IJEEC

International Journal of Electrical Engineering and Computing
Vol. 9, No. 2 (2025)

Case Study
UDC 007.52:[621.354:004.11
DOI 10.7251/IJEEC2502089P

Artificial Intelligence Approaches to Battery Health Assessment: Opportunities, Challenges and Future Directions

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Abstract— **Accurate estimation of the state of health and remaining useful life of lithium-ion batteries is essential for ensuring the reliability, safety and longevity of electric vehicles, stationary storage systems and portable electronics. Traditional approaches based on electrochemical diagnostics, equivalent circuit models and reduced-order physics-based methods provide valuable mechanistic insights but face significant limitations under dynamic real-world operating conditions. Recent advances in artificial intelligence have transformed battery diagnostics by enabling data-driven extraction of degradation-sensitive features from voltage, current and temperature measurements. Machine learning algorithms such as random forests and support vector regression demonstrate strong state of health estimation accuracy when combined with engineered features, while deep learning models, including convolutional neural networks, long short-term memory, convolution long short-term memory and attention-based architectures, achieve state-of-the-art performance by learning nonlinear temporal patterns directly from raw time-series data. Hybrid physics-informed neural networks further enhance interpretability and generalization by embedding electrochemical constraints into model architectures. In addition to supervised learning, reinforcement learning has emerged as a promising method for adaptive battery management, enabling real-time optimization of charging strategies, thermal control and power allocation to minimize degradation and extend battery lifetime. When integrated into digital twin frameworks, artificial intelligence models support continuous, real-time state of health/remaining useful life tracking and predictive maintenance across large battery fleets. Despite these advances, challenges remain in data availability, domain shift, model interpretability, computational constraints and the absence of standardized validation protocols. Future research will focus on physics-informed hybrid artificial intelligence, transfer learning for cross-chemistry generalization, federated learning for privacy-preserving fleet deployment and standardized benchmarking frameworks. Together, these developments signal the emergence of next-generation intelligent battery management systems that combine accurate health estimation with adaptive, degradation-aware control.**

Keywords-artificial inteligence; lithium-ion batteries; state of health; data-driven prognostics;

I. INTRODUCTION

Lithium-ion batteries have become the dominant energy storage technology for electric vehicles (EV), grid-scale storage systems and portable electronics due to their high energy density, long cycle life and decreasing cost per kilowatt-hour. Ensuring their safe and efficient operation, however, requires accurate monitoring of internal states such as state of charge (SOC), state of health (SOH), state of energy (SOE), state of power (SOP), state of temperature (SOT), state of safety (SOS) and remaining useful life (RUL), of which SOH monitoring is critical to battery management for balancing the trade-off between maximizing system performance and minimizing battery degradation [1], [2]. Traditional diagnostic and modeling approaches, including incremental capacity analysis, differential voltage analysis, electrochemical impedance spectroscopy and equivalent circuit or electrochemical models, provide essential mechanistic insights but face significant challenges when deployed under dynamic real-world conditions characterized by fluctuating temperatures, irregular load profiles and partial cycling [3], [4]. These conditions cause degradation mechanisms such as solid electrolyte interphase (SEI) growth, lithium plating and electrode microstructural changes to evolve in nonlinear and path-dependent ways that traditional models often struggle to capture.

The increasing availability of large-scale cycling datasets and operational telemetry from electric vehicles has accelerated the adoption of artificial intelligence (AI) in battery diagnostics. Machine learning (ML) techniques can provide a viable alternative and a useful tool for modelling battery behavior [5]. These methods, such as random forests or support vector regression, have demonstrated strong performance in capacity fade and SOH estimation when applied to engineered features extracted from selected charge–discharge intervals [3]. In addition to this, auto regressor (AR), and Gaussian process regression (GPR) act as common methods to estimate SOH and RUL [6]. Deep learning (DL) methods, including feed-forward neural networks (FNNs), convolutional neural networks (CNNs), long short-term memory (LSTM) networks, temporal convolutional networks (TCNs) and attention-based architectures, further advance this capability by autonomously learning degradation-sensitive temporal patterns directly from raw voltage, current and temperature time-series data, achieving sub-percent prediction errors in studies [6]-[9]. Recent studies highlighted that LSTM, FNN, and CNN neural network algorithms achieved the best performance, with a mean absolute percentage error of around 0.5%, compared to about 1.5% for FNN and 2% for CNN networks [10].

Hybrid approaches that integrate physics-based constraints into neural architectures, commonly known as physics-informed neural networks (PINNs), provide an additional layer of interpretability and generalization by embedding electrochemical principles into the learning process [11]. These models address limitations associated with black-box DL methods and improve robustness under sparse or noisy data conditions.

In parallel with advances in supervised learning, reinforcement learning (RL) has emerged as a powerful complementary technology for adaptive battery management. Unlike supervised ML/DL models that estimate SOH or RUL from historical data, RL agents learn optimal control strategies, such as fast-charging protocols, thermal management policies or power allocation schemes, by interacting with an environment and maximizing long-term performance and safety objectives. Recent work demonstrates that deep RL frameworks can significantly reduce battery aging during fast charging, suppress thermal stress and optimize charge–discharge schedules more effectively than conventional rule-based or constant-current/constant-voltage (CC/CV) methods [12], [13], [19]. When combined with digital twin (DT) simulators, RL agents can be trained safely at scale, enabling real-time, degradation-aware decision-making in modern battery management systems.

Despite significant progress, AI-driven battery health estimation still faces notable challenges, including data scarcity, poor generalization across chemistries and manufacturers, limited interpretability of deep models, computational constraints in onboard battery management system (BMS) hardware and the lack of standardized validation protocols [4], [11]. Addressing these issues is essential for the widespread deployment of AI-enhanced diagnostic and control algorithms in safety-critical applications such as electric vehicles.

This work provides a comprehensive review of traditional, machine learning, deep learning, physics-informed and reinforcement learning methodologies for SOH and RUL estimation, highlighting their strengths, limitations and potential integration into next-generation intelligent battery management systems.

