, and overall cost-effectiveness, aiming to advance beyond current battery technologies. However, with the help of BMS, the above-mentioned challenges of LIBs can be overcome by charge/discharge control, state monitoring, thermal management, and early fault detection.

2.2. Battery Management System

BMS are crucial for EV applications because they monitor battery performance and health, control charging and discharging cycles, ensure safety, and optimise battery life. The BMS performs crucial activities such as detecting voltage V(k), current I(k), and temperatures T(k) of individual cells in a battery pack, calculating battery conditions, and preventing overcharging, overdischarging, and overheating [44]. It also balances charge and discharge across all battery cells, communicates with other systems in the vehicle, and compensates for battery age and degradation over time [45]. BMS software governs hardware operations and analyses sensor information to make intelligent decisions.

This section analyses various BMS architecture topologies, including centralized, modular, and distributed, and their suitability for EV applications, as illustrated in Table 4. Centralized BMS, characterized by a single control unit, offers cost-effectiveness and ease of maintenance but suffers from complex wiring and limited scalability [46]. Modular BMS, with its scalable design and reduced wiring complexity, strikes a balance between cost and performance. Decentralized BMS, featuring dedicated modules for each cell or string, provides excellent scalability, flexibility, and safety but comes at a higher cost and requires more space [47]. The choice of BMS topology depends on factors such as battery pack size, desired safety level, cost constraints, and scalability requirements. Centralized BMS is often suitable for smaller battery packs, while modular and decentralized topologies are preferred for larger packs or applications with stringent safety demands.

The decentralized BMS is utilized for individual cell-level monitoring. At the same time, the Modular or Centralized BMS is utilized for system or pack-level monitoring through accurately estimating the battery state. Individual battery cell state estimation enhances the estimation accuracy, allows early fault detection, improves battery safety and supports Battery Digital Twin modelling. However, individual cell estimation presents challenges such as increased system complexity due to additional sensors and wiring, higher costs, and high-power consumption. Real-time monitoring of hundreds of cells leads to data overload, requiring robust communication protocols and powerful onboard processors. Furthermore, validation of accurate estimation needs advanced algorithms to handle sensor noise, data drift, and scalability across large battery packs/systems. In spite of these difficulties, cell-level monitoring is crucial for next-generation EVs and energy storage systems where performance, safety, and predictive control are of great importance.

System or module-level state estimation is simple and cost-effective as it requires fewer sensors, limited wiring, simplifies data handling and computation when compared to individual cell state estimation. Enables faster implementation with conventional estimation algorithms such as Kalman filters or equivalent circuit models. However, this method's estimation accuracy comes down. As a result, early warning signs of imbalance or failure may go undetected, increasing the risk of reduced performance, thermal instability, or safety hazards. System-level estimation is efficient for broad monitoring.

However, integration of accurate Multiphysics battery pack/system modelling with advanced prediction techniques (ML/DL) would enable accurate battery state estimation. For example, the study [48], proposes a novel method for accurate estimation of a battery's SOH using a cross-generative adversarial network (CrGAN) to address incomplete sensor data. Several identical cells are chosen to collect offline data. Health indicators (HIs) are then derived from the voltage data using a singular value decomposition (SVD) algorithm. Finally, an SOH model is built by integrating kernel ELM and extreme learning machine (ELM) using Adaboost, with HIs as inputs and SOH as outputs. The approach reconstructs missing data and yields highly accurate SOH assessments. Results indicate optimal accuracy with just 10 sensors and highlight strategies for efficient sensor placement.

Fig. 1 illustrates the functional block diagram of a typical BMS architecture, showcasing how different topologies integrate essential functions such as monitoring, balancing, and communication with other vehicle systems. To efficiently perform these activities, BMS designs rely on accurate measurements and data acquisition. Precise data collection is extremely important for accurate state estimation, defect detection, and performance optimisation [49]. Effective communication within the BMS is facilitated by protocols like the Controller Area Network (CAN) bus, ensuring seamless data exchange and coordinated control [50].

3. Battery Modelling

Battery modelling is vital for BMS because of its capacity to predict as well as estimate crucial battery states, including SOC, SOH, state of energy (SOE), and state of power (SOP). These estimations are necessary for efficient battery management, which guarantees safe use, peak performance, and precise estimations of the amount of residual range or power that is available. By simulating battery performance under various settings, models also aid in the prediction and prevention of safety hazards such as thermal runaway [51]. Their purpose is to simulate the effects of various operating situations and design factors on battery performance, longevity, and safety, which helps with design and optimisation. Real-time monitoring and diagnostics allow for prompt problem identification and quick intervention to avoid failures. Performance optimisation, which includes temperature management, voltage balancing, and regulation of both charging and discharge rates, results in improved energy efficiency, power generation, and overall battery lifespan. Fundamentally, battery modelling functions as a virtual laboratory, offering perceptions of the battery's behaviour and facilitating well-informed choices for dependable, safe, and efficient functioning [52].

There are three main variants of battery models, as shown in Fig. 2, that are designed to meet different requirements of BMS. Grey box models, also known as equivalent circuit models (ECMs). Various types of ECMs, such as R-int, Thevenin (1RC), Enhanced Thevenin (2RC), PNGV, GNL, and impedance models, are represented in Table 5 along with their characteristics and equations. White box models, i.e., electrochemical models (Ems) such as P2D, SPM, SPMe, and NGTK. The

Table 4
Comparison of Battery Management System (BMS) Topologies for Electric Vehicles.

BMS Topology	Description	Positive aspects	Negative aspects	Suitability for EVs
Centralized	A single control unit manages all cell monitoring, balancing, and communication via multiple wires connected to each cell.	Lowest cost (Fewer components) Lightest weight (single control unit) Easy maintenance (Centralized access)	Complex wiring (increased short circuit risk) Single point of failure (central controller) Limited scalability (fixed number of cells)	Smaller battery packs (cost-effective for limited cell count)
Modular	The system comprises multiple identical BMS modules that manage specific battery sections and communicate with a central master module.	Reduced long cable requirements Moderate weight (multiple modules) Scalable	Higher costs compared to centralized BMS Cell balancing challenges.	Medium-sized battery packs where expandability might be needed later
Decentralized	Each cell or string has its own dedicated BMS module for monitoring, balancing, and communication with a central controller.	Simplified wiring High measurement accuracy (specialized modules) Highly scalable and flexible (easy cell addition/removal) No single point of failure (increased safety)	Highest Cost (separate module per cell) Heaviest Weight & More space requirement Power Consumption Complex communication	Larger battery packs in EVs where scalability and safety are crucial

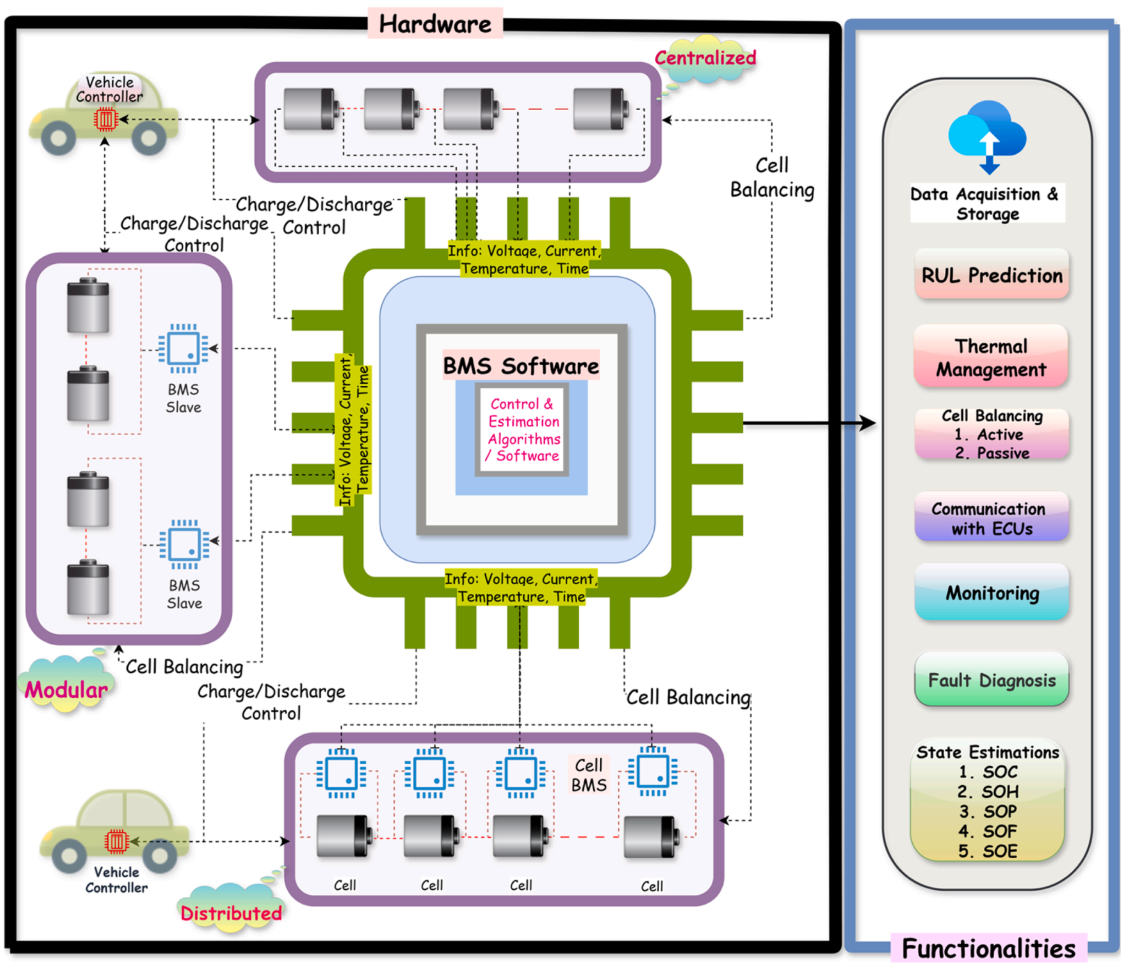


Fig. 1. Functional diagram of Battery Management System with different architecture topologies.

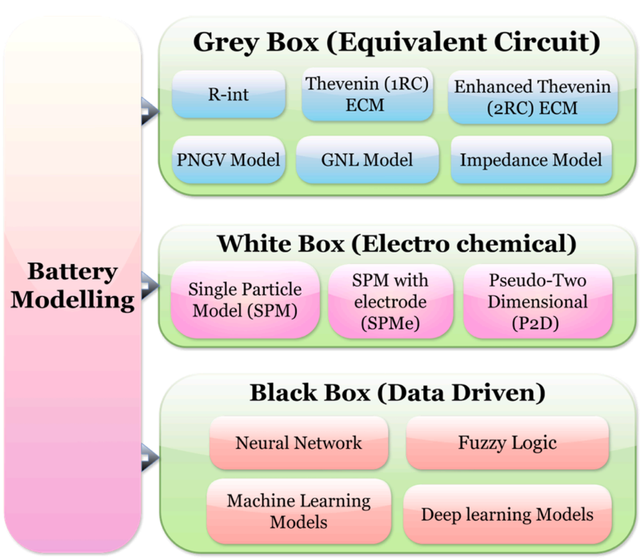


Fig. 2. Battery Modelling Methods.

black box models are referred to as data-driven models, i.e, AI and ML/DL models.

The hybrid modelling, i.e., MSMD (Multi-Scale Multi-Domain) battery modelling methodology, incorporates electrochemical, thermal, and electrical physics across many spatial and temporal dimensions, applying a white-box, physics-based framework. It makes it possible to simulate battery behaviour in real-world scenarios with great fidelity, which helps with safety analysis, thermal management, and design optimisation. The hierarchical structure facilitates precise forecasting of performance from electrode-level responses to pack-level thermal dynamics.

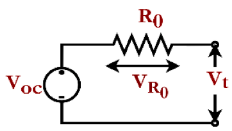
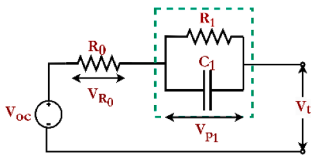
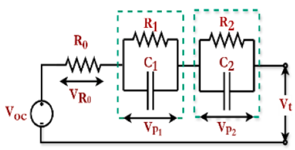
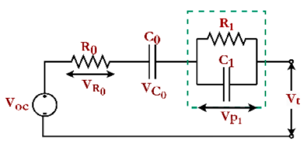
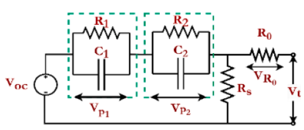
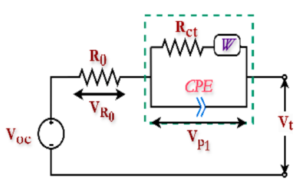
A detailed review and discussion are already provided for battery modelling in the existing literature [56–69]; therefore, this article omits that section.

3.1. Parameter Identification

Parameter identification is an essential part of battery modelling and state estimation, which allows for a precise representation of the battery's behaviour. It aids in the accurate determination of the current state, performance forecasting, and model verification. Precise parameters are crucial for efficient battery management, ensuring safety, and maintaining model accuracy. Frequent updates of these parameters enable the model to adjust and to changes in the battery's performance over time, ensuring accuracy even in the face of ageing or fluctuating conditions. This approach enhances the security, effectiveness, and reliability of battery systems in diverse applications.

Popular parameter identification methods include genetic algorithm (GA), recursive least squares (RLS), forgetting factor recursive least squares (FFRLS), and particle swarm optimisation (PSO). For example, the study [66] identifies battery model parameters using recursive least squares (RLS) and multi-swarm particle swarm optimisation (MPSO) algorithms, with data obtained from dynamic stress tests (DST). While

Table 5
Comparison of Battery Equivalent Circuit Models [53–55].

ECM Type	Diagram	Equation	Characteristics
R-int		$V_t = V_{oc} - V_{R_0}$	• Simplicity and straightforward execution; • Minimal computational complexity; • Neglects polarisation effects; • Limited state prediction; • Reduced precision and dynamic performance.
Thevenin		$V_t = V_{oc} - V_{R_0} - V_{p_1}$	• A basic and intuitive structure; • Low calculation complexity; • Good expandability; • Constant parameter assumption; • Reduced accuracy at low SOC.
Enhanced Thevenin		$V_t = V_{oc} - V_{R_0} - V_{p_1} - V_{p_2}$	• Reduced estimation error; • Improved accuracy-complexity trade-off; • Increased computational time compared to Thevenin ECM.
PNGV		$V_t = V_{oc} - V_{R_0} - V_{C_0} - V_{p_1}$	• High accuracy; • Excellent dynamic characteristics; • Electrochemistry consideration; • Limited low-frequency impedance modelling; • Increased computational complexity; • Neglect of charging process.
GNL		$V_t = V_{oc} - V_{R_0} - V_{p_1} - V_{p_2}$	• Increased accuracy; • Clear physical meaning; • Consideration of overcharge and over discharge; • Complex structure, calculation and time consumption; • Limited practical applicability
Overall Impedance		$V_t = V_{oc} - V_{R_0} - V_{p_1}$ $Z(\omega) = R_{el} + \dfrac{1}{Z_{CPE} + \dfrac{1}{R_{ct} + Z_w}}$ $Z_{CPE} = \dfrac{1}{C(j\omega)^{\alpha}}$ $Z_w = \dfrac{\sigma(1-j)}{\sqrt{\omega}}$	• Electrochemical Impedance Spectroscopy (EIS)-based; • Detailed electrochemical insights; • Excellent parameter identification; • Suitable for dynamic conditions; • Invasive Measurement; • Sensitivity to temperature and ageing; • Overall impedance is determined by ohmic resistance, Warburg impedance (Z_w), charge transfer resistance, and CPE.