II. Battery State of Health Estimation

State of Health estimation refers to the process of quantifying the degradation level of a battery relative to its nominal, fresh condition, and is defined as the current capacity or internal resistance of the battery compared with that of a new one [28], [29]. It reflects the battery's ability to store and deliver energy compared to its original performance and is most commonly expressed as a normalized metric, such as remaining capacity or health percentage. SOH is a latent variable, meaning it cannot be measured directly and must be inferred from observable electrical, thermal, and operational signals. The general SOH estimation process, independent of the specific estimation technique, is illustrated in Fig. 1.

In practice, SOH estimation begins with a battery operating under real-world conditions, including charging, discharging, and exposure to varying temperatures and load profiles. These operating conditions induce measurable responses in the battery, most notably voltage, current, temperature, and time- or cycle-related data. The quality and availability of these measurements are critical, as they form the foundation for any health assessment strategy.

The measured signals are subsequently processed to remove noise, compensate for sensor inaccuracies, and align data across different operating regimes. From these processed signals, diagnostic indicators are extracted that are sensitive to internal degradation mechanisms. Such indicators may represent changes in capacity, internal resistance, voltage response characteristics, or energy efficiency, each of which correlates with aging phenomena such as loss of lithium inventory, growth of internal resistive layers, or active material degradation.

The core of SOH estimation lies in interpreting these diagnostic indicators using an estimation framework or model. Depending on the chosen methodology, this framework may rely on empirical relationships, equivalent circuit

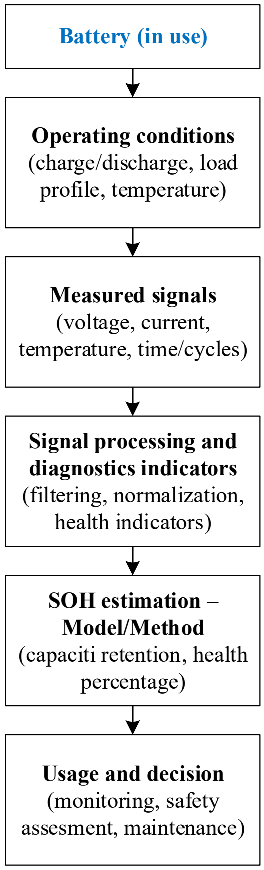

Figure 1. Battery SOH estimation process

representations, electrochemical principles, or data-driven mappings. Regardless of the approach, the objective is to establish a reliable relationship between observable indicators and the underlying degradation state of the battery.

The output of the estimation process is the SOH value, typically expressed as a percentage of the nominal capacity or as a normalized health index. This estimated SOH provides actionable information for battery monitoring, maintenance planning, safety assessment, and lifecycle management. In battery management systems, SOH estimates are essential for preventing overuse of degraded cells, enabling predictive maintenance, and ensuring safe and efficient operation throughout the battery's service life.

III. Traditional Battery State Assessment Methods

Traditional methodologies for evaluating the internal state and degradation level of lithium-ion batteries form the historical and theoretical basis on which modern diagnostic and prognostic techniques are built. These approaches include experimental diagnostic procedures, model-based estimation methods and hybrid strategies that combine measurement-driven indicators with simplified physics. Although they are valuable for physical interpretability and controlled laboratory analysis, traditional methods encounter limitations when applied to dynamic, real-world operating environments such as electric vehicles or grid-interactive storage systems. This section reviews the main categories of traditional SOH estimation techniques and their role in contemporary battery research.

A. Experimental and Diagnostic Methods

Diagnostic techniques such as open-circuit voltage (OCV) analysis, incremental capacity analysis (ICA), differential voltage analysis (DVA), and electrochemical impedance spectroscopy (EIS) have long been used to extract internal health information from lithium-ion cells. ICA and DVA are particularly sensitive to electrochemical aging because they quantify characteristic peak shifts in voltage–capacity derivatives that correspond to loss of active material, changes in reaction overpotential and SEI layer growth. These analyses require slow, highly controlled charge–discharge cycles, making them excellent for laboratory studies of degradation mechanisms but unsuitable for high-power or transient operating regimes typically encountered in electric vehicle use cases.

Recent literature highlights that despite their impracticality for real-time onboard estimation, ICA and DVA remain fundamental tools for generating high-quality labels for machine learning datasets and for validating the interpretability of AI-based feature extraction pipelines [3], [14]. Similarly, EIS offers unparalleled sensitivity to early-stage degradation by measuring frequency-dependent resistance components but requires specialized instrumentation and cannot be implemented during normal EV driving. In practice, these techniques serve as offline diagnostic benchmarks rather than operational tools for online SOH estimation.

B. Model-Based Estimation Methods

Model-based approaches constitute the second major category of traditional SOH estimation techniques. The model-based method commonly consists of two steps [34]. The first step is to establish a degradation model to simulate the aging of the battery, in which, some parameters of the model indicate the SOH of the battery. These models mainly include Electrochemical Model (EM) and Equivalent Circuit Model (ECM). The second step is to update the parameters of the model to obtain the current SOH of the battery. Equivalent circuit models, such as Thevenin and high-order RC models, approximate a battery's dynamic electrical response using lumped resistive-capacitive networks. ECMs support real-time estimation through Kalman filtering [27] and remain widely used in commercial BMS because of their simplicity, low computational cost and ease of parameter fitting. Nevertheless, ECM parameters drift significantly as the battery ages, and these models have difficulty capturing nonlinear or path-dependent degradation phenomena without frequent re-identification.

Electrochemical models, such as the Doyle-Fuller-Newman (DFN) model and its reduced-order variants, provide a more physically grounded representation. They encode ion diffusion, charge-transfer kinetics, electrolyte transport and thermodynamic equilibria, enabling high-fidelity simulation of mechanisms such as lithium plating and SEI layer formation. However, the need to solve coupled partial differential equations makes DFN models computationally expensive and incompatible with embedded microcontrollers found in BMS. Even reduced-order implementations require extensive parameter calibration, limiting their practicality in fielded systems [4].

Despite their limitations, both ECM and DFN models continue to play critical roles in research. ECMs support fast prototyping of estimation algorithms, while electrochemical models provide physically interpretable ground truth for validating AI-driven frameworks and hybrid physics-informed architectures.

C. Limitations and Role in Modern Battery Analytics

Although traditional methods remain indispensable in controlled laboratory settings, they face intrinsic limitations in real-world battery prognostics. Their dependence on highly regulated cycling conditions prevents widespread deployment in systems where load patterns change rapidly, temperatures oscillate unpredictably and full charge–discharge cycles rarely occur. Additionally, traditional approaches lack mechanisms for handling uncertainty, noise and variability across chemistries, manufacturers and application domains.

Recent surveys on SOH estimation emphasize that traditional methods now serve primarily as benchmarking and calibration tools rather than operational diagnostic systems [4], [14]. In particular, datasets derived from ICA, DVA and EIS measurements are increasingly used to label and validate machine learning models providing a bridge between physically interpretable diagnostics and automated AI-driven estimation pipelines [3], [15]. As machine learning and physics-informed neural networks continue to advance, traditional methods maintain their relevance by offering physically meaningful features, validation frameworks and mechanistic insights that purely data-driven systems cannot easily replicate. Table 1. gives comparative analysis of traditional lithium-ion battery state assessment methods.

TABLE I. COMPARATIVE ANALYSIS OF TRADITIONAL LITHIUM-ION BATTERY STATE ASSESSMENT METHODS

Method	Principle/Measurement	Main Advantages	Main Limitations	Typical Use Case
Open-Circuit Voltage and Relaxation	Measures cell voltage at (near) equilibrium to infer SOC/SOH from voltage–capacity curves and their shift over aging;	Simple to implement; no special hardware; good for approximate capacity fade assessment under controlled conditions;	Requires long rest times to reach equilibrium; inaccurate under dynamic EV conditions; sensitive to temperature and hysteresis;	Laboratory characterization; calibration of SOC/SOH models;
Incremental Capacity Analysis	Uses derivative dQ/dV during slow charge/discharge; shifts and distortion of IC peaks correspond to loss of active material, SEI growth, etc.	Very sensitive to aging; can distinguish different degradation modes; useful for SOH tracking in controlled tests;	Requires slow, low-noise cycling; not directly applicable in highly dynamic EV profiles; needs high-resolution data;	Aging mechanism identification; generating labels/features for data-driven SOH models;
Differential Voltage Analysis	Uses derivative dV/dQ; analyzes changes in voltage–capacity slope to track electrode and electrolyte changes;	Provides complementary information to ICA; effective for identifying changes in cathode/anode behavior;	Needs stable cycling; sensitive to measurement noise; less suited for online BMS;	Detailed lab aging studies; feature extraction for ML/DL models;
Direct Capacity Measurement (Full Charge–Discharge Test)	Measures usable capacity by cycling between defined voltage limits at low C-rate;	Direct, intuitive SOH measure; reference method for capacity fade;	Time-consuming; impractical in EV field operation; accelerates aging if done frequently;	Benchmarking aging tests; ground truth for SOH label generation;
Electrochemical Impedance Spectroscopy	Applies small AC perturbation over a range of frequencies; analyzes complex impedance response (Nyquist/Bode plots);	Highly sensitive to early degradation; can separate ohmic, charge-transfer and diffusion contributions; rich diagnostic information;	Requires specialized equipment; difficult to apply during normal driving; sensitive to temperature and SOC;	Laboratory diagnostics; parameter identification for ECM/DFN models; constructing EIS-based SOH indicators;
Equivalent Circuit Models with Parameter Identification	Fits simple RC or Thevenin circuits to dynamic voltage/current response; tracks changes in internal resistance and time constants;	Low computational cost; suitable for embedded BMS; integrates naturally with Kalman filtering for SOC/SOH estimation;	Parameters drift with aging and temperature; limited ability to capture complex nonlinear degradation; requires frequent recalibration;	On-board SOC/SOH estimation in commercial BMS; fast prototyping;
Physics-Based Electrochemical Models (DFN and Reduced-Order)	Solve coupled PDEs describing ion diffusion, charge transfer and transport in electrodes/electrolyte; track internal states and degradation mechanisms;	High physical fidelity; can simulate specific degradation mechanisms (SEI, lithium plating, etc.); useful as virtual lab;	Computationally intensive; demanding parameterization; not directly suitable for real-time embedded BMS;	High-fidelity simulation; digital-twin cores; generation of synthetic training data for AI models;

IV. AI METHODS FOR BATTERY SOH ESTIMATION

Conventional SOH estimation techniques, often based on complex electrochemical models or extensive laboratory testing, tend to require a large number of measurements, advanced instrumentation, and high computational cost [33]. Artificial intelligence has emerged as a transformative tool for estimating the state of health of lithium-ion batteries, addressing many of the limitations inherent in traditional diagnostic techniques. Unlike conventional methods that rely on controlled laboratory conditions, predefined physical models or handcrafted features, AI-based approaches can learn complex nonlinear degradation patterns directly from operational data. Through machine learning, deep learning, physics-informed modeling and, more recently, reinforcement learning, AI enables accurate, scalable and real-time prediction of battery aging under diverse and highly dynamic conditions. These methods leverage large datasets of voltage, current, temperature and cycling histories to infer degradation mechanisms, model long-term capacity fade and internal resistance growth, and provide robust estimates even in the presence of noise, partial cycling or irregular load profiles. AI-based SOH estimation therefore represents a key advancement toward next-generation battery management systems capable of adaptive diagnostics, predictive maintenance and optimized operational control.

A. Rationale for Data-Driven Approaches

The increasing complexity of degradation phenomena in lithium-ion batteries, especially under real-world usage conditions characterized by variable loads, partial cycles, fluctuating temperatures and heterogeneous usage patterns, challenges the applicability of traditional model-based methods. A data-driven SOH estimation model functions on mass data without necessary dependence on the battery internal degradation mechanism [28]. Data-driven approaches, leveraging machine learning or deep learning, offer a flexible alternative by learning empirical mappings between observable telemetry (voltage, current, temperature, cycle count) and internal health indicators, thereby capturing nonlinear, path-dependent effects that are difficult to model analytically [4], [7], [16]. Moreover, as extensive aging datasets become more available, either from laboratory cycling or from fleets of EVs, data-driven algorithms become increasingly viable for robust SOH estimation at scale. In [30], a model that continually learn new aging information while maintaining the ability to estimate the health of batteries that have similar aging conditions to the learned information before, was developed.