*__Note.__ V_t: terminal voltage; V_{oc}: open circuit voltage; V_{R_0} – voltage across ohmic resistance (R_0); V_{p_1}, V_{p_2}: polarization voltage; R_1, R_2: polarization resistance; R_s: self-discharging resistor; C_0: energy storage capacitor; V_{C_0}: voltage across C_0; R_{ct}: charge transfer resistance; ω: AC frequency; R_{ct}: charge transfer resistance; σ: coefficient (values between 0 to 1); α: coefficient = 0.5; Z_w: Warburg impedance.

RLS is typically used for first-order RC equivalent circuit models, MPSO generally achieves higher modelling accuracy, as evidenced by lower MAE and RMSE values. The study concludes that MPSO outperforms RLS in parameter identification accuracy, particularly in capturing dynamic battery behaviour, though neither method is superior across all temperatures.

For real-time adjustment, the methodology consists of weighted least squares, iteratively reweighted least squares (IRLS), and variable forgetting factor recursive least squares (VFFRLS). This [67] approach enhances the precision of estimating battery model parameters, improving the accuracy of SOC and capacity estimation. However, the real-time adjustment requirements can be computationally intensive, which may affect system performance in resource-constrained environments. In [68], the parameter identification is done with the help of the forgetting factor, which is optimised using the Sparrow Search Algorithm (SSA). The study [69] employs the AFOPSO (Adaptive Fractional-Order Particle Swarm Optimisation) algorithm to perform offline parameter identification.

The Maximum Correntropy Criterion-based Gradient Ascending Scheme (MCCGA) is a method used in the study [70] to identify model parameters of the second-order RC model, specifically the ohmic resistance, polarisation resistances, and polarisation capacitances. This method provides precision, robustness, and effectiveness in determining parameters while also maintaining robustness against non-Gaussian noise. In [71], the Forgetting Factor Alternating Generalised Least Squares (FF-AGLS) method for offline parameter identification identifies Thevenin model parameters across temperature variations, offering insights into parameter fluctuations and uncertainty. However, it requires extensive offline testing, limiting real-time parameter capture. The hybrid PSO-GA method is utilised in [72] to identify the Partial Adaptive Fractional Order Model's (PA-FOM) optimal parameter that improves efficiency and precision of state estimation in LIBs by minimising the errors between the predicted and measured battery terminal voltage.

GA and PSO are effective for global optimisation but are limited to offline use due to their iterative processes. RLS is preferred for real-time identification but has limitations in confirming the least squares, leading to potential biases. FFRLS improves convergence speed, while recursive restricted total least squares (RRTLS) addresses identification biases caused by measurement errors. Accurate model parameter identification is essential for reliable battery state estimation.

4. SOC Estimation

Estimating the SOC is a crucial component of BMS in EVs. It entails determining the battery's leftover capacity, which is critical for estimating range, managing energy, and maintaining battery health [73]. Estimating a battery's SOC accurately is difficult because of the intricate and nonlinear characteristics of battery behaviour. Furthermore, temperature changes and aging add complexity to the estimation process [74]. There are three approaches for estimating SOC, as shown in Fig. 3: deterministic, non-deterministic, and hybrid [75].

4.1. Deterministic Approaches

Deterministic approaches can be divided into two categories: experimental-based and model-based approaches. Fig. 5 represents the work flow of model-based SOC estimation. These methods use proven physical or mathematical correlations to calculate the state of charge [76]. This approach utilises established physical or mathematical relationships to compute the state of charge. Experimental-based methods further include techniques such as Coulomb Counting (CC), Open Circuit Voltage (OCV), and AC impedance [14]. Model-based methods, such as equivalent circuit models (ECMs) and electrochemical models (EMs), employ filters and observers for estimation. Examples of filters include Kalman, particle, and H-infinity filters, while observers include Sliding Mode, Luenberger, and nonlinear observers [77–79]. Based on deterministic approaches, Table 6 provides a critical analysis of SOC deterministic estimation methods. The detailed discussion of various deterministic approaches is provided in the following sections.

4.1.1. Coulomb Counting

Coulomb Counting (CC), sometimes referred to as the Ampere-hour Integral Method (AhIM), is a commonly employed approach for approximating SOC in batterypacks, especially in EVs, because of its straightforwardness and convenient implementation. This method calculates the SOC by adding up the charging and discharging currents over time, starting from the initial SOC [95]. The SOC equation is

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_i) + \frac{\int_{t_i}^{t} I_{pack}(t)dt}{Q_n} * 100\ \% \tag{1}$$

Whereas SOC(t) is estimated SOC at time t. SOC (t_i) is the initial SOC. Q_n is the nominal capacity of the battery pack. I_{pack} is the current flowing into/out of the battery at time t. Although this method is simple and affordable, but it has notable disadvantages, such as the build-up of measurement inaccuracies, the requirement for precise initial SOC information, and the challenge of accurately determining the Coulombic efficiency, which is influenced by charging/discharging rates, temperature, and battery degradation over time [96]. Enhanced Coulomb Counting (ECC) approaches have been devised to address these problems by adding strategies such as voltage thresholds, adaptive SOC resets, and expansions of Peukert's equation [97]. These methods are employed to accurately account for changes in capacity and enhance accuracy. Although there have been advancements, Coulomb Counting still relies on accurate current measurements and regular recalibration to ensure dependability. It is typically used in combination with other approaches to improve SOC estimates.

4.1.2. Open Circuit Voltage

The OCV approach calculates the SOC of battery packs by comparing the battery's voltage during rest periods to its reference waveform. This approach is easy and accurate, but requires a long rest interval for continuous tracking, and it is sensitive to temperatures and battery aging [98]. In actual applications, it is more suitable for initial calibration than real-time monitoring. Despite its shortcomings, OCV remains a cost-effective and accurate approach for determining SOC [99].

4.1.3. AC Impedance

The AC impedance technique is a non-destructive method for assessing battery SOCs by measuring their impedance using an AC (alternating current) pulse over a range of frequencies. This approach gives a deep insight into the battery's internal dynamics, which are intimately tied to its SOC [100]. By injecting an AC signal and evaluating

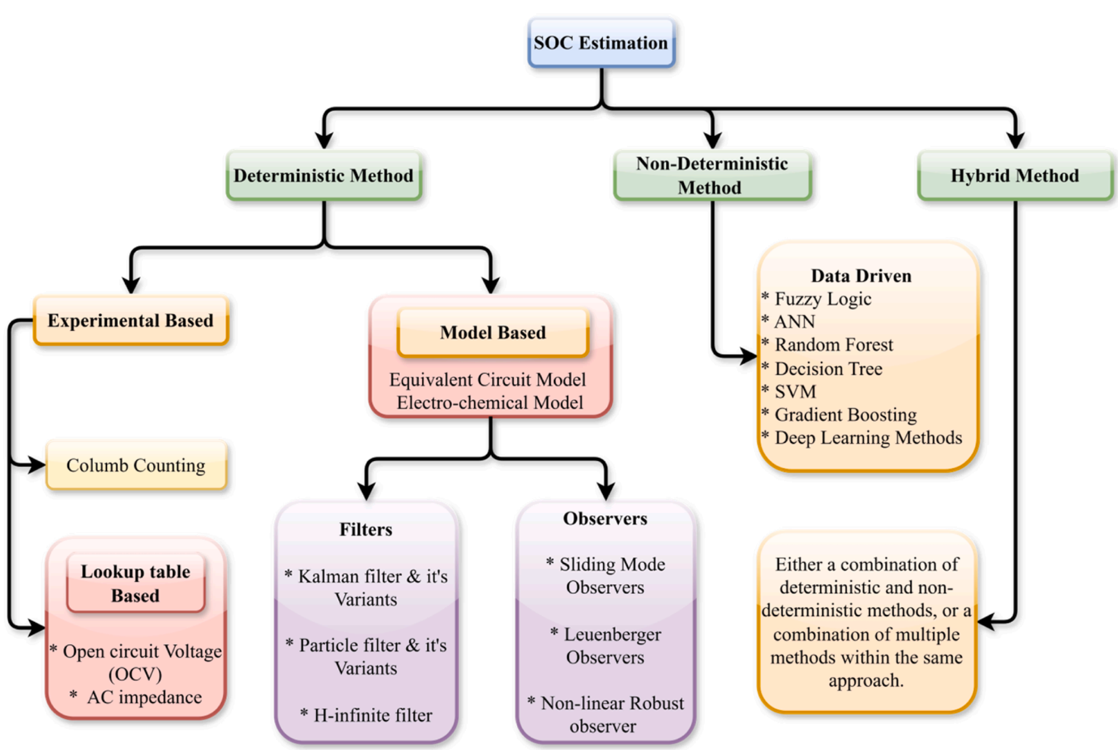


Fig. 3. Classification of LIB's SOC estimation methods.

Table 6
Critical Analysis of Deterministic Approaches for SOC Estimation Methods.

Reference	Description	Test profiles/ Drive cycles	Battery	Parameter extraction	Battery model	Filters/ Observers	Temperature	Performance matrices			Suitability for BDTs
								RMSE (%)	MAE (%)	Other	
[80]	The Model Fusion Method (MFM) improves real-time co-estimation of SOC & SOP in EV batteries, enhancing battery management and safety under dynamic conditions.	DST, UDDS	INR18650-25R	PSO-GA	2RC+1RC	DEKF	-	0.288	0.350	-	Suitable for dynamic SOC/ SOP estimation; high BDT potential under real-time conditions; limited inherent multi-physics combinations.
[81]	The OCV is corrected using the internal resistance correction method, and the corrected voltage provides a precise estimate of the state of charge.	-	FST 18650	-	PNGV	KF	-	-	-	-	Basic OCV model; low BDT suitability due to lack of multi-domain modelling.
[82]	The model uncertainty & parameter variations were addressed and experimentally confirmed to achieve a high level of accuracy.	UDDS	INR-18650-25R (SAMSUNG)	HPPC	1RC	Robust SMO	-	-	0.70	AME = 1.84	Robust observer; moderately suitable for BDTs due to handling of uncertainties.
[83]	Beneficial for reducing the oscillation and estimation error	UDDS	LiFePO4 and LiNMC	Capacity test, SoC-OCV test, Discharge hybrid pulse test	2RC	AEKF	25 ± 2°C	-	-	-	Focus on error reduction; useful but limited scope for full-scale BDT deployment.
[84]	This article proposed a distributed spatial–temporal online correction algorithm for the state of charge (SOC) three-dimensional (3-D) state of temperature (SOT) co-estimation of battery	FUDS, US06	NMC/graphite (Prismatic)	HPPC	1RC	AKF	10°C to 30°C	-	-	Relative Error = 1.01% to 3.05%	High relevance for BDTs with temperature co-estimation and spatial correction.
[85]	The problem of battery model parameter divergence from the true value greatly affects the estimation accuracy under realistic dynamic loading conditions. SOC-SOE Co-estimation	DST, US06	NCR18650B, VTC6 NMC 18650, ANR26650M1B	Pulse discharge test, SoC-OCV, CC-CV and robust linear least square	2RC	DFFAEKF	5°C, 25°C and 45°C	<1.1	-	-	Strong BDT relevance with SOC-SOE co-estimation and parametric robustness; but, primarily electrical with thermal consideration, limited multi-physics.
[66]	UKF performs better than EKF in terms of accuracy and convergence. But both shows resilience to current noise.	DST, FUDS	B18650CD battery (LiNMC)	RLS, MPSO	1RC	EKF, UKF	0°C to 50°C	0.228 to 3.35	-	-	EKF/UKF tested; foundational but moderately suitable for advanced BDTs.
[72]	It has been demonstrated that the precision of SOC and SOP estimation is increased with the partial adaptation of LIB's FOM.	DST, FUDS, UDDS	INR18650-25R LiNMC	PSO-GA	FOM	AEKF	20°C	0.678 to 1.038	0.562 to 0.976	-	Feature-oriented modelling aligns well with BDT modular frameworks; enhances electrical/ electrochemical fidelity, but broader multi-physics is often absent.
[86]	This method achieves fast and reliable SOC estimation in large-scale EVs.	CLTC	lithium-ion	curve fitting approach	1RC	AUKF	0°C and 25°C	-	-	Error less than 2%	Scalable for fleet-level SOC; suitable for cloud-integrated BDT.
[87]	UKF was used to minimize noise with better filtering effect	-	A123, LFP	HPPC, Least square algorithm	PNGV	Improved UKF	-	-	-	Estimation error within 1.5%	Noise-resilient estimation; limited for complex BDTs without Multiphysics.
[67]	Capacity iterative loop estimation is suggested to accurately estimate Li-ion battery SOC and capacity	NEDC	LiFePO4, Cylindrical	HPPC, VFFRLS	1RC	-	25°C, 45°C	<2	-	-	Suitable for aging-aware BDTs; focuses on aging/ electrical, not

(continued on next page)

Table 6 (*continued*)

Reference	Description	Test profiles/ Drive cycles	Battery	Parameter extraction	Battery model	Filters/ Observers	Temperature	Performance matrices			Suitability for BDTs
								RMSE (%)	MAE (%)	Other	
	from ageing. And PSO is for best correction interval of SOC										comprehensive multi-physics.
[68]	Enhances the adaptability in three ways.	DST, US06	lithium-ion	FFRLS+SSA	2RC	ASRUKF	-10°C to 40°C	0.32 to 1.13	0.16 to 0.88	MxAE (0.81 to 2.35)	Adaptability across range; supports edge-intelligent BDT systems.
[88]	The Proposed algorithm provides a reliable and consistent estimation of SOC for LIB, surpassing the constraints of conventional UKF methods.	DST, FUDS	INR18650-20R	BCFFRLS	2RC	O-MIAUKF	25°C	-	-	Estimation error = 0.8%	Accurate co-estimation; appropriate for modular and scalable BDTs.
[70]	The MCCGA scheme employs correntropy & gradient ascent techniques to accurately and robustly identify ECM parameters, effectively managing noise that is not Gaussian in nature.	-	INR18650-20R	MCCGA	2RC	-	-	0.0009 to 0.0047	6.33E-07 to 2.24E-05	MSE (4.19E-04 to 0.0027)	Advanced parameter estimation; highly suitable for virtual twin modelling.
[89]	This joint algorithm provides precise and resilient identification of parameters in online and SOC estimation of LIBs in diverse conditions	DST, FUDS	NCR-18650B	AMMFG	2RC	H-infinite	25°C	0.0075 to 0.0118	0.0064 to 0.0103	Running time	Precise online SOC estimation; beneficial for BDT real-time operations.
[90]	SGASMO has reduced chattering, better accuracy, and robustness compared to conventional and mainstream improved SMOs	DST, ECE	18650 lithium-ion	OCV-SOC curve	2RC	SGASMO	25°C	1.653 - 1.852	0.836 to 1.118	-	Improved SMOs; moderately aligned with BDT predictive diagnostics
[91]	This method estimates the SOC and SOH. It is needed to address the relationships with factors such as cycle numbers and temperature.	UDDS	Li-ion battery	Curve fitting	2RC	ASMO	-	-	-	-	Basic curve-fitting; less dynamic for scalable BDT platforms
[71]	Developed to tackle SOC calculation misalignment difficulties in EVs during severe load shocks and temperature fluctuations	DST, FUDS	LR18650EH (LFP), 18650 NCM battery	FF-AGLS	1RC	Robust FO-PIO	0 °C, 25 °C, and 45 °C	1.68 to 2.10	0.14 to 0.16	-	Robust to harsh loads; suitable for BDTs in adverse real-world use.
[92]	Demonstrates excellent SOC and temperature accuracy under complicated loads, initial guess deviations, & model mismatches through simulations and testing.	UDDS	lithium-ion pouch cell	series of electrochemical tests	2RC	Enhanced SMO	25°C	-	-	Average error of <2 %	Primarily electrical, limited multi-physics. Handles initial guess/model mismatch; supports adaptive BDTs.
[78]	This approach displays good accuracy and little computing load compared to current integral method and EKF	ECE	NCM	-	2RC	Extended SMO	It is conducted on real roads i. e. outdoors	0.0006	0.0005	Maximum error = 0.0015%	Low computation load; suitable for BDT edge implementations.
[69]	The suggested observer, which has been verified using real-time experimental data, has greater accuracy in estimating state of charge and faster computation time compared to classic EKF and FEKF	DST, FUDS, BJDST, US06	INR 18650-20R (CALCE Battery Research Group)	AFOPSO	FOM (1RCPE)	FO-Observer	0°C, 25°C, 45°C	0.62 to 1.26	0.54 to 1.03	Maximum error = 1.30% to 2.69%	Validated in real-time; excellent BDT candidate for SDVs.
[93]	The P2D model is designed to improve computational efficiency by disregarding electrolyte dynamics. It combines an enhanced	New European driving cycle	Li-ion battery (ICR18650-26J) manufactured by Samsung	double-scale dual particle filter (D-PF)	SPMe	PSO-PF	25°C and 40°C	0.0024 to 0.0078	0.0018 to 0.0059	-	High-fidelity SPMe model; critical for electrochemical BDTs.

(*continued on next page*)

Table 6 (*continued*)

Reference	Description	Test profiles/ Drive cycles	Battery	Parameter extraction	Battery model	Filters/ Observers	Temperature	Performance matrices			Suitability for BDTs
								RMSE (%)	MAE (%)	Other	
	particle filter along with an electro-chemical model to estimate the real-time SOC in battery systems.	(NEDC), UDDS									
[94]	The paper shows a way to accurately estimate the SOC and SOH of LIBs using a simplified P2D model and PF algorithm.	UDDS	NCM	PSO	P2D	Particle filter (PF)	25°C	0.93 to 1.13	-	maximum absolute error (MxAE) 1.64 to 1.95	P2D-based RUL & SOC estimation; strong alignment with BDT lifecycle tools

the resultant impedance spectrum, a look-up table may be built that maps impedance values to certain SoC levels. However, conventional measurements are often made offline, requiring the battery to be in a stable state. Recent improvements promise to provide real-time impedance measurement, but they face difficulties in real-world applications due to the need for specialized equipment and maintaining a consistent condition during measurement.

4.1.4. Kalman Filter and Its Variants

The simple Kalman Filter (KF) is ideal for linear systems, but it falls short of real battery behaviour due to its oversimplified assumptions [101]. The Extended Kalman Filter (EKF) improves the handling of nonlinearities but faces issues with linearisation [102]. To improve performance under ageing and temperature fluctuations, the Adaptive EKF (AEKF) introduces online tuning of noise covariances [103,104]. It is further enhanced by the Forgetting Factor AEKF (FF-AEKF) [105], which provides more flexibility in response to real-time parameter changes in dynamic driving cycles.

To manage more significant nonlinearities and statistical constraints, the Sigma-Point EKF (SP-EKF) and Square-Root EKF (SR-EKF) were developed to achieve greater accuracy and numerical stability. The Unscented Kalman Filter (UKF) enhances performance by removing the need for Jacobian matrices, proving advantageous in complex models and in estimating the state of charge (SOC) where hysteresis may be a concern [106]. The Adaptive UKF (AUKF) [107] and its improved variants, such as the O-MIAUKF, further enhance robustness by dynamically responding to changes in system behaviour and measurement uncertainty.

Advanced Kalman filters like the Cubature Kalman Filter (CKF) and its extensions (e.g., MCCKF, AFCKF, ASRCKF) provide promising accuracy even under challenging conditions, such as high-dimensional data, noise, or battery ageing, albeit often at a higher computational cost [108–110]. Fig. 4 illustrates the progressive evolution of Kalman Filter techniques applied to SOC estimation.

4.1.5. Particle Filter

PF is a non-Gaussian distribution-based approach used to assess the SOC of battery packs. It employs Monte Carlo simulation to accommodate non-Gaussian distributions by producing random variables representing different battery states. These particles are allocated weights depending on their chance of being the genuine SOC. Researchers are enhancing PF by including online OCV estimates, utilising Cubature PFs for improved accuracy, and constructing Double Scale Dual Adaptive PFs to balance accuracy and processing economy. Wang et al. [111] developed a particle filter-based SOC estimator to solve problems in EV applications, including temperature variations and drift current disturbances. The method used to estimate SOC showed good accuracy, with RMSE and MAEE below one percent. In order to estimate SOC online, Chen et al. [112] provide a PF-based method for open-circuit voltage calculation. However, PF's fundamental constraint remains its computational intensity.

4.1.6. H-infinity filter

In comparison to EKF and UKF, H-infinity filter-based SOC calculation is more reliable in complex situations, including battery ageing and varied operating circumstances. However, it may display a larger fluctuation in estimating errors due to high correlations between battery open-circuit voltage and SOC. Researchers are studying advances such as incorporating the Thevenin model, applying twin H-infinity filters for simultaneous SOC and capacity estimates, and merging H-infinity with UKF. The study by Li et al. [89] uses the H-infinity filter (HIF) for SOC estimation in LIBs. The HIF is chosen for its robustness in managing many sorts of noise, including coloured noise. The authors integrate the HIF with the Auxiliary Model Modified Forgetting Gradient (AMMFG) technique for online parameter identification and SOC calculation. The combination permits excellent SOC estimation accuracy, low

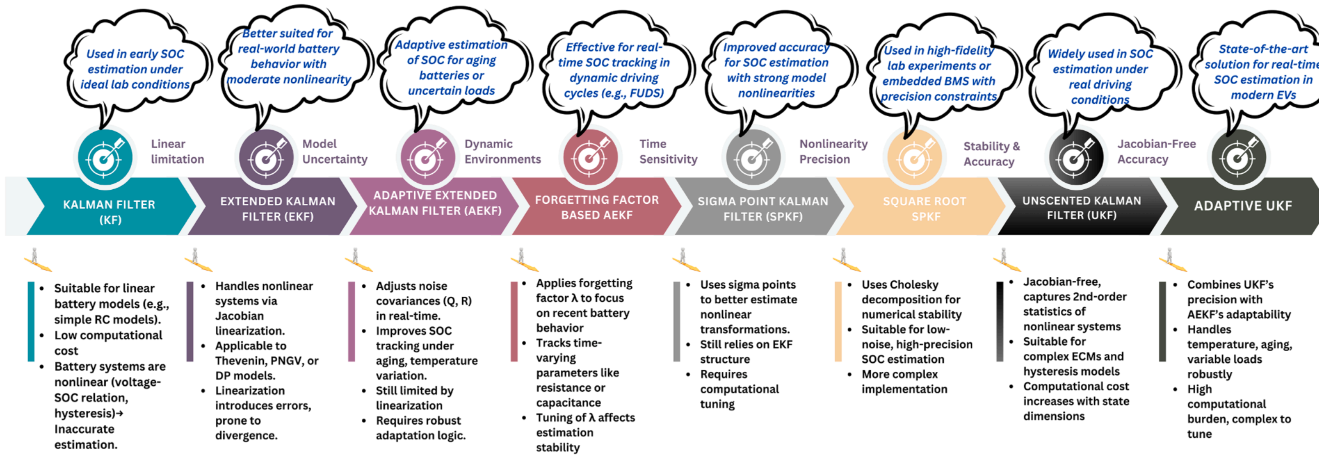


Fig. 4. The upgradation of Kalman Filters in SOC Estimation.

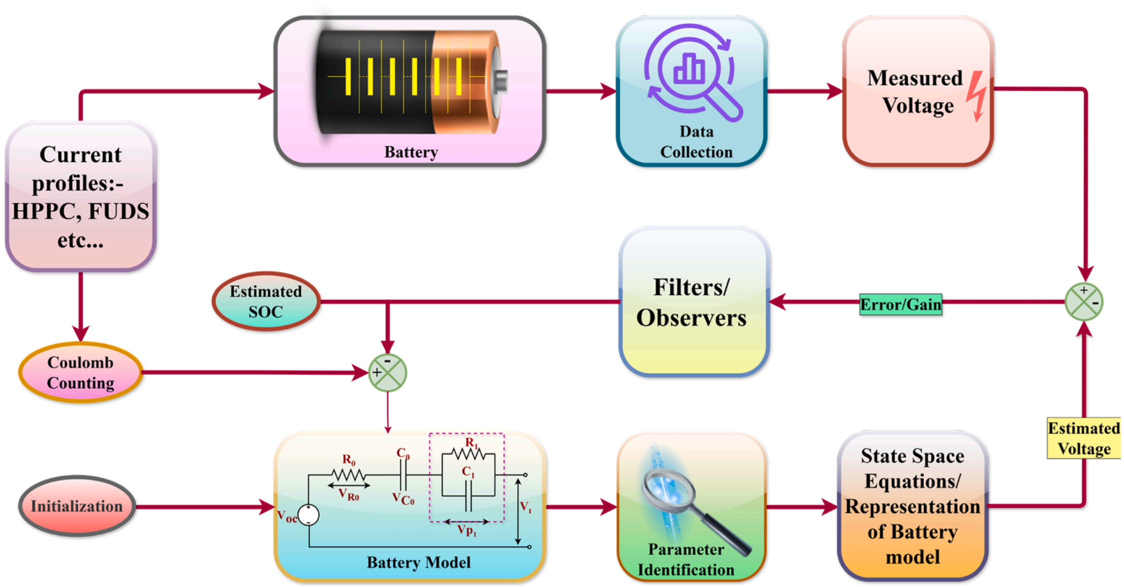


Fig. 5. Work flow of Model based SOC estimation.

computational complexity, and resilience to initial value errors, which qualify it for real-time deployment in battery management systems. Challenges include the influence of age, temperature, and hysteresis on H-infinity filter performance, which remains an active field of research.

4.1.7. *Sliding Mode Observer*

SMO is a method employed in battery management systems to accurately estimate the SOC of a battery pack. The system reduces the discrepancy between the real and observed states by employing a feedback mechanism. This mechanism employs a switching function based on the battery model's inaccuracy to move the estimated voltage towards a hypersurface. This method guarantees resilience against inaccuracies in the model, significant noise in the measurements, and disruptions in the environment. SMOs may be classified into two categories based on their switching gain: constant and adaptive.Additionally, they can also be categorised as either first-order or second-order observers. They provide quicker convergence, more accuracy in estimating SOC, and reduced computing expense in comparison to techniques such as EKF. SMOs encounter obstacles such as chattering, which may be alleviated by the use of strategies such as adaptive switching gain. For example, Ghalami Choobar et al. [92] developed an adaptive gain SMO for measuring SOC and temperature inside a commercial Li-ion pouch cell, demonstrating the need to incorporate thermal impacts in the SOC estimate. The paper combines a connected ECM and a unique thermal model, establishing accurate predictions under complicated load profiles and model mismatch.

He et al. [78] present an extended sliding mode observer (eSMO) for real-world vehicle SOC estimation, concentrating on a low-computation, high-precision technique. The eSMO takes workload voltage error as input and improves SOC estimation accuracy compared to current integral methods, as well as extended Kalman filters under the same operating cycle. Qian et al. [90] propose a switching gain adaptive sliding mode observer (SGASMO) to increase estimation accuracy and eliminate chattering in SOC estimation. Chen et al. [113] developed an Adaptive Switching Gain Sliding Mode Observer (ASGSMO) to improve SOC estimates in EVs under variable discharge current profiles. The approach automatically adjusts switching gains in order to compensate for modelling mistakes and eliminate chattering, displaying improved performance in comparison to conventional SMOs.

4.1.8. *Luenberger observer*

Luenberger observer (LO) functions by developing an observer model and employing a feedback loop to remove the disparity between true and estimated states. LOs are notable for their simple implementation and adequate precision in comparison to KF. Nevertheless, their performance might worsen under high nonlinearities because of their intrinsic linear character. Modified LOs have been developed to manage battery nonlinearities and variable parameters more successfully. For example, Septanto et al. [114] developed a method for estimating the SOC using a discrete-time LO. This method guarantees asymptotic stability, given certain assumptions. The approach employs a model of a second-order equivalent circuit and a piecewise linear approximation. The observer gain conditions are derived from the principles of Lyapunov stability theory, which shows the observer can track actual the SOC [115] devised a modified LO to enhance the accuracy of initial SOC estimation and its ability to withstand disturbances and uncertainties. The observer uses an adaptive rule and a robust term to estimate the SOC in real-time, outperforming conventional approaches and EKFs. The revised approach presents a hopeful resolution for real-world implementations.