A recent comprehensive review demonstrates that DL-based methods consistently outperform classical ML and model-based approaches in SOH estimation tasks, especially when large, diverse datasets are available, and when models are trained to operate under variable charging/discharging regimes [7]. The flexibility of data-driven models allows them to adapt to unknown or complex degradation modes, such as combined capacity fade, impedance rise, or intermittent lithium plating, which vary across cells and usage histories.

B. Machine Learning Methods

Traditional ML methods remain relevant in SOH estimation due to their relatively small computational footprint, interpretability, and requirement for less data. For instance, in [3], feature extraction from a selected voltage interval during charging, derived using incremental capacity analysis, was used as input for random forest regression (RFR) or support vector regression (SVR), resulting in accurate SOH predictions with limited data. This approach reduces the data requirement compared to full-cycle based methods and demonstrates that carefully engineered features can yield effective capacity fade estimates even under constrained data conditions [3]. ML methods can model nonlinear relationships and temporal degradation patterns directly from cycling data [35].

Further, hybrid feature-engineering pipelines combining temporal features, temperature history, internal resistance estimates and statistical descriptors of voltage/current curves have been shown effective in ensemble regressors such as gradient-boosted trees or random forests. These models preserve interpretability of feature importance metrics, facilitating insight into which operational patterns or signal characteristics most strongly correlate with degradation, a property highly valued in industrial BMS design.

C. Deep Learning Architectures: From Time-Series Learning to Hybrid Models

Deep learning brings a paradigm shift by enabling end-to-end learning directly from raw or minimally processed time-series data collected during battery operation, without the need for handcrafted features. For example, a recent systematic review [7] shows that architectures including CNNs, recurrent neural networks (RNNs), TCNs and transformer-based models have been successfully employed for SOH estimation of lithium-ion batteries in EV contexts, achieving high accuracy and robustness across varying datasets.

One notable recent contribution proposed a hybrid DL model that merges convolutional feature extraction, Kolmogorov-Arnold network layers and bidirectional LSTM (BiLSTM), using incremental energy features derived from charging and discharging data to estimate SOH with high precision [17]. This hybrid approach leverages the ability of CNNs to detect localized features, the flexibility of Kolmogorov-Arnold mappings for nonlinear transformation, and the temporal modeling strength of LSTM networks, enabling accurate SOH prediction even under complex and irregular cycling profiles [17].

Another work demonstrated that deep learning frameworks remain effective under real-world constraints by exploiting short-time working condition windows instead of full-cycle data, thereby reducing the data collection burden and computational cost [18]. This development is especially relevant for fleet-level deployment or real-time BMS, where full-cycle capture is impractical.

D. Challenges and Considerations in AI-Based SOH Estimation

Despite the advantages, AI-based methods for SOH estimation come with challenges that warrant careful consideration. First, data quality and representativeness remain critical: models trained on laboratory cycling data may not generalize to field conditions, where load profiles, temperature fluctuations and user behaviors differ substantially. Second, deep learning models often require large amounts of labeled aging data for training; obtaining such data is costly and time-consuming, especially for full lifetime degradation trajectories. Third, interpretability remains a concern because black-box DL models may provide accurate predictions, but without explainable decision logic, their adoption in safety-critical BMS systems can be limited.

Furthermore, hybrid models combining physics-based knowledge with data-driven learning are being explored to mitigate these issues, but integrating such constraints without sacrificing flexibility remains a complex task. The balance between generalization, interpretability, computational efficiency and reliability under unseen conditions defines the current frontier of AI-based battery diagnostics research.

V. Machine Learning and Deep Learning Models for SOH and RUL Estimation

Machine learning and deep learning have become central pillars of modern battery prognostics, offering powerful alternatives to traditional physics-based and feature-engineered methods for estimating the state of health and remaining useful life of lithium-ion batteries. ML techniques provide flexible, data-driven mappings between diagnostic features and degradation states, while DL architectures can learn hierarchical temporal and nonlinear patterns directly from raw voltage, current, and temperature signals. These models have demonstrated superior performance under diverse operating conditions, including dynamic load profiles, partial cycling and variable temperatures, scenarios where conventional approaches typically underperform. With advancements such as attention mechanisms, hybrid CNN-LSTM frameworks, physics-informed networks and reinforcement learning–assisted management strategies, AI-driven battery diagnostics are rapidly evolving toward more accurate, interpretable and deployable solutions for next-generation battery management systems.

A. Overview of Machine Learning Approaches

Machine learning has become a central component of battery state of health estimation because it offers a practical balance between accuracy, computational efficiency and transparency. Instead of depending on complex electrochemical formulations, ML methods learn empirical relationships between voltage, current, temperature and cycling behavior and the underlying degradation mechanisms. This learning capability makes ML particularly useful for real-world conditions where batteries operate under irregular load profiles, partial cycles and fluctuating temperatures. Even relatively simple ML algorithms, such as RFR and SVR, have demonstrated strong predictive capability when supplied with informative engineered features, such as incremental capacity or differential voltage descriptors extracted from selected charging windows [3].

In addition to their computational efficiency, ML models also offer interpretability through feature-importance analysis, allowing engineers to identify specific operational patterns that contribute most to degradation. This makes ML suitable for integration into commercial battery management systems, where explainability and robust performance are essential.