4.1.9. Proportional-Integral Observers

To reduce errors between predicted and observed battery voltages, the proportional-integral observer (PIO) uses proportional-integral calibration, resulting in a reliable SOC estimation. PIOs offer excellent accuracy, decreased calculation time, as well as robustness towards model disruptions. Nevertheless, they can be vulnerable to parameter uncertainty and complicated operating situations. Modified PIOs, including adaptive and dual-circuit state PIOs, solve these constraints. In their study, Wang et al. [71] provide a robust full-order proportional integral observer (RF-PIO) as a means to enhance SOC estimates in EVs when subjected to intense load shocks and variations in temperature. The RF-PIO utilises an innovative proportional link, which improves robustness without adding computational complexity. Despite the presence of uncertain model parameters and high-frequency noise interference, the approach consistently maintains a level below 2.11%. Therefore, PIO remains a common option for real-time SOC estimates in EV applications.

4.1.10. Non-Linear Observers

NLOs are a powerful tool for accurately predicting battery packs' SOC using non-linear algebraic formulas. They offer excellent accuracy, low computing cost, and quick convergence, making them preferable to approaches like EKF and SMO. But NLOs demand gain matrices to reduce mistakes. This could be a disadvantage. NLOs can tolerate uncertainty in important characteristics, such as inner resistance, but they require careful planning and stability proof. Zhuang et al. [116] provide a nonlinearity-aware adaptive (NAA) observer to accurately estimate the surface concentration and SOC of LIBs. The observer strikes a balance between accuracy and computational efficiency, demonstrating excellent accuracy in estimating SOC and surface concentrations. Enhanced variants, including input-to-state stability theory-based NLOs and discrete-time NLOs, have been developed to increase accuracy and resilience.

4.2. Non-Deterministic Methods

Non-deterministic or data-driven approaches use machine learning and deep learning techniques in the EV industry for various applications, as represented in the Fig. 6. For Example, the study [117] demonstrated the ability of ML classifiers to distinguish EV types from anonymized charging session data without any hardware requirements. Moreover, validated the work through real-world experiments. The author in [118] proposed an integrated deep learning (DL) and computational fluid dynamics (CFD) framework to predict early thermal runaway events in batteries under extreme conditions. A hybrid bio-inspired optimizer and deep neural network (DNN) model, proposed in [119] for optimizing the power allocation in EV energy management systems. These approaches are versatile and capable of processing several forms of input data, rendering them suited for intricate and non-linear battery behaviour.

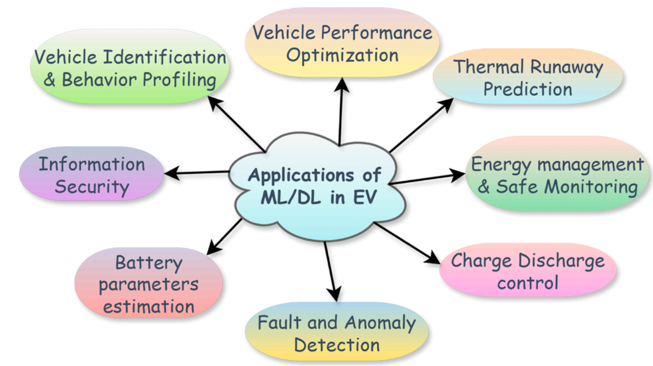


Fig. 6. Applications of ML/DL in EVs.

Hence, researchers have utilized these approaches for battery parameter estimations such as SOC, SOH, RUL, etc., as these parameters are intricate and difficult to measure, and accurate estimation is essential for optimal battery performance and longevity.

Nevertheless, they are very dependent on the calibre and volume of training data and may exhibit a deficiency in interpretability when compared to deterministic models. Table 7 presents a critical analysis of non-deterministic approaches for SOC estimation. The following subsections discuss various data-driven SOC estimation methods.

4.2.1. Fuzzy logic

Fuzzy logic (FL) is extensively employed in the estimation of the SOC of battery packs due to its capacity to effectively manage uncertainties and rectify model inaccuracies. FL methods use data-derived linguistic principles to establish the correlation between battery measurements and SOC, thereby mitigating the effects of errors and uncertainties. Although FL by itself may not yield very precise estimations, it is frequently utilised in conjunction with techniques such as filters, observers, and neural networks (NNs) to augment accuracy. Bera et al. [135] combined fuzzy logic with a redacted extended Kalman filter (REKF) and the recursive least squares with forgetting factor (RLSFF) algorithm to dynamically modify the forgetting factor for online parameter identification. In steady-state settings, this approach has greater performance when compared to EKF and UKF, achieving an MAE of 0.25% and an RMSE of 0.48%.

The authors [136] suggested the use of a fuzzy logic sliding mode observer (FLSMO) to estimate the SOC. A 2RC ECM is utilised. The incorporation of a fuzzy logic controller to adaptively modify the sliding mode gain. When using the FUDS scenario, the FLSMO algorithm displays excellent SOC estimate accuracy, with an average error of 0.86% and a maximum error of 2.37%. The algorithm also displays a high convergence rate and surpasses both the standard SMO and the EKF. Techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [137] are being developed to enhance accuracy and filter noise. Despite their advantages, FL-based techniques require extensive calibration and rely on heuristics or human experience, necessitating systematic approaches for designing membership functions.

4.2.2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are becoming more commonly used to estimate SOC in battery packs. This is because they possess the capability to manage intricate, non-linear models with exceptional computational efficiency and minimal expense. It mimics the function of biological neural networks in the human brain. In order to change weights and connections, a significant amount of training datasets is necessary. ANNs, such as Feedforward Neural Networks (FFNN), Backpropagation Neural Networks (BPNN), and Radial Basis Function Neural Networks (RBFNN), exhibit exceptional precision, resilience, and swift convergence in diverse scenarios, encompassing fluctuating

Table 7
Critical Analysis of Non-Deterministic Approaches for SOC Estimation Methods.

Reference	Description	Test profiles/ Drive cycles	Battery/ Dataset	Methods	Inputs	Temperature	Performance Matrices			Suitability for BDTs
							RMSE (%)	MAE (%)	Others	
[120]	BiLSTM beats LSTM and GRU, yielding a 2% or lower RMSE & 5% maximum error, with 70 hidden neurons identified as appropriate to minimise overfitting.	-	3Ah LG HG2 cell/Hamilton's McMaster University	BiLSTM-BOA	$V(k)$, $I(k)$, $T(k)$, $V_{avg}(k)$, and $I_{avg}(k)$	$-10°C$, $0°C$, $10°C$, $25°C$.	0.12 to 0.16	-	Maximum error (0.822 to 1.327%)	High-accuracy, suitable for real-time BDTs under varying temperatures; robust for complex temporal dependencies;
[121]	Introduces an adaptive LSTM network with a fractional-order memory unit that utilises the Hausdorff difference to improve the SOC estimation accuracy. It outperforms the original LSTM model in terms of accuracy across different operating situations.	DST, UDDS	$LiNixCoyMn1-x-yO2$ LIB, also known as NMC	LSTM-H	$V(k)$ and $I(k)$	$10°C$	0.01527 to 1.01898	0.01106 to 0.01331	-	Advanced BDTs for high-precision, adaptive SOC; high computational complexity;
[122]	This method effectively captures long-term time dependencies in both backward and forward directions, utilises the NAG algorithm to minimise oscillations and enhance training stability	BJDST, DST and US06 (for training), LA92, UDDS, FUDS (For testing)	LG 18650HG2 lithium-ion battery dataset McMaster University. Samsung 18650 $LiNiMnCoO_2$/Graphite lithium-ion batteries by the (CALCE) at University of Maryland	Bi-GRU + Nesterov Accelerated Gradient (NAG) algorithm	$V(k)$, $I(k)$, and $T(k)$	$0°C$, $25°C$ and $45°C$	less than 2.5%	-	-	Well-suited for BDTs in real-time environments; Bi-GRU + NAG ensures bidirectional learning and robustness to cycle variations.
[123]	The CNN-LSTM network has high precision, outperforms standalone LSTM and CNN networks, and is capable of adapting to the impact of ambient temperature and battery aging.	DST, FUDS, and US06	LFP/ Experimental	CNN-LSTM	$V(k)$, $I(k)$, $T(k)$, $V_{avg}(k)$, and $I_{avg}(k)$	$0°C$, $10°C$, $20°C$, $30°C$, $40°C$, and $50°C$	0.64 to 1.50	0.54 to 1.15	-	Excellent for BDT integration—CNN-LSTM combination supports spatial and aging adaptation crucial for digital representation.
[124]	Enhances prediction performance by using a multi-channel extended CNN-based model and an RNN-based data representation model.	-	Dataset collected by relevant scholars is derived from Red Star X1 electric vehicles, which are produced by Do - Fluoride Chemicals Co., Ltd	RNNs-CNNs	$V(k)$, $I(k)$, and $T(k)$	-	-	0.029	-	Moderate suitability; although promising architecture, application-specific and lacks generalizability insight for broader BDT ecosystems.
[125]	The suggested model boosts estimation accuracy and displays improved performances over RBFNN, GRNN, and ELM models across varied temperatures and EV drive profiles.	DST and FUDS	NMC/ CALCE	BPNN-BSA	$V(k)$, $I(k)$, and $T(k)$	$0°C$, $25°C$, and $45°C$	0.57 to 1.74	0.38 to 0.87	MAPE (9.63 to 20.09%)	High adaptability for BDTs—BPNN-BSA supports rapid deployment across battery types with strong performance over multiple cycles.
[126]	In this estimation framework, time-frequency characteristics are captured using STFT, long- and short-term dependencies are captured using sophisticated	HWFET, LA92, UDDS, US06, and NN (Combination)	Panasonic 18650PF Li-ion Battery Data	Depthwise-Separable Convolution Neural Network (DWS CNN)	$V(k)$, $I(k)$, and $T(k)$	$-20°C$, $-10°C$, $0°C$, $10°C$, $25°C$	0.22 to 3.45	0.18 to 2.97	maximum error (0.80 to 9.82%)	Highly suitable; STFT + CNN enables feature-rich, real-time inference for DTs operating under complex dynamic conditions.

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Table 7 (*continued*)

Reference	Description	Test profiles/ Drive cycles	Battery/ Dataset	Methods	Inputs	Temperature	Performance Matrices			Suitability for BDTs
							RMSE (%)	MAE (%)	Others	
	techniques like ASPP, skip connection, and separable convolution, and features are efficiently extracted from 2-D spectrograms using a CNN network.									
[127]	The study demonstrates the generalization of DNNs in estimating SOC for unseen drive cycles, revealing the optimal number of hidden layers for minimal error.	DST, FUDS, BJDST, US06	INR 1865020R LiNiMnCoO2, NMC Li-ion/ CALCE battery dataset	DNN	$V(k)$, $I(k)$, and $T(k)$	0, 25, and 45°C	3.68	-	MSE (0.13%)	Moderate potential for BDTs; generalization across cycles shown, but lacks real-time deployment and explainability validation.
[128]	The article introduces a temperature-compensated Bi-LSTM with integrated attention mechanisms (AMBi-LSTM) for co-estimating SOC and SOH, enhancing feature allocation and prediction accuracy without high computational load.	DST UDDS	LiNiCoAlO2	AMBi-LSTM	Reference OCV, loading current, measured Voltage and Temperature	0°C, 10°C, 25°C, and 40°C	0.875 to 1.025	0.574 to 0.891	average time consumption (ATC)	Strong fit—attention-enhanced Bi-LSTM co-estimates SOH and SOC with temperature compensation, aligning with BDT goals.
[129]	In scenarios involving concatenated temperature data and lower temperature environments, the CNN-Bi-LSTM-AM model exhibited better performance in capturing temporal and spatial dependencies.	UDDS LA92 US06	INR18650HG2 NMC/ McMaster dataset	CNN-Bi-LSTM-AM	voltage $V(k)$, current $I(k)$, battery temperature $T(k)$, average terminal voltage $V_{avg}(k)$, and averaged current $I_{avg}(k)$	room temperature	1.27	0.75	Training time = 180 min	Suitable for cold-start and real-time SOC mapping in BDTs; attention mechanisms improve interpretability and time-resolution.
[130]	The LSSVM-based model uses GWO and sliding window methods for accurate SOC estimation, achieving high robustness and accuracy with errors within 1%.	DST, FUDS	NMC/ Experimental dataset	LSSVM-GWO	$V(k)$, $I(k)$, and $T(k)$	0°C, 25°C, and 45°C	0.12 to 0.19	0.23 to 0.53	-	Good candidate for BDTs; LSSVM-GWO demonstrates high robustness, although integration with DT real-time pipelines is not explored.
[131]	The SVM-CKF algorithm, which combines the generalization power of SVM with the accuracy of CKF, is better than other methods at estimating the SOC of LiBs with validated results.	BBDST, DST	Li-ion	1RC-SVM-CKF	Voltage value, SOC estimate $s(k)$, Voltage error	25°C	-	-	Maximum error is about 0.450%	Reasonably suitable—SVM-CKF shows reliable results, but interpretability and multi-source fusion for BDTs are limited.
[132]	The improved barnacle mating optimizer (IBMO) enhances SVM for accurate SOC estimation, outperforming other models with a 0.0042% RMSE.	-	Li-ion, 18650 type	IBMO-SVM	$V(k)$, $I(k)$, and $T(k)$	24°C	0.0042		MAPE (0.61%), R^2 (0.9994)	Excellent for BDT frameworks; ultra-low RMSE with IBMO-enhanced SVM ensures accurate and stable digital state tracking.
[133]	A differential search algorithm (DSA) optimizes a random forest regression	DST, FUDS	LiNCA, LiNMC	random forest regression (RFR)-	-	0°C, 25°C, and 45°C	0.704 to 0.901	0.193 to 0.346	SOC error (-4.39 to 4.89)	Strong BDT applicability; model-free and filter-free architecture increases

(*continued on next page*)

Table 7 (*continued*)

Reference	Description	Test profiles/ Drive cycles	Battery/ Dataset	Methods	Inputs	Temperature	Performance Matrices			Suitability for BDTs
							RMSE (%)	MAE (%)	Others	
	(RFR) model for accurate EV battery SOC estimation, and it is filter-free and model-free, demonstrating high accuracy and robustness across various battery types and driving conditions.			differential search algorithm (DSA)						scalability for varied battery chemistries.
[134]	The AdaBoost-BPNN model outperforms conventional methods, such as standalone BPNN and PSO-BPNN models, achieving superior SOC estimation accuracy, especially in challenging discharge scenarios and pulse current conditions.	FUDS, US06, DST	$LiFePO_4$/CALCE battery dataset	AdaBoost–BPNN	*V* (*k*), *I*(*k*), and *T* (*k*)	0°C, 20°C, 30°C and 50°C	0.63	-	Maximum error = 2.61%	Moderate BDT fit; AdaBoost improves resilience, but lacks interpretability features crucial for DT decision support.

temperatures and driving cycles. In [125], the performance of BPNN for SOC estimation is enhanced with the help of the Backtracking Search Algorithm (BSA). This method utilises voltage, current, and temperature as input variables. The model utilises varying numbers of hidden neurons under different situations. The evaluation is based on metrics such as RMSE, MAE, Mean Absolute Percentage Error (MAPE), and SOC error. The MAPE of the BPNN-BSA model is 7.12%, which is considerably better than the performance of other models such as RBFNN-BSA (14.58%), GRNN-BSA (23.39%), and ELM-BSA (18.47%). The schematic representation of a typical ANN architecture is shown in Fig. 7(a).