B. Deep Learning Architectures for SOH and RUL Prediction

Deep learning extends the capabilities of ML by learning directly from raw time-series signals with minimal feature engineering. Architectures such as CNNs, LSTM networks and TCNs have shown superior performance over traditional ML methods due to their ability to model nonlinear dynamics and long-range temporal dependencies [7]. Recent hybrid models have further advanced the state of the art by combining CNNs, LSTMs and attention mechanisms, enabling networks to extract both fine-grained and long-term aging patterns. A prominent example is a CNN-LSTM-attention framework optimized through metaheuristic search, achieving sub-percent errors in SOH estimation under diverse cycling protocols [8]. Study [31] proposes a multi-modal deep learning feature extraction method based on charging data to extract comprehensive and effective health indicators that reflect the SOH of the battery for subsequent estimation.

For RUL prediction, CNN-LSTM fusion architectures have also proved effective in learning both local degradation features and global capacity fade trends, outperforming classical prognostic methods under non-uniform operating conditions [9]. These advances highlight the ability of DL models to model complex degradation trajectories using high-dimensional, noisy and non-stationary data.

TABLE II. COMPARISON OF PHYSICS-BASED, MACHINE LEARNING, DEEP LEARNING, HYBRID AND REINFORCEMENT LEARNING METHODS FOR BATTERY SOH/RUL ESTIMATION AND MANAGEMENT

Method Category	Model Characteristics	Data Requirements	Strengths	Limitations
Physics-Based Models	Governed by electrochemical and thermodynamic equations; mechanistic modeling of SEI growth, diffusion, kinetics;	Requires detailed parameterization; EIS, lab characterization; physical parameters;	High interpretability; grounded in physics; good for simulation and diagnostics;	Computationally intensive; parameter identification is difficult; limited performance in dynamic real-world operation;
Machine Learning	RF, SVR, Gradient Boosting; uses engineered features (IC/DV, resistance features);	Moderate-sized datasets; extracted diagnostic features;	Interpretable, fast, low computational load; good for embedded BMS;	Cannot fully capture nonlinear temporal aging; depends on hand-crafted features;
Deep Learning	CNN, LSTM, GRU, ConvLSTM, attention mechanisms;	Large raw time-series datasets (voltage, current, temperature);	Learns nonlinear and temporal patterns directly; state-of-the-art SOH/RUL accuracy;	Opaque (black box); needs large datasets; high computational cost;
Hybrid Physics-Informed Neural Networks	Combines differential equations (electrochemical, thermal) with neural network structure;	Requires both training data and physical constraints;	Higher interpretability; better robustness; improved extrapolation beyond training distribution;	Complex architecture and training process; domain knowledge needed;
Domain Adaptation/ Transfer Learning Models	Self-attention domain adaptation; cross-chemistry and cross-condition generalization;	Shallow-cycle datasets; limited labeled data;	Useful when data is scarce; generalizes across chemistries and labs;	Requires careful calibration; still emerging;
Reinforcement Learning	DQN, PPO, Actor-Critic RL agents for charging, thermal control, and power management;	Interaction with environment or digital twin; real-time operational data;	Learns optimal long-term charging/thermal policies; can reduce degradation; adaptive and real-time;	Requires safe training environment; complex to validate for safety-critical BMS;
Digital Twin–Integrated Models	Hybrid DT + AI frameworks (ML/DL/RL + physics simulators);	Continuous real-time telemetry; physical models;	Enables real-time SOH/RUL monitoring, predictive maintenance, control and anomaly detection;	Requires cloud–edge integration and cybersecurity; model complexity;

TABLE III. COMPARATIVE PERFORMANCE OF ML, DL AND RL MODELS FOR BATTERY SOH/RUL ESTIMATION AND MANAGEMENT

Model Type	Algorithm/Architecture	Dataset/Conditions	Performance Metrics (Reported)	Key Outcome
Machine Learning	RF, SVR	Selected charging voltage interval (12–50% SOC)	RMSE: <2.5% SOH (RF), MAE: ≈2%	Feature-based ML achieves strong SOH estimation with limited data
Deep Learning	Hybrid CNN-LSTM-Attention	Benchmark cycling data; full & partial cycles	RMSE: 0.87%, MAE: 0.82%	Attention-based DL achieves sub-percent SOH estimation accuracy
	CNN-LSTM Fusion + Grey Relational Analysis	Realistic variable cycling data	RUL error: <5%, R^2: >0.97	Hybrid DL captures both localized and long-term degradation trends
	Hybrid Pack-Level DL Classifier-Regressor	Series-connected battery pack with cell inconsistency	SOH Classification Accuracy: 96.4%; Regression MAE: ≈3%	DL effective for pack-level SOH estimation with heterogeneous cells
	ConvLSTM with Attention + Metaheuristic Optimization	Multi-feature energy increment dataset; EV-like operation	RMSE: 0.75%, MAE: 0.68%	Advanced DL with metaheuristics yields highest reported SOH accuracy
Domain Adaptation (DL)	Self-Attention Domain-Adaptation Network	Shallow-cycle dataset; cross-domain	MAE: ≈2% after domain alignment	Transfer learning significantly reduces data requirements
Reinforcement Learning	DQN Charging Controller	Fast-charging environment; real EV-like constraints	Charging time reduced by ~30%; degradation greatly reduced vs. CC/CV	RL learns optimal fast-charging strategy while mitigating SEI growth
	DRL-based Charging Optimization	Real multiple-cycle EV operational dataset	SOH degradation reduction: up to 20% vs. baseline CC/CV	DRL adaptively regulates charging to minimize capacity fade
	RL Thermal + Health Management Agent	EV-like load profiles; combined cooling and aging optimization	Temperature deviation reduced by >15% and aging suppressed	RL balances power demand, temperature and longevity in real-time

C. Recent Developments and Specialized DL Models

Modern studies have expanded DL applications beyond single cells to include pack-level diagnostics, where cell inconsistency and differential aging complicate modeling tasks. Hybrid deep learning models have achieved high accuracy in SOH classification and estimation for series-connected cells, demonstrating their applicability in electric vehicle battery packs [19]. Furthermore, emerging research in domain adaptation and transfer learning shows that deep models can successfully adapt across chemistries, manufacturers or shallow-cycle datasets, thereby reducing the need for exhaustive long-life cycling experiments [20].