4.2.3. Support Vector Machines

SVMs are powerful supervised machine learning algorithms that are used to estimate the SOC in battery packs. They utilise hyperplanes to separate classes, delivering higher accuracy compared to neural networks. Nevertheless, SVMs entail intricate mathematical computations and a time-consuming trial-and-error process. The researchers have devised enhancements like fuzzy least square SVM (FLSSVM) and least square SVM (LSSVM) to address these challenges. These aim to diminish noise sensitivity and enhance generalization. Support Vector Regression (SVR) has displayed satisfactory performance in battery SOC estimation.

In [138], the SOC is estimated using an SVM of a lithium iron manganese phosphate (LiFeMnPO4) battery cell from an experimental dataset. Another researcher proposed an optimized SVR with a dual search optimisation process to estimate SOC, and the proposed method was tested with an advanced vehicle simulator (ADVISOR) [139].

4.2.4. Gradient Boosting

Gradient Boosting is a novel methodology, a machine-learning algorithm that uses decision trees. It is becoming increasingly popular for battery state assessment because of its effectiveness and strong predictive potential. Its ability to learn quickly, especially when using parallel computing, suggests that it is a suitable method for estimating SOC.

Guanzheng et al. [140] introduced natural gradient boosting (NGBoost) for probabilistic SOC estimation. The suggested strategy is validated using both public and self-constructed datasets, demonstrating improved mean errors. The research [141] employs and contrasts two distinct algorithms: SVR and extreme gradient boosting (XGBoost). Utilised experimental test data from a lithium-ion phosphate battery cell to train and assess these models. Both algorithms attain elevated accuracy, with a coefficient of determination (R^2 score) ranging from 97% to 99%. XGBoost combines ageing effects for precise SOC predictions, employing higher computation speeds, making it appropriate for real-time SOC estimation applications across battery duration.

4.2.5. Convolutional Neural Networks

CNNs have been increasingly employed in battery SOC calculation. The schematic representation of a typical CNN architecture is shown in Fig. 7(b). The article [142] presents a closed-loop architecture employing a deep convolutional neural network (DCNN) to construct a universal state-of-charge estimator. The approach uses a two-dimensional CNN for feature extraction, transfer learning, and pruning operations. Experiments demonstrate the approach obtains RMSEs of less than 2.47% with fine-tuning and maintains RMSEs below 1.78% in hierarchical settings with severe disturbances. Another article [143] proposes a method that combines symmetric padding convolutional layers and a total variation loss function that uses U-Net-based SOC estimation to increase accuracy at data edges. At constant temperature, the approach obtains a MAE of 1.1%, an RMSE of 1.4%, and under different driving conditions, 1.5% and 1.8%. These results demonstrate the method's high accuracy. A deep fully convolutional network (FCN) model [144] for accurate and efficient SOC calculation for Li-ion batteries, incorporating variable ambient temperatures and driving cycles. The model outperforms conventional deep learning models (LSTM, GRU, and CNN), reaching 0.85% RMSE and 0.7% MAE at 25°C and 2.0% RMSE and 1.55% MAE at different ambient

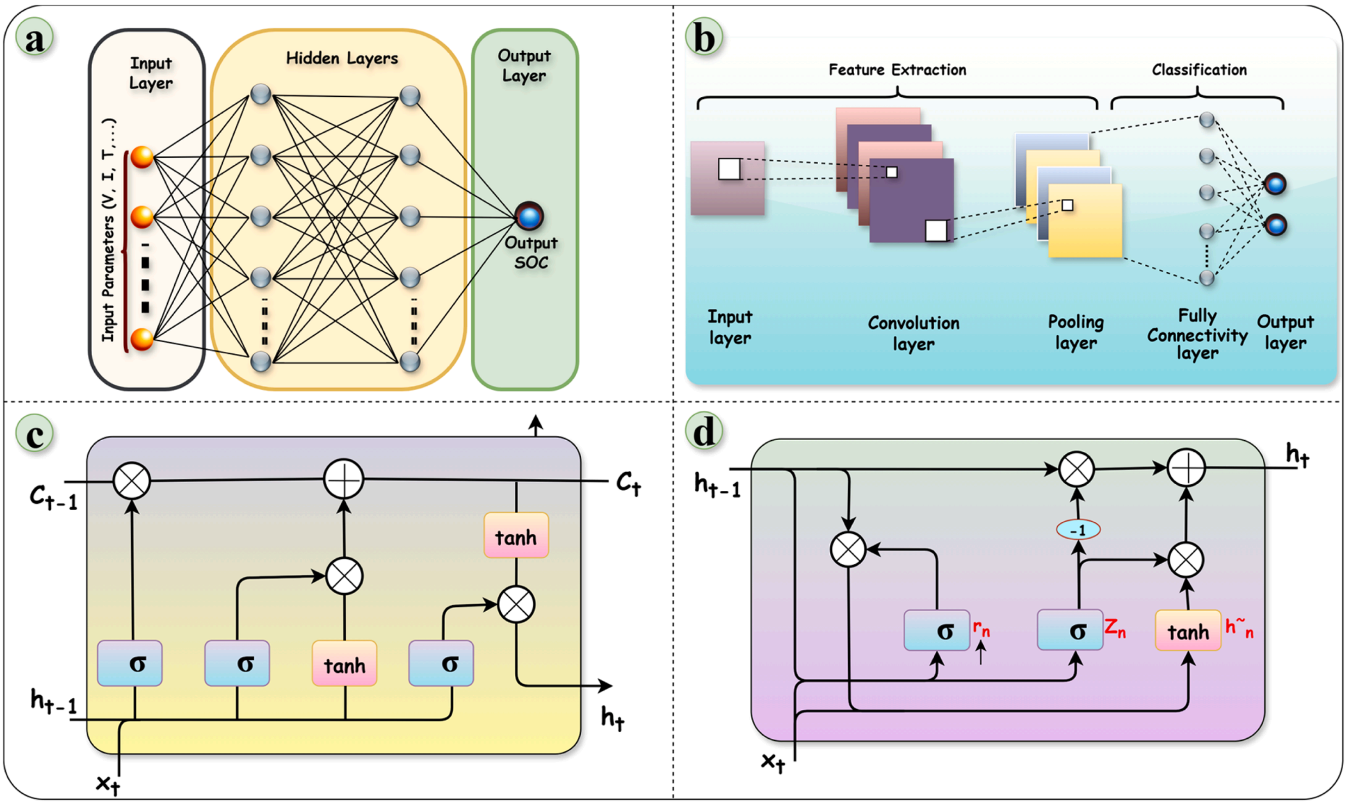

Fig. 7. (a) ANN, (b) CNN, (c) LSTM, and (d) GRU.

temperatures, indicating its superior performance.

4.2.6. *Recurrent Neural Networks*

Recurrent Neural Networks (RNNs) estimate the SOC using hidden layers and past/historical input data. For handling time-series issues and forecasting nonlinear systems, this has proven to be especially effective and computationally robust. Clockwork Recurrent Neural Network (CWRNN) is proposed in [145], to improve the accuracy and efficiency of SOC of lithium-ion batteries. The CWRNN, a modified RNN architecture, divides the hidden layer into multiple modules with different clock speeds, capturing both long-term dependencies and rapid changes in battery behaviour. The model is trained on a public dataset and tested under various drive cycles and temperatures. The results show that the CWRNN outperforms traditional methods in SOC estimation accuracy, with a RMSE of less than 1.29%. The method's robustness under varying temperatures further enhances its applicability in diverse operating environments.

RNN has variants such as Nonlinear Auto Regressive with eXogenous Input Neural Network (NARXNN), Long Short-Term Memory (LSTM) Network, and Gated Recurrent Unit (GRU). The challenge of precisely measuring the SOC of LIBs is examined in [ref]. It advocates adopting dynamic neural networks, notably the NARXNN, to overcome the nonlinear and unstable nature of SOC estimation. The authors offer an open-loop NARXNN model, which improves on the original closed-loop model. The findings indicate higher estimation accuracy than UKF and BPNN.

LSTM utilises historical data to forecast future events. Fig. 7(c) represents the schematic representation of a typical LSTM architecture. Bidirectional LSTM (Bi-LSTM): analyses information from both the past and the future to interpret and predict current scenarios. In [146], the SOC of LIB is estimated using LSTM and BiLSTM. These network models are well-suited for handling sequential data and learning temporal dependencies in battery behaviour. The Bi-LSTM model outperforms the LSTM model in terms of SOC estimation accuracy (DST, 25°C, RMSE: 0.42%), with the best performance achieved with the ADAM optimiser and 50 hidden units.

The GRU with activation function layers (GRU-ATL) is proposed for accurate SOC estimation of LIBs, overcoming obstacles associated with nonlinear chemical reactions. The model (GRU-ATL) [147] beats GRU and LSTM models in SOC prediction accuracy and stability, with a steady MAE of 0.7-1.4% and RMSE between 1.2-1.9%. This makes it suitable for complex vehicle operating situations. Fig. 7(d) represents the schematic representation of a typical GRU architecture.

4.3. *Hybrid Approaches*

State of Charge estimation techniques that combine deterministic and non-deterministic methods, or the combination of two or more methods, fall under hybrid approaches. This approach is becoming increasingly popular for battery state estimation, thanks to the combined advantages of each method.

For instance, a hybrid strategy combining support vector machines (SVM) and a CNN-LSTM model was suggested in a recent study [148] to jointly estimate the SOC and SOH. The CNN-LSTM integrated feature extraction and sequential data handling for SOC calculation, whereas the SVM estimated SOH by examining charging and discharging timings. This technique successfully connected the SOC and SOH, boosting estimation accuracy and robustness. CNN's advantage, i.e., feature extraction, and LSTM's capability of handling sequential data are combined to estimate SOC. This method shows better estimation accuracy with an RMSE of 0.39% and a MAE of 0.33%.

The estimation of battery state depends on sensor measurements (temperature, voltage, current, etc.). These parameters inherently face limitations in fully inferring the complex Multiphysics dynamics occurring inside lithium-ion battery cells. This limitation can restrict the accuracy of battery state estimation. This 'accuracy barrier' can be overcome by the incorporation of sophisticated, non-invasive sensing technologies that offer a deeper understanding of the battery's internal condition. Ultrasonic sensors are a particularly promising type of advanced sensing technology for monitoring the state of batteries, thanks to their real-time capabilities and non-destructive nature. Ultrasonic waves propagate through the battery, and their characteristics, such as Time of Flight (TOF) and Signal Amplitude (SA), change in response to internal phenomena like lithium-ion intercalation/deintercalation, density changes, and structural evolution within electrode materials.

One notable example is the study [149], which introduces a novel ultrasonic method for estimating the uneven state of charge (SOC) distribution in LIBs. The multi-site detection is utilized rather than traditional single-site approaches. By combining Gaussian process regression-active learning (GPR-AL) and a deep residual-pooling extreme learning machine (DR-PELM). The proposed method improves the estimation accuracy and reduces noise impact. Results show high SOC estimation accuracy, with general errors of 2.88% and distribution errors of 0.37%. In another study, Bian et al. proposed an integrated sensor framework combining novel mechanical (e.g., cell expansion, force), thermal, gas, optical (e.g., light intensity, peak wavelength from Fiber optic sensors), and additional electrical (e.g., anode/cathode potentials) sensors with traditional current and voltage measurements. Three Unique datasets were generated, and an explainable machine-learning approach (LSTM network) was utilized for estimation. The SOC estimation accuracy improves from 46.1% to 74.5%. The integration of advanced sensors, often integrated with a Battery digital twin framework, enables multi-physics-aware battery diagnostics and helps in building high-fidelity battery management systems (BMSs) for electric vehicles and grid storage.

The researchers explored various combinations, including SVM-CKF, CNN-LSTM [150], RNN-CNN [124], RNN-GRU [151], LSTM-AEKF [152], LSTM-RNN [153], LSTM-NARXNN [154], Improved LSTM-AEKF [155], CNN-BiLSTM [129], CNN-BiGRU [156], GRU-AKF [157] and NARXNN-UKF [158] etc.

5. SOH estimation and RUL prediction

Accurate SOH estimation and RUL prediction are critical for LIBs, helping the BMS identify potential issues before they cause catastrophic failures. It also optimises battery performance and efficiency, allowing for adjustments in charging protocols and thermal management strategies. It contributes to cost reduction and sustainability, allowing for timely replacements and repurposing of batteries in second-life applications. The flow diagram for SOH/RUL prediction is shown in Fig. 9. The following sections discuss SOH estimation and RUL prediction.

5.1. SOH ESTIMATION

The SOH of any battery can be defined in two aspects. For instance, we can define the SOH of a battery in terms of the increase in ohmic resistance that occurs during the ageing process of LIBs, as illustrated below.

$$SOH_{\Omega} = \frac{\Omega_{EOL} - \Omega_{now}}{\Omega_{EOL} - \Omega_{BOL}} * \ 100\ \% \tag{2}$$

Where $\Omega_{now,}$ Ω_{BOL} and Ω_{EOL} are the battery's internal resistance at present, beginning of life (BOL), and end of life (EOL). This estimation method is not suitable for online BMS because the degradation process makes it difficult to measure the battery's internal resistance. A current study often defines SOH as the ratio of the battery's present capacity to its initial capacity. The equation is

$$SOH_{Q} = \frac{Q_i}{Q_p} * 100\ \% \tag{3}$$

Here, Q_i and Q_p represent the initial and present battery capacities. SOH estimation approaches are grouped into deterministic, non-deterministic, and hybrid approaches as shown in Fig. 8.

Deterministic approaches include experimental and model-based methods. The offline experiments/tests, such as EIS [159], Ampere-hour Integration Method (AhIM) [160], etc., are conducted to measure or extract various health indicators (HIs), such as the battery's ohmic resistance, voltage, etc. Despite its accuracy, it consumes more time, specialised equipment is required, and it is limited to offline estimation. The Incremental Capacity Analysis (ICA) examines the incremental variation in battery capacity relative to voltage during the charging or discharging process [161]. Differential Voltage Analysis (DVA) examines a battery's voltage derivative in relation to its capacity. Both methods provide insights into the battery's chemical processes within and deterioration mechanisms; however, they may be susceptible to measurement noise [148].

Model-based SOH estimation methods uses EM/ECM/degradation models along with filters or observers. In [12], the proposed Unscented particle filter (UPF) algorithm, a combination of UKF and PF for SOH estimation, was established in the state space model. The MAX error is lower than 5% and has good adaptability for LIBs degradation. Higher-Order SMO (HOSMO), along with Generalised Super-Twisting Observer (GSTO), is proposed in [162] for SOH estimation. In this method, a 1RC equivalent circuit model is used and has a better MAE of $<$2%.

Non-deterministic, i.e., data-driven approaches, include machine learning (ML) methods such as ANN, SVM/SVR [148], random forest, decision tree, regression, etc., and deep learning (DL) methods such as RNN, CNN, LSTM, etc. The research [163] proposes the use of mean ohmic resistance (MOR), a robust and accurate HIs, and a hierarchical extreme learning machine (HELM) for online estimation of SOH, with errors below 3.36 percent in a variety of temperatures (10°C, 25°C, and 40°C) and dynamic situations.

To overcome the high computation burden, the study [164] comes with a new health indicator (HI), i.e., equal voltage range sampling count number (EVRSCN) for SOH estimation. Gaussian process regression (GPR), along with its kernel function, is adopted and implemented in MATLAB, providing an RMSE of $<$1% for EVRSCN-based SOH estimation. In [165], the SOH of LIB is estimated in a multistage process. First health indicators (HIs) are extracted using an incremental capacity (IC) curve with the help of a Gaussian filter. Secondly, an ANN-based method is utilised for SOH estimation in multistage. This method shows greater performance and robustness to heavy partial charging. To increase the accuracy and robustness, instead of a multistage approach, the study [166] adopted a multi-segment SOH estimation. In contrast to previous approaches, the CC charging stage is broken into short chunks, and HIs are extracted with the help of an HP filter. Then, a kernel-ridge regression (KKR)-based estimator is used for SOH estimation.

Both the capacity (Q) deterioration and ohmic growth are taken into account in the study [167] for SOH estimation. This study uses LIB datasets (NASA, BEXEL) and an RNN to estimate SOH based on ohmic resistance and capacity. In [168], Bi-LSTM is used to estimate SOH along with a Discrete Wavelet Transform (DWT) to denoise and a mutual information (MI) feature selection algorithm for HI optimisation. This method shows a better accuracy of MAE, which is less than 0.3535.

It is difficult to estimate SOH accurately for large battery packs with incomplete sensor data. To address this, the researcher [48] proposed a cross-generative adversarial network (CrGAN) based accurate SOH estimation method. Several identical cells are chosen to collect offline data. Health indicators (HIs) are then derived from the voltage data using a singular value decomposition (SVD) algorithm. It accurately augments voltage data for all cells. Finally, an SOH model is built by integrating kernel ELM and extreme learning machine (ELM) using Adaboost, with HIs as inputs and SOH as outputs. The method quantifies inconsistencies and suggests optimal sensor deployment (10 sensors, 0.43% error)

Thus, for SOH estimation, the HI extraction is a crucial step. Deterministic methods can effectively extract HIs with high accuracy.

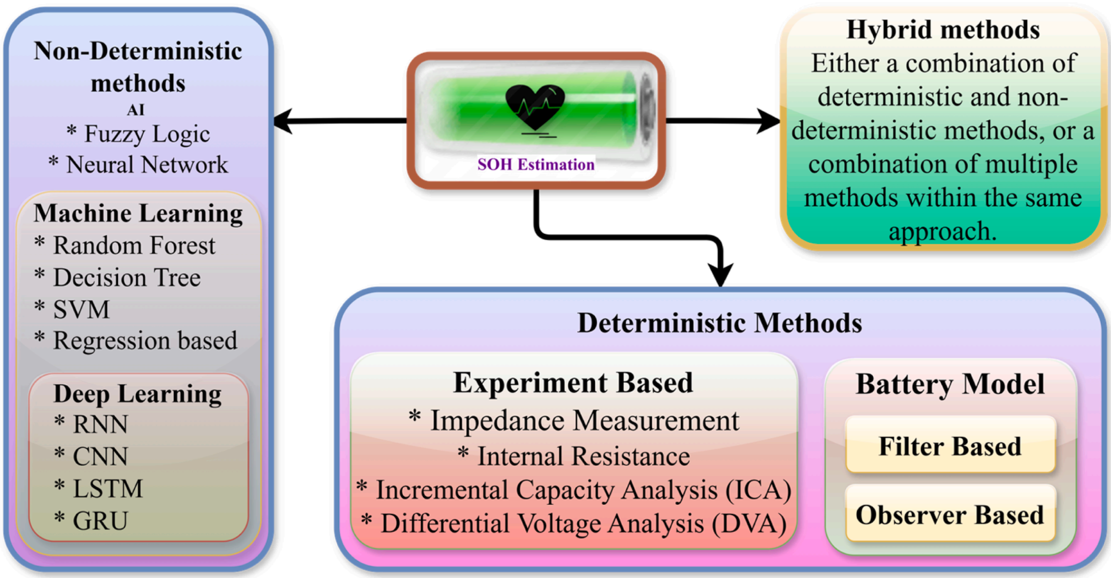

Fig. 8. Classification of LIB's SOH estimation methods.

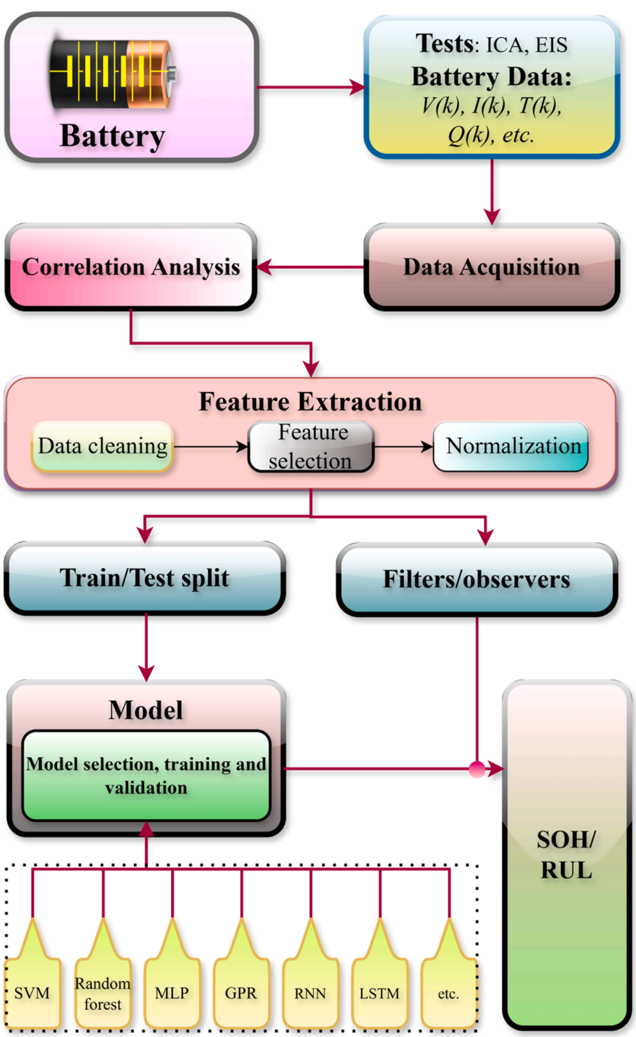

Fig. 9. SOH/RUL prediction flow diagram.

Subsequently, non-deterministic methods can leverage these extracted HIs to map nonlinear degradation patterns and achieve more precise SOH estimation.

The prediction of Remaining Useful Life (RUL) is critical for maintaining the safety, efficiency, enhancing performance, and cost-effectiveness of systems utilising LIBs. The RUL of LIB denotes the time or number of cycles left until the battery's capacity declines below an acceptable threshold, often between 20-30% of its rated capacity [169]. The estimation relies on predicting the battery's future SOH and identifying when it reaches the failure threshold.

The RUL prediction approaches can be classified similarly to SOH estimation methods: deterministic, non-deterministic and hybrid approaches. Hybrid methods have gained significant attention in recent literature due to their ability to combine the strengths of deterministic and data-driven approaches. The hybrid RUL prediction methods are analysed in Table 8.

The RUL is predicted with respect to capacity fade or/and internal resistance growth to predict the end of life (EOL) of the battery. In [179], a hybrid method combines an EIS-based ohmic resistance growth and a regression-based capacity degradation model to predict the RUL. The model is updated using a particle filter and validated using experimental data. The prediction error is $<1\%$ in many cases. The LIB's RUL is predicted in [181], with multi-kernel SVR (MKSVR), and it is optimised by the Grey Wolf cuckoo search (GWOCS) optimisation model. The results show that the proposed method has better accuracy compared to single-kernel SVR with RMSE less than 0.028. In reference [182], an RNN is combined with a signal analysis method called differential thermal voltammetry (DTV) to predict the RUL of LIB. The RMSE is less than 1% for the proposed method. Data-driven RUL forecasts require high-quality training data. Mayemba et al. presented an open-source degradation dataset from 25 unique sources, addressing their limitations and highlights [183].

6. Battery Digital Twin

The idea of digital twins was first presented by University of Michigan professor Grieves in a course on complete product lifecycle management in 2003 [184]. A Digital Twin is a virtual replica of a physical object. It replicates the physical object by synchronizing real-time data. Earlier, there was a technological limitation, but Digital twins have become popular due to technological advancements in recent years [185].

Table 8
Critical Analysis of SOH/RUL estimation methods.

Reference	Description	Battery/ Dataset	Method	Temperature	Tools/ Software Used	SOH/RUL Estimation	Performance metrices			Suitability for Battery Digital Twin (BDT)
							RMSE (%)	MAE (%)	Others	
[163]	The study suggests using the hierarchical extreme learning machine (HELM) and mean ohmic resistance (MOR) a strong and accurate health indicator for estimating SOH online, with errors below 3.36 percent in a range of temperatures and dynamic conditions.	Datasets of No. 30 (NEDC profile) and No. 43 (JP1015 profile) were chosen/ NEDC, UDDS, JP1015	1RC+FFRLS for HI Extraction, HELM for SOH estimation	10°C, 25°C, and 40°C	DC charger ITECH IT6532D, electronic load ITECH IT8511 A+	SOH	0.6245 to 1.8852	0.65 to 1.33	Maximum error = 1.22 % to 2.81%	This method offers fast online SOH estimation. Suitable for real-time BDT use; however, may need integration with thermal/ electrical models for full twin mapping.
[164]	The study presents the equal voltage range sampling count number (EVRSCN), a new health indicator for estimating the SOH of LIBs online. achieves high accuracy and strong resistance to noise while reducing computational burden.	Oxford dataset, Sandia National Laboratory (SNL) dataset, Center of Advanced Life Cycle Engineering (CALCE)	GPR+EVRSCN	40°C	MATLAB	SOH	Less than 0.5%	-	-	EVRSCN + GPR is noise-robust and low-computation. Highly BDT-compatible for onboard SOH monitoring but lacks electrochemical interpretability.
[170]	The study introduces a new method for estimating the SOH using partial constant-voltage (CV) charging data. This method achieves high accuracy in estimation, is resistant to partial charging, and requires minimal computational resources.	LiNiCoAlO2 (NCA) batteries from NASA Dataset	ICA-based method	25°C	-	SOH		Around 2%	-	ICA from partial CV charging is fast and lightweight — ideal for embedded BDT environments, but limited to early-life phase without degradation modelling.
[165]	The study proposes a multistage SoH estimation method using artificial neural networks to fuse health indicators from partial charging data, achieving high accuracy, robustness to	NCA batteries from NASA dataset and LCO battery numbered #35 from CALCE Dataset	ANN	40°C, 25°C	Arbin LBT21014 tester	SOH	-	less than 1.23%	-	Multistage ANN fusion works across chemistries and charging regimes. Promising for scalable DT deployment. Needs thermal coupling for full fidelity.

(continued on next page)

Table 8 (*continued*)

Reference	Description	Battery/ Dataset	Method	Temperature	Tools/ Software Used	SOH/RUL Estimation	Performance metrices			Suitability for Battery Digital Twin (BDT)
							RMSE (%)	MAE (%)	Others	
	cell inconsistency, and applicability across different battery types.									
[171]	This method integrates a Prior Knowledge-based Neural Network (PKNN) with a Markov chain, thereby improving both accuracy and reliability.	IFP1865140 type commercial batteries	Prior knowledge-based neural network (PKNN)	Room temperature	NEWARE CT-8004	SOH		0.041	MSE (%^{2}) =0.0030	PKNN + Markov Chain adds memory and reliability. Moderate BDT suitability due to model simplicity; fusion with physical insights can improve integration.
[172]	The study presents an online method for estimating lithium-ion battery SOH using an Unscented Particle Filter (UPF) algorithm and health indicators, achieving a maximum error of less than 5% and demonstrating robustness and applicability across various battery types.	CALCE and NASA Dataset	Unscented particle filter (UPF)	-	-	SOH	0.00065	-	Maximum error = 0.0385, Maximum Relative Error (MRE) = 3.8483% Average Width of Confidence Interval (AWCI) = 0.0374	UPF is well-suited for BDTs offering uncertainty quantification and robustness across platforms. High suitability for digital twin prognostics.
[173]	The study develops an online SoH estimation method using a novel energy-based health indicator (HI) from discharge data, incorporating voltage sequences and discharge rates, achieving high accuracy with an RMSE of 1.23%.	$LiCoO_2$ batteries	Savitzky – Golay (SG) filter + ELM	-	-	SOH	1.23	-	-	Energy-based HIs with ELM enable fast data-driven diagnosis. Good for lightweight BDTs; however, generalization to varying load conditions may require retraining.
[166]	To improve accuracy and robustness, the study used short partial charging segments and kernel ridge regression. Validated with real partial charging cycles, it achieves high accuracy and generality at a	NMC cells of the SNL dataset CALCE dataset	Kernel ridge regression	25°C	Python 3.6. AMD Ryzen 5 4600H CPU and 16 GB RAM	SOH	-	≤1.64%	-	KRR with partial segments is efficient and accurate. BDT-ready due to generalization and fast inference but lacks deeper electrochemical insight.