D. Reinforcement Learning for Adaptive Battery Management

In addition to supervised ML and DL methods used for SOH and RUL estimation, reinforcement learning has gained increasing attention for its ability to autonomously optimize battery operating conditions. Unlike supervised learning, which passively predicts battery health indicators, RL actively interacts with the environment and learns control policies that optimize long-term battery performance. This is particularly relevant for charging strategies, thermal regulation and power allocation, where the effects of operational decisions accumulate over time and influence degradation trajectories.

Several studies demonstrate that deep reinforcement learning (DRL) algorithms, such as deep Q-networks (DQN) or proximal policy optimization (PPO), can design optimal charging protocols that significantly reduce capacity fade compared to conventional CC/CV) methods [21], [22]. RL-based policies adapt charging currents in real time based on feedback such as temperature, voltage gradients or estimated internal resistance, resulting in improved safety and reduced SEI-related aging. RL has also been integrated with battery thermal management systems, where agents learn to balance cooling effort, power demand and aging minimization under vehicle-like load fluctuations [23], [24].

A growing research direction involves combining RL with digital twin simulators to ensure safe, scalable training without risking physical assets. In these frameworks, the RL agent interacts with a high-fidelity electrochemical or data-driven virtual battery model, enabling millions of simulated charge and discharge cycles to be performed rapidly and safely. As digital twin infrastructure for batteries matures, RL-based management is expected to become a foundational component of next-generation intelligent BMS architectures.

E. Advantages and Limitations of Data-Driven and RL Approaches

ML and DL methods provide high predictive accuracy and strong generalization when trained on sufficiently rich datasets, while RL methods extend these capabilities to real-time decision-making for charging optimization, thermal control and power management. However, all learning-based methods face challenges related to data availability, model interpretability, domain shift and computational constraints. DL and RL algorithms in particular require substantial datasets and high-fidelity simulators, and their deployment in embedded systems demands model compression, rigorous safety validation and robust uncertainty handling.

Despite these challenges, data-driven SOH/RUL estimation combined with RL-based control strategies represents a promising path toward fully adaptive, predictive and health-aware battery management systems. Comparison of physics-based, machine learning, deep learning, hybrid and reinforcement learning methods for battery SOH/RUL estimation and management are given in Table 2. while Table 3. summarizes performance of ML, DL and RL models for battery SOH/RUL estimation and management. Table 4. contains overview of common machine learning, deep learning, physics-informed and reinforcement learning models for SOH/RUL prediction and battery management.

VI. Challenges in AI-Based Battery Health Estimation

Artificial intelligence has significantly advanced the accuracy and scalability of battery state of health and remaining useful life estimation, yet several critical challenges continue to limit its reliability and widespread deployment. AI models must contend with heterogeneous and often scarce battery aging datasets, strong sensitivity to domain shifts across chemistries and operating conditions, and the lack of standardized evaluation protocols. Deep learning architectures, while powerful, frequently behave as black-box systems whose decisions are difficult to interpret, raising concerns in safety-critical applications such as electric vehicles and renewable energy storage. Model robustness, generalization, computational constraints in embedded battery management systems, and the need for physics consistency further complicate real-world implementation. Understanding these limitations is essential for

TABLE IV. Overview of Common Machine Learning, Deep Learning, Physics-Informed and Reinforcement Learning Models for SOH/RUL Prediction and Battery Management

Method Category	Representative Algorithms	Key Input Features / Data Requirements	Strengths	Limitations
Traditional Machine Learning	RF, SVR, Gradient Boosting	Engineered features (IC, DV curves, voltage interval features, resistance estimates);	Interpretable, computationally efficient, small datasets sufficient	Requires manual feature engineering, limited temporal modeling
Convolutional Neural Networks	1D-CNN, multi-channel CNN	Raw voltage/current curves, incremental capacity curves;	Powerful local pattern extraction, robust to noise	Limited modeling of long-term time dependencies
Recurrent Neural Networks	LSTM, GRU, BiLSTM	Full or partial cycling time-series, temperature history;	Captures temporal degradation trends, suitable for RUL	Requires large sequences, higher computational cost
Hybrid CNN–RNN Architectures	CNN-LSTM, CNN-GRU, ConvLSTM	Raw + derived signal features; energy increments;	State-of-the-art SOH/RUL accuracy; multi-scale degradation learning;	High complexity; needs large training datasets;
Attention-Based Models	CNN-LSTM-Attention, Transformer-like models	Raw time-series + engineered features;	Learns long-range dependencies; strong generalization;	Black-box behavior, high computational cost
Physics-Informed Neural Networks	Physics-informed SOH models, hybrid electrochemistry+DL	Combines electrochemical constraints with time-series data (e.g., SEI evolution, kinetic parameters);	Improves interpretability and extrapolation; reduces data requirements;	Training complexity; requires physical domain knowledge
Domain Adaptation/Transfer Learning	Self-attention domain adaptation, cross-chemistry adaptation	Shallow-cycle or heterogeneous datasets;	Works with limited data; adaptable across chemistries;	Requires careful calibration; not yet standard;
Reinforcement Learning	DQN, PPO, Actor-Critic agents	Environment interaction; digital twin simulators; charging/thermal states, constraints;	Learns optimal charging/thermal control policies; reduces degradation; real-time adaptive control;	Needs high-fidelity simulators; safety constraints; computational complexity;
Digital Twin–Integrated Models	AI-enhanced digital twins (DT + ML/DL/RL)	Real-time EV telemetry + physical models;	Enables continuous SOH/RUL tracking, predictive maintenance	Complex multi-layer integration; cybersecurity issues;

guiding future research toward more transparent, validated and industry-ready AI-based prognostic solutions.

A. Data Availability, Quality and Representativeness

One of the most critical barriers to reliable AI-based SOH estimation is the limited availability of high-quality battery aging datasets. Training deep learning models typically requires long-duration cycling data covering the full battery lifetime under multiple temperatures, load conditions and charging protocols. However, acquiring such datasets is costly and time-intensive: cycling experiments may take months or years, and many battery manufacturers restrict access to proprietary test data. As emphasized in recent literature, publicly available datasets often include only a few cells, limited operating conditions, or incomplete life-cycle trajectories [7], [14].