(*continued on next page*)

Table 8 (*continued*)

Reference	Description	Battery/ Dataset	Method	Temperature	Tools/ Software Used	SOH/RUL Estimation	Performance metrices			Suitability for Battery Digital Twin (BDT)
							RMSE (%)	MAE (%)	Others	
	low computational cost.									
[174]	The study introduces a SOH-coupled electro-thermal-aging model for LiFePO4/ graphite batteries, enabling simultaneous estimation of SOC, SOH, temperature, and internal resistance, validated through numerical simulations and experimental data.	LiFePO4/ graphite battery	ECM + electro-thermal-aging (ETA)	25°C, 35°C, 45°C, 55°C, and 65°C	MATLAB/ Simulink	SOH	0.029 to 0.042	-	-	Electro-thermal-aging model aligns closely with BDT goals, offering multi-domain simulation and co-estimation. Excellent suitability.
[175]	This study provides a unified DL algorithm employing LSTM RNNs for accurate RUL of LIBs, attaining great accuracy under difficult settings, with RUL error within 10 cycles.	LR1865SK LIB	LSTM+RNN	Room temperature	Arbin BT2000 battery test system	RUL	-	-	MSE % = 0.04 to 0.13	LSTM-RNNs enable robust RUL forecasting. Strong candidate for predictive digital twins, especially when paired with temperature/ load profiles.
[176]	The research provides an FBM-based degradation model, leveraging CTMC for mode switching, to forecast RUL, identify mode changes, and estimate parameters by maximum likelihood.	NASA Prognostics Center of Excellence	fractional Brownian motion (FBM) based degradation model	-	-	RUL	-	-	Average MSE = 2.9624×10^5	FBM + CTMC model excels in probabilistic degradation mapping. Suitable for long-term BDT forecasting, but lacks real-time adaptability.
[177]	A hybrid CNN-LSTM-DNN model improves LIB's RUL prediction accuracy and error, balancing performance and execution time, validated with NASA and CALCE datasets.	NASA and CALCE datasets	CNN+LSTM+DNN	24°C	Python	RUL	0.0043 to 0.0203	0.0029 to 0.01199	R^2 (0.7486 to 0.9935)	CNN-LSTM-DNN hybrid balances performance and efficiency. Highly adaptable for BDTs, particularly in cloud-based or edge-augmented setups.
[178]	A hybrid technique integrating condition monitoring, RNNs, and	battery degradation dataset from the data repository of Prognostics	State space + RNN	-	MATLAB	RUL	<0.0319	<0.0293	R^2 (0.9832)	State-space + RNN + GA blends physics and AI well. Excellent fit for hybrid BDTs

(continued on next page)

Table 8 (*continued*)

Reference	Description	Battery/ Dataset	Method	Temperature	Tools/ Software Used	SOH/RUL Estimation	Performance metrices			Suitability for Battery Digital Twin (BDT)
							RMSE (%)	MAE (%)	Others	
	state-space estimation enhances RUL accuracy for Li-ion batteries. Validated with NASA data, it uses a single exponential model and deep learning, boosting predictions using genetic algorithm optimisation.	Centre of Excellence at NASA								focused on adaptive control and long-range health prediction.
[179]	A hybrid method integrating capacity degradation with internal resistance growth models employing particle filtering improves RUL estimation accuracy for LIBs, displaying higher prediction precision over time and prolonged data availability.	LIR2032	EIS+PF	Room temperature (25°C)	MATLAB, ARBIN BT2000 battery testing equipment	RUL	0.0298 and 0.0179	-	R^2 (0.9891 and 0.9895)	Capacity + resistance + PF reflects strong real-world degradation. High BDT compatibility, though computation load may limit real-time use.
[180]	This paper compares various machine learning algorithms for estimating battery RUL, highlighting that PSO-ELM and WOA-ELM hybrid methods achieve the lowest RMSE values, outperforming other algorithms like LightGBM, random forest, and LSTM.	NASA battery dataset	ECM+SMO/ PSO-ELM or WOA-ELM	24°C	-	RUL	1.46	-	-	ML comparison framework identifies optimal hybrid estimators. Offers a reference model pool for BDT tuning but lacks system-level integration.
[181]	The study presents a GWOCS-MKSVR model for lithium-ion battery RUL prediction, enhancing accuracy to over 95.4% with high stability and adaptability, verified with NASA battery aging data.	Aging data set of B5, B6, and B7 batteries from NASA, PCoE Research Centre	GWOCS-MKSVR	-	-	RUL	0.0145 to 0.0266	0.0107 to 0.0133	-	GWOCS-MKSVR achieves high accuracy with good generalization. High suitability for scalable BDT platforms, especially for edge-cloud orchestration.

6.1. Digital Twin Technologies for Battery Management System

The digital twin encompasses three processes: data collection from the physical system, digital model creation/representation, and giving feedback about the physical system. For this, DT uses four technologies, such as the Internet of Things (IoT), extended reality (XR), artificial intelligence (AI), and cloud, which are shown in Fig. 10. How these technologies can advance the BMS is discussed in the following sections:

6.1.1. Internet of Things

Real-time battery data acquisition is challenging when the vehicle is on the road. However, with the help of IoT sensors and communication protocols such as MQTT, HTTP, and AMQP, battery data can be acquired for processing and storing. The primary technology for DT is IoT, which necessitates a continuous flow of information from the physical system. As a result, DT ensures that the battery data is collected throughout its life.

6.1.2. Cloud Computing

The onboard BMS has limited storage and computation. Due to this, high-accuracy battery state estimation methods (computationally intensive) cannot be implemented. However, cloud computing, a DT technology with high storage, provides high computational capability over the Internet. Thus, DT overcomes the limitations (storage space, computation power).

6.1.3. Artificial Intelligence (AI)

Researchers are currently using AI techniques for various battery state estimation methods, as described in non-deterministic state estimation methods. The integration of generative AI (GenAI) within digital twins constitutes a significant development in simulation and predictive analytics. In the automobile industry, for instance, corporations deploy digital twins in SDV, software-defined vehicles, to simulate vehicle performance under varied conditions, considerably speeding up the development process and enhancing product reliability and safety. Therefore, Gen AI technology enhances the BMS by humans like decision-making and helps in battery state estimation, life prediction, and fault identification.

6.1.4. Extended Reality (XR)

XR comprises cutting-edge technologies such as augmented reality (AR), virtual reality (VR), and mixed reality (MR). These technologies are necessary for a futuristic intelligent BMS for 3D battery model construction and to deliver a realistic feeling to the user. As a result, the XR technology of the Digital Twin allows us to emulate battery conditions in virtual environments. Table 9 provides a review of battery digital twin implementation in existing literature.

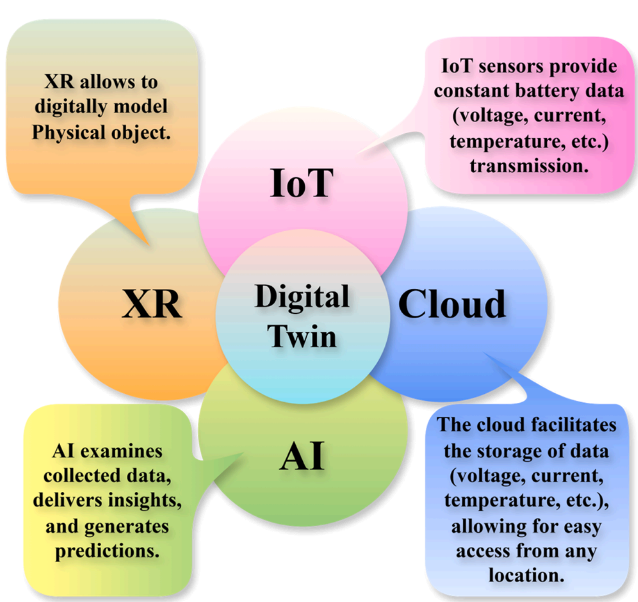

Fig. 10. DT's technologies [186].

6.2. Functions of Battery Digital Twin

- **Real-time monitoring:** Digital twins continuously monitor critical battery variables such as state of health (SOH), state of charge (SOC), remaining usable life (RUL), and temperature, delivering real-time information on battery status [198].
- **Predictive analytics:** BDTs use data-driven models to foresee possible problems, such as battery degradation or heat concerns, allowing proactive steps to be applied [199].
- **Fault diagnosis:** Digital twins can help locate the source of troubles, such as a damaged component or an unbalanced charging process, allowing for quicker issue resolution [200].
- **Performance optimisation:** Depending on usage patterns and external circumstances, they recommend the most efficient way to charge and discharge batteries [201].
- **Lifecycle management:** Digital twins monitor batteries from manufacturing to end-of-life, helping evaluate whether they can be reused or discarded [202].
- **Simulation and validation:** Control techniques and software changes can be tested digitally on the twin before being deployed to the genuine system, lowering risk [198].
- **Data-driven maintenance:** Maintenance can be arranged based on real usage and wear rather than fixed schedules, saving time and cost [201].

Therefore, by simulating batteries' behaviour and features, Battery Digital Twins (BDTs) allow for real-time monitoring and study of battery health, performance, and possible problems. This enhances battery performance and lifespan by enabling proactive maintenance, optimal charging and discharging techniques, and early fault detection. BDTs also help cut costs by simulating scenarios and analysing control solutions in a virtual environment. Additionally, BDTs offer predictive analytics and real-time monitoring, which make it possible to optimise battery management techniques. They also reduce the need for actual prototypes by accelerating research and development of novel battery technologies.

Very few researchers employ DT for battery state estimation [203–205]. The paper [206] presents a digital twin architecture for predicting EV battery condition. The method employs a hybrid approach (the 2RC Model, XGBoost, and SVR techniques) for SOC and SOH estimation. This enhances battery management by enabling real-time monitoring, precise status estimates, and predictive maintenance. The design integrates virtual copies for precise monitoring and forecasting capabilities.

Wang et al. [207] estimate LIB battery states (SOC, SOH, SOP) using cloud-side-end collaboration and DT. The method uses a 5G transceiver module for continuous data transmission between BDT and a real battery. The twin is developed using an equivalent circuit-based model and the particle filter. At 25°C, 3C discharge rate, this method has RMSE and MAE of 0.02% and 0.27%. The author in [208] presents a DT framework for BMS onboard SOC estimation, which relies on Coulomb counting and employs a deep learning (DL) network to estimate SOH in the cloud. Here, the DT was deployed on the Microsoft Azure platform, and the SOH estimation accuracy of MSE was 0.022%.

Based on the existing literature [203–208], the framework for battery digital twin is provided in Fig. 11.

Table 9
Critical Review of Battery Digital Twin (BDT) Implementations: Technologies, Validation, and Research Gaps.

Title/Reference	Function/ Application	IoT/ Edge layer	Cloud/Data Layer	AI/ML (Digital Model)	XR/ Visualization	Validation & Metrics	Identified Gaps
Design of power lithium battery management system based on digital twin [187]	Real-time SoC estimation, voltage/ current/temp monitoring, 3D visualization	TI BQ76 board, UART, Hall current sensor	Local PC, SQL Server	2-RC ECM, FFRLS, HIF-PF	Unity3D (3D model, real-time UI)	SoC error <1%, voltage error <0.8%, validated on 16 × 18650 cells, BBDST profile	Scaling to pack/ module, integration with cloud, real-world deployment
State-of-health estimation by virtual experiments using recurrent decoder–encoder-based lithium-ion digital battery twins trained on unstructured battery data [188]	Virtual SOH estimation, robust to unstructured data, no SOC dependency	-	-	Encoder-decoder RNN (GRU-based), virtual SOH testing	-	SOH error: 0.3–1.1%, validated on real driving cycles	Model generalization, real-world robustness, temperature effects
Improved Digital Twin of Li-Ion Battery Based on Generic MATLAB Model [189]	SOC/SOH estimation, fast charging analysis	Custom testbed, direct current/ voltage sensing	MATLAB/ Simulink	3D data fitting, empirical models	-	MAE <0.02V, SoH tracked to 79%, validated on Samsung INR18650-25R (Experiment)	Lack of real-time cloud, model transferability.
Digital Twin for Real-time Li-Ion Battery State of Health Estimation with Partially Discharged Cycling Data [190]	SOH Estimation	-	-	ECM + LSTM + SVM	-	RMSE 1.08±0.36 and validated using Massachusetts Institute of Technology dataset	Model updating; knee-point detection
Digital Twin-Supported Battery State Estimation Based on TCN-LSTM Neural Networks and Transfer Learning [191]	SOC, SOH and RUL estimation	-	-	2RC + temporal convolutional network (TCN) and the long short-term memory (LSTM)	-	RMSE: SOC 1.1%; SOH < 0.8%; RUL < 0.9%; validated on NASA dataset	Real time implementation
State of charge estimation for lithium-ion batteries based on a digital twin hybrid model [192]	SOC estimation	-		ECM + VFFRLS + AUKF + NN	-	MAE and RMSE are 0.0046 and 0.0065. Simulation experiments.	Real time implementation with integration of BDT technologies is required
Digital twin and cloud-side-end collaboration for intelligent battery management system [193]	SOC, SOP and SOH estimation	5G data transmission module	Host computer	ECM + PF	-	RMSE = 0.3% and MAE = 0.1%. Experimental Validation	Need for advanced AI/ML modelling; Assumption of constant battery parameters.
Validation and Implementation in the Cloud of Cell-Level Models of a Digital Twin Simulation Platform [194]	Proposes a Digital Twin Simulation Platform (DTSP)	Message Queuing Telemetry Transport (MQTT)	Amazon Web Services (AWS), Relational Database such as PostgreSQL or MySQL.	Electro thermal model (Lumped + ECM and SPKF)	Amazon QuickSight as a visualiser	Error of 0.0124 V	Integrating advanced AI/ML modelling is required.
Prediction of the Battery State Using the Digital Twin Framework Based on the Battery Management System [195]	SOC and SOH Estimation	-	-	ECM+EKF+XGBoost	-	RMSE = 0.009%; MAE = 0.007%; NASA dataset	Real time implementation; Lack of using BDT technology
Digital twin for electric vehicle battery management with incremental learning [196]	SOC and SOH Estimation	CAN (controller area network) communication	Microsoft Azure cloud platform	Continuous wavelet transforms (CWT) + Continual Learning with Reservoir Sampling algorithm + KF	-	MAE = 0.022% and Validated using NASA dataset	Real-time implementation; Cloud, XR integration
Development of self-adaptive digital twin for battery monitoring and management system [197]	SOC estimation	-	Matlab/ Simulink environment	ECM+Self adaptive PSO +EKF	-	RMSE = 0.41%. Simulation experiment,	Real-time implementation; XR integration

6.3. *Multi-physics Simulation for Battery Digital Twin*

Electric Vehicle Batteries, such as LIBs, are electrochemical energy storage devices. It is sensitive to temperature. For implementing Battery Digital Twins (BDTs), accurate Multiphysics battery modelling is required. I.e., there is a need to integrate Electrochemical models (for Simulating ion transport, reaction kinetics, and charge distribution). Thermal models (for predicting heat generation, temperature distribution, and heat dissipation within cells and packs). Mechanical models (for understanding stress, strain, and volume changes during cycling and

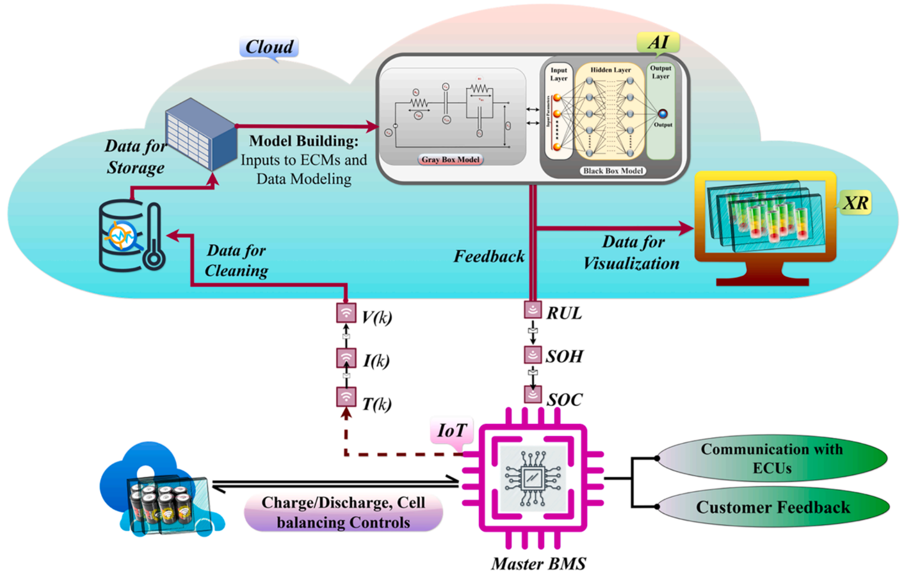

Fig. 11. Battery Digital Twin (BDT) framework.

their impact on degradation), and Aging models (for predicting capacity fade and resistance increase due to various degradation mechanisms). Data-driven model (involves AI/ML for accurate battery parameters prediction).

As the battery is sensitive to temperature, the battery thermal management system (BTMS) has become an integral part of the BMS. In a study [209], a novel Multiphysics battery model is developed to design and optimize BTMS. Here, electrochemical, aging and heat transfer models are integrated and found that the formation of solid electrolyte interphase (SEI) in aged batteries accelerates the temperature and leads to battery thermal runaway. BTMS performs Well with brick-shaped nanoparticles, which decreases the capacity fade and increases the battery safety and longevity. Crucially, Multiphysics simulation forms an indispensable component of a sophisticated BDT for electric vehicle batteries. BDT provides a holistic and accurate representation of the battery's condition under diverse operating conditions. For instance, variations in battery temperature led to changes in its internal resistance as well as alterations in the battery's electrochemical reactions. Through the Multiphysics simulation of these interconnected phenomena, the BDT can effectively predict the risks associated with thermal runaway, enhance BTMS strategies, and provide more precise forecasts for SOC, SOH, and RUL. According to existing literature, as shown in Table 9, current research on digital twin-based battery state estimation has primarily focused on electrical models. Very few studies have addressed the electro-thermal components. There is a growing trend toward offering multiphysics and digital twin solutions. Leading companies such as Siemens (Siemens Xcelerator), General Electric (Predix Platform), Oracle (Oracle IoT Digital Twin), ANSYS (ANSYS Twin Builder), Amazon Web Services (AWS IoT TwinMaker), and Microsoft (Azure Digital Twins), among others, are providing these digital twin solutions.

6.4. Challenges of Battery Digital Twin

6.4.1. Data Acquisition and Management Complexity

- **Heterogeneous Data Streams and Volume:** EV batteries generate vast quantities of heterogeneous data, including electrical (voltage, current), thermal (temperature distribution), mechanical (expansion, force), and emerging non-electrical sensor data (ultrasonic, optical, acoustic emissions). For instance, battery packs with thousands of cells can generate millions of real-time data points, severely limiting communication bandwidth.
- **Data Quality and Availability**: Battery DTs depend on reliable, high-resolution data. Sensor constraints, inadequate calibration, and outmoded technology hinder data accuracy and availability, affecting model fidelity and limiting the twin's predictive & diagnostic relevance.
- **In-situ Measurement Limitations:** There is still a need for indirect inference and model-based predictions since it is challenging to obtain direct, high-resolution measurements of internal battery states (such as localized lithium concentration, active material degradation) without jeopardizing cell integrity.

6.4.2. Model Fidelity and Accuracy Limitations

- **Coupled Multi-physics Phenomena:** Accurately modelling the complex connection of electrochemical, thermal, mechanical, and aging processes within the LIBs is computationally demanding and difficult. Capturing these interactions dynamically across different operating conditions and aging phases is a key obstacle. For instance, precisely predicting how localized temperature variations influence SEI growth and capacity fade requires highly sophisticated coupled models.
- **Complex Degradation Mechanisms:** Battery aging is a complicated process involving numerous linked degradation pathways. Developing predictive models that effectively capture these non-linear, time-dependent phenomena under varied real-world usage conditions, across different battery chemistries, poses a substantial problem for precise SOH and RUL estimates.
- **Time-Varying Model Behaviour:** Reliable real-time parameterization techniques are required because model parameters might change dramatically in response to shifting variables, including temperature, SOC, C-rates, and deterioration levels. Simple models, while computationally cost-effective, may fall short in some operating conditions, such as high C-rates (e.g., >3C).

6.4.3. Computational Burden and Real-time Implementation

Resource Constraints on Edge Devices: Executing high-fidelity, multi-physics BDTs in real-time on resource-limited onboard Battery Management Systems (BMS) is often not feasible due to their significant computational demands and memory needs. This highlights the necessity for crafting computationally efficient reduced-order models or surrogate models that can still provide adequate accuracy.

6.4.4. Processing Requirements

Handling a substantial volume of real-time data in the cloud requires powerful processors and advanced data fusion through sophisticated signal processing algorithms. The high sampling rates, communication delays, and computational load, especially concerning cell-level SOC estimations, are challenging the performance.

6.4.5. Validation and Verification Complexities

- **Absence of True Ground Truth:** It is very challenging to directly validate through experimentation the battery's internal states and deterioration pathways that the BDT predicts, since a damaging post-mortem study is frequently needed. It makes gathering "ground truth" data for complete model validation a substantial hurdle.
- **Long-term Performance Verification:** BDTs throughout the entire operational lifespan of a battery pack necessitate significant, time-consuming, and expensive long-term cycling testing under different conditions.

6.4.6. Standardization, Interoperability, and Data Security

- **Lack of Uniform Standards and Legislation:** There is currently no widely accepted standard or consensus on the definition, architecture, functional requirements, or features of battery BDTs. The inherent transparency of battery data throughout its value chain raises concerns about technical and trade secrets, necessitating proper legislation concerning data privacy and transparency levels.
- **Intellectual Property Concerns:** In order to provide thorough and interoperable BDTs, manufacturers could be hesitant to divulge secret battery data, operational algorithms, or specific model specifications.
- **Cybersecurity Risks:** As BDTs grow more integrated and crucial for vehicle functions, they provide a perfect target for possible attackers, similar to SCADA systems. Compromised communication lines or manipulated sensory data/DT feedback might mislead battery control and protection algorithms, potentially leading to hazards of battery fires and accidents. Securing BDTs needs comprehensive strategies spanning access control, network security, data integrity, and model integrity, according to standards like IEC 27400-2022 and IEC 62443.

6.4.7. Complexity and Cost of Implementation

The implementation of BDTs involves substantial initial investment in infrastructure, including sophisticated sensor components, IoT gateways, cloud-based servers, and high-performance processors. While these expenditures can be justified in the near term due to long-term advantages across the value chain. The significant upfront investment remains a hurdle for first pilot setups or full-scale deployment. Some use cases, like simple SOC calculation, may not now give sufficient value to justify the increased DT complexity, as onboard BMS systems are already effective. More promising use cases are those delivering value for fleet management, reuse, and battery passports.

7. Discussions

The landscape of battery state estimation has undergone a profound evolution, transitioning from the foundational reliance on model-based estimations to the adaptive prowess of machine learning, and culminating in the cutting-edge paradigm of digital twins. Initial investigations are carried out on the performance of equivalent circuit models, which rely on well-defined mathematical relationships and physical principles to predict battery states. Table 6 provides a comprehensive overview of various deterministic approaches employed for state of charge estimation in Li-ion batteries. A common thread running through these approaches is the reliance on mathematical models, primarily Equivalent Circuit Models (ECMs), to represent the battery's electrical behaviour.

The choice of battery model is a critical factor influencing both the accuracy of SOC estimation and the computational resources required. Simpler models, such as the 1RC, are computationally efficient but may sacrifice accuracy, particularly under dynamic operating conditions where the battery's behaviour is more complex. In contrast, more sophisticated models like the 2RC and Fractional-Order Models (FOMs) can better capture these complexities, leading to improved estimation accuracy, but at the cost of increased computational demands. The accurate identification of model parameters is another key determinant of reliable SOC estimation. The critical analysis reveals a range of techniques employed for this purpose, including pulse discharge tests, Hybrid Pulse Power Characterisation (HPPC), and optimisation algorithms like Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA). These methods aim to extract precise parameter values that enable the models to reflect the battery's true behaviour accurately. The selection of an appropriate filtering or observer algorithm is equally important, as it directly impacts the system's ability to handle measurement noise and model uncertainties.

The review showcases the prevalence of Extended Kalman Filters (EKFs), Unscented Kalman Filters (UKFs), and Adaptive Kalman Filters (AKFs) in this role. These algorithms offer varying degrees of complexity and adaptability, allowing for effective state estimation even in the presence of noise and model inaccuracies. Finally, performance metrics like RMSE and MAE enable objective evaluation and comparison of different SOC estimation methods in terms of the accuracy and reliability of each approach. Initially, model-based estimations, rooted in the electrochemical and equivalent circuit models, were predominant. These methods, while offering interpretability and accuracy under controlled conditions, grappled with the inherent complexities and nonlinearities of battery behaviour, particularly as batteries aged or operated under diverse conditions. The reliance on precise parameter identification and the computational burden associated with these models further limit their real-time applicability, especially in the dynamic environment of electric vehicles.

In contrast, non-deterministic methods, such as data-driven approaches based on machine learning, leverage statistical patterns and correlations within large datasets to estimate battery states. These methods excel in handling complex and nonlinear relationships, offering adaptability and robustness to uncertainties. LIBs are highly nonlinear; hence, ML/DL approaches are used for accurate state estimation. Table 7 presents a critical analysis of various non-deterministic approaches, primarily employing machine learning and deep learning techniques, for SOC, and Table 8 presents a critical analysis of SOH/RUL estimation in Li-ion batteries. The table showcases a wide array of algorithms, including LSTM, Bi-LSTM, GRU, CNN, RNN, BPNN, DNN, and SVM, each with its unique strengths and weaknesses. The choice of algorithm depends on factors like computational complexity, accuracy requirements, and the specific characteristics of the battery and application. These methods leverage the power of data-driven modelling to capture intricate patterns and nonlinearities in battery behaviour, often surpassing the capabilities of traditional model-based approaches. The use of diverse battery types and datasets, along with the consideration of temperature effects, further enhances the adaptability and robustness of these techniques.

By recognising the strengths and limitations of both deterministic and non-deterministic methods, hybrid approaches have emerged as a promising avenue for improving the accuracy and reliability of battery state estimation. These approaches combine the physical insights of model-based methods with the adaptability of data-driven techniques. For instance, hybrid approaches can leverage ECMs or electrochemical models to provide initial state estimates, which are then refined and corrected using machine learning algorithms based on real-time measurements. This synergistic combination allows for a more comprehensive and accurate representation of battery behaviour, accounting for both the underlying physical principles and the dynamic operating conditions. The advent of digital twin technology has opened new possibilities for battery state estimation and management. Digital twins create virtual replicas of physical batteries, enabling real-time monitoring, analysis, and optimisation of battery performance. By integrating sensor data, battery models, and machine learning algorithms, digital twins can provide a holistic view of battery health, predict future behaviour, and enable proactive maintenance strategies. The application of digital twins in battery management systems is still in its early stages. Still, it holds immense potential for improving the safety, reliability, and longevity of batteries in electric vehicles.

The future development trends of BDTs for state estimation (such as standardization, cybersecurity, 6G, etc.) are to provide quicker, accurate, integrated and transparent solutions. Advancements will see the fusion of multi-physics and multi-scale models, harnessing data from next-gen sensors like ultrasonic and Fiber-optic systems for granular, real-time insights into battery health. Self-updating digital twins, enriched by explainable AI and transfer learning from cloud and edge data, are set to drastically improve safety, efficiency, and lifespan in energy storage and EV applications. Edge-cloud collaboration will ensure fast, efficient estimations at the device level while leveraging cloud analytics for fleet-wide diagnostics and long-term planning. Digital twins will increasingly trace batteries' full lifecycle, enhancing manufacturing, operation, repurposing, and recycling, thus supporting a sustainable circular economy.

8. Conclusion

The review concludes that Li-ion batteries, with their superior energy density and longevity, have emerged as the dominant battery technology for EVs. However, due to their sensitivity to temperature, aging, and safety risks, sophisticated BMS are required to ensure safe and efficient operation. This review has examined various battery modelling techniques, ranging from simplified equivalent circuit models to complex black box approaches. Additionally, we have delved into the evolution of battery state estimation methods, including SOC estimation, SOH prediction, and RUL estimation. The emergence of hybrid approaches that combine the strengths of different methods holds promise for achieving a more comprehensive understanding of battery behaviour.

As research in this field progresses, there is anticipation of even more sophisticated BDT frameworks that leverage advancements in IoT, cloud computing, AI, and extended reality, which further enhance the following services.

- Vehicle-to-Grid (V2G) Integration through DT technology enables Smart Charging Infrastructure. Here, EV batteries are getting charged from the grid as well as supplying the power to the grid in demand situations [210].
- Digital Twinning of the vehicles transforms the vehicles into self-driven/autonomous-driven vehicles (SDV) with the help of Advanced Driver Assistance Systems (ADAS). The data from these systems and the grid helps the SDV's energy management system to allocate a suitable time for charging and intelligent system coordination under varying driving conditions.
- The maintenance cost comes down by utilizing the predictive and advance fault diagnostic capabilities of Digital Twin, which schedules the maintenance by knowing the complete vehicle conditions.
- BDTs will assist in estimating second-life potential and end-of-life decision-making for used batteries, promoting circular economy strategies and regulatory compliance in EV battery reuse and recycling.

In conclusion, incorporating digital twin technology in the field of EV battery management systems provides various advantages, including the battery passport, which tracks from materials mining to second life and also until recycling. The battery passport enables battery swapping. The ongoing advancement of cutting-edge battery technologies, BMS, and digital twin integration presents a viable route to a future of sustainable and electrified transportation. The knowledge gathered from this review will help advance this important area of study and innovation.

CRediT authorship contribution statement

S. Ramshankar: Writing – review & editing, Investigation, Formal analysis, Conceptualization. **M. Manimozhi:** Validation, Supervision, Resources, Methodology.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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