Furthermore, laboratory datasets frequently fail to represent real-world electric vehicle usage patterns, which include variable C-rates, regenerative braking, temperature fluctuations and partial cycles. This mismatch introduces dataset shift, causing AI models trained in controlled environments to underperform when deployed in actual BMS applications. Transfer-learning and domain-adaptation approaches attempt to mitigate this challenge but require careful implementation and validation [20].

B. Generalization Across Chemistries, Manufacturers and Cycling Regimes

Lithium-ion batteries differ significantly across chemistries (NMC, LFP, NCA), electrode formulations, manufacturing tolerances and pack-level configurations. Degradation pathways, such as SEI growth, cathode microcracking or lithium plating, manifest differently depending on the chemistry and operating conditions. As a result, AI models trained on one type of cell often fail when applied to another. Recent studies confirm that even small variations in cycling temperature, charging profile or manufacturer batch can lead to substantial prediction errors if not properly accounted for [4], [7].

Ensuring model generalization requires either extremely diverse training datasets, explicit domain adaptation mechanisms or hybrid models integrating physics-based constraints. Without such approaches, AI-based SOH estimation risks becoming overly specialized and unreliable for deployment across heterogeneous battery fleets.

C. Interpretability, Explainability and Safety Requirements

A major challenge for the adoption of AI methods in safety-critical applications such as EVs is the limited interpretability of deep neural networks. Traditional model-based estimation methods offer clear, physically meaningful parameters (e.g. ohmic resistance or diffusion coefficients), whereas deep learning models operate as high-dimensional nonlinear function approximators with limited transparency. Integrating physical models with data-driven models can enhance the interpretability and transparency of the overall system, thereby fostering greater trust and reliability in the predictions [32].

This black-box nature complicates validation, certification and troubleshooting, especially when predictions influence safety-relevant decisions such as charge acceptance limits or thermal management. Recent surveys highlight that explainable AI (XAI) remains underdeveloped for battery applications, and that PINNs may offer a promising path by embedding electrochemical constraints into the learning process to improve transparency and reliability [11], [13], [25].

D. Computational Constraints and Deployment Challenges

Commercial battery management systems operate on embedded microcontrollers with limited memory, processing power and energy budget. Deep learning models, particularly convolutional and recurrent architectures, may require millions of parameters and substantial computational resources, making them difficult to deploy without model compression or distillation.

Moreover, real-time operation demands low-latency prediction, especially in EV applications where SOH estimation may influence charging control, thermal regulation or power-limiting decisions. Only a small subset of research on AI-based SOH estimation explicitly considers inference latency, memory footprint or computational scalability, creating a gap between academic prototypes and deployable BMS solutions [7], [26].

E. Lack of Standardized Metrics, Protocols and Validation Frameworks

Evaluation methodologies for SOH estimation vary widely across studies, making direct performance comparison challenging. Researchers use different metrics (MAE, RMSE, R^2), state definitions (capacity-based, impedance-based, hybrid), preprocessing techniques and cycling protocols. This heterogeneity hinders reproducibility and slows progress toward regulatory or industrial standards.

Recent reviews stress the urgent need for standardized testing frameworks, benchmark datasets and unified validation procedures to ensure reliable comparison of AI-based SOH models and to accelerate their certification for industrial use [4], [14]. Digital-twin-oriented methodologies have been suggested as a potential solution, enabling closed-loop validation of AI models against physical models and real-world data streams [12].

VII. Future Directions in AI-Driven Battery Health Estimation

A. Integration of Physics-Informed AI and Hybrid Modeling

A major direction for future research lies in the deeper integration of physics-based constraints into machine learning frameworks. Physics-informed neural networks, electrochemical constraint-regularized architectures and hybrid models that incorporate surrogate electrochemical behavior are expected to bridge the gap between empirical accuracy and physical interpretability. Given the promising results recently demonstrated for degradation modeling and long-term prognosis [11], [13], next-generation SOH estimation algorithms will likely adopt hybrid learning structures capable of fusing mechanistic laws with data-driven flexibility. Such models may enable robust extrapolation beyond the training domain, improve stability under sparse or noisy data, and support certification for safety-critical industrial applications.

Furthermore, hybrid frameworks enabling real-time parameter identification (e.g. SEI resistance growth, diffusion coefficients or charge-transfer kinetics) may help unify traditional analytic diagnostics with modern AI inference engines. This synergy is expected to become central in EV BMS architectures within the next decade.

B. Development of Universal and Transferable Battery Health Models

The increasing diversity of lithium-ion battery chemistries, formats and operating environments demands models that can generalize across a wide spectrum of conditions. Transfer learning, meta-learning and domain-adaptation methods show promise for enabling cross-chemistry, cross-manufacturer and cross-environment SOH estimation. Initial studies already demonstrate that domain adaptation using self-attention networks significantly improves SOH inference when only shallow-cycle data are available [20].

Future work will likely focus on large-scale foundation models for battery health (analogous to developments in natural language processing and computer vision) trained on multisource datasets covering various chemistries (NMC, LFP, NCA), formats (18650, pouch, prismatic) and use patterns (EV, grid storage, consumer electronics). These universal models may eventually be fine-tuned for specific applications using small amounts of new data, reducing the burden of long-term cycling experiments

C. Federated Learning and Edge-AI for Privacy-Preserving Fleet Deployment

As EV manufacturers accumulate massive quantities of operational data from vehicles in the field, concerns regarding data privacy, proprietary control and communication bandwidth limit the direct centralization of cell-level telemetry. Federated learning offers a promising solution by allowing distributed training across vehicles while keeping raw data local. Each device contributes model updates rather than raw sensor streams, preserving privacy and minimizing network load.

Edge-AI architectures, combining embedded inference with cloud synchronization, may enable real-time SOH estimation at the vehicle level while continuously improving the global model. This hybrid cloud–edge deployment strategy supports scalable fleet-level monitoring and may shorten the development cycle for adaptive BMS software. Emerging digital twin frameworks already incorporate such distributed intelligence structures, suggesting strong potential for real-world integration [12].

D. Model Interpretability and Explainability

Despite the rapid progress in machine learning and deep learning for battery SOH/RUL prediction, interpretability remains one of the most pressing challenges. Models deployed in electric vehicles and grid-scale storage must operate under strict safety and reliability constraints, and their decisions, especially in boundary or abnormal operating conditions, must be transparent and traceable. Traditional deep learning architectures often function as opaque black boxes, providing no direct means for operators or engineers to understand how input variables contribute to outputs.

Recent research has begun addressing this gap through XAI and hybrid optimization techniques. Paper [25] demonstrated that integrating PSO optimization with interpretable deep learning enables models to identify which temporal features most strongly correlate with degradation trajectories, while still achieving competitive prediction accuracy. The work illustrates that high-performance SOH models can be both accurate and explainable, showing which voltage, current or temperature signatures are most relevant to predicted aging behavior. This direction is critical for earning regulatory acceptance, improving diagnostic confidence, and enabling BMS engineers to validate predictions in safety-critical environments.

Future work will likely expand on these ideas by combining interpretable DL with physics-informed modeling, uncertainty quantification, and domain adaptation to create models that are not only powerful but also transparent, robust and generalizable across battery chemistries and applications.

E. Digital Twins and Real-Time

Digital twin systems have emerged as a powerful framework for integrating physical models, sensor data and AI predictions into a unified dynamic representation of a battery or battery pack. As reviewed in recent work [12], AI-enhanced digital twins can continuously synchronize with field measurements, enabling real-time SOH estimation, fault detection, charging optimization and RUL forecasting.

The future of SOH estimation will likely involve multi-scale battery digital twins that incorporate cell-level degradation models, pack-level electrical and thermal interactions, and vehicle-level operational context. AI models embedded within these twins can adapt using online learning mechanisms as new data become available. This approach supports proactive maintenance, warranty analytics and extended battery lifetimes.

F. Standardization, Benchmarking and Regulatory Frameworks

One of the most important future directions concerns the establishment of standardized datasets, evaluation protocols and safety-certification methodologies. Current research suffers from inconsistent cycling procedures, nonuniform data-splitting strategies and incompatible metrics. Industry-wide benchmarks, similar to those used in autonomous driving or computer vision, will be game-changing for the validation and comparison of SOH estimation methods [4].

Regulatory bodies and standards organizations will need to define certification pathways for AI-based BMS algorithms. Future standards may specify minimum training data requirements, robustness testing, uncertainty quantification and explainability thresholds. Interoperability frameworks may also emerge, ensuring that AI-based health estimation modules can be deployed reliably across different EV platforms and energy storage systems.

G. Explainability, Uncertainty Quantification and Reliability

As AI becomes central to BMS design, future work must address the critical issues of explainability and uncertainty quantification. Techniques for interpretable deep learning, model confidence estimation and Bayesian neural networks are promising. These methods enable BMS designers to assess when predictions are trustworthy and to detect out-of-distribution conditions. Physics-informed explainable models, in particular, may offer a strong balance between mechanistic transparency and predictive accuracy [11], [26].

Increasing reliability under noisy conditions, model deterioration, hardware limitations and adversarial disturbances will also remain a major focus. Robust AI models capable of operating with minimal calibration and self-correcting through online learning or self-supervised strategies will be essential for next-generation battery platforms.

VIII. CONCLUSION

The rapid expansion of electric vehicles, renewable energy systems and distributed storage technologies has elevated the importance of accurate and reliable battery state-of-health and remaining useful life estimation. While traditional methodologies, such as electrochemical diagnostics, equivalent circuit models and reduced-order physics-based approaches, remain essential for understanding degradation mechanisms and generating high-quality reference data, their limitations under dynamic operating conditions highlight the need for more adaptive and data-rich diagnostic tools.

Artificial intelligence has become a transformative enabler in this domain. Machine learning methods provide robust and interpretable SOH estimates when supported by carefully engineered features, whereas deep learning architectures can autonomously extract degradation-sensitive representations from raw voltage–current–temperature data, achieving state-of-the-art predictive accuracy. Hybrid, physics-informed neural networks further enhance generalization by combining the flexibility of data-driven learning with the interpretability and physical consistency of electrochemical models.

Beyond prediction, reinforcement learning introduces a new dimension to battery management by enabling agents to learn optimal charging, thermal control and power regulation strategies that minimize long-term degradation. When combined with high-fidelity digital twins, RL- and DL-based control policies can be trained safely and efficiently, supporting real-time, adaptive and fleet-wide battery management solutions.

Conventional, commercially available BMSs usually provide SOH estimates that are good enough for safe operation and warranty management, but they often fall short of being highly accurate and consistently reliable across all real-world conditions, especially as batteries age, operate under highly dynamic loads, or experience wide temperature swings. In practice, traditional SOH can be stable but not always precise, especially near end-of-life or under unusual duty cycles. AI methods can outperform traditional SOH estimation in challenging regimes because they can learn nonlinear, history-dependent degradation patterns from large datasets, use partial-cycle data effectively (important for EV usage), fuse many signals (voltage/current/temperature, operational context, sometimes impedance or diagnostics) to improve sensitivity, and adapt to different conditions using transfer learning/domain adaptation. AI-based approaches can improve accuracy, sensitivity, and adaptability, but they introduce new validation, robustness, and explainability challenges that matter a lot for real products.

Despite significant progress, several challenges remain unresolved. These include the scarcity of comprehensive aging datasets, limited generalization across chemistries and manufacturers, the black-box nature of deep models, computational constraints in embedded BMS hardware, and the absence of standardized validation procedures. Addressing these gaps will require closer integration of physics-informed AI, domain adaptation techniques, federated learning architectures and rigorous benchmarking frameworks.

Overall, the convergence of advanced AI methods, reinforcement learning, and digital twin technologies points toward a new generation of intelligent battery management systems capable of delivering accurate health diagnostics, predictive maintenance, and degradation-aware control. These developments are poised to significantly enhance battery safety, performance and lifetime in both existing and future energy storage applications.

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