State of Health (SOH) Monitoring for Battery Management System (BMS) in Electric Vehicles

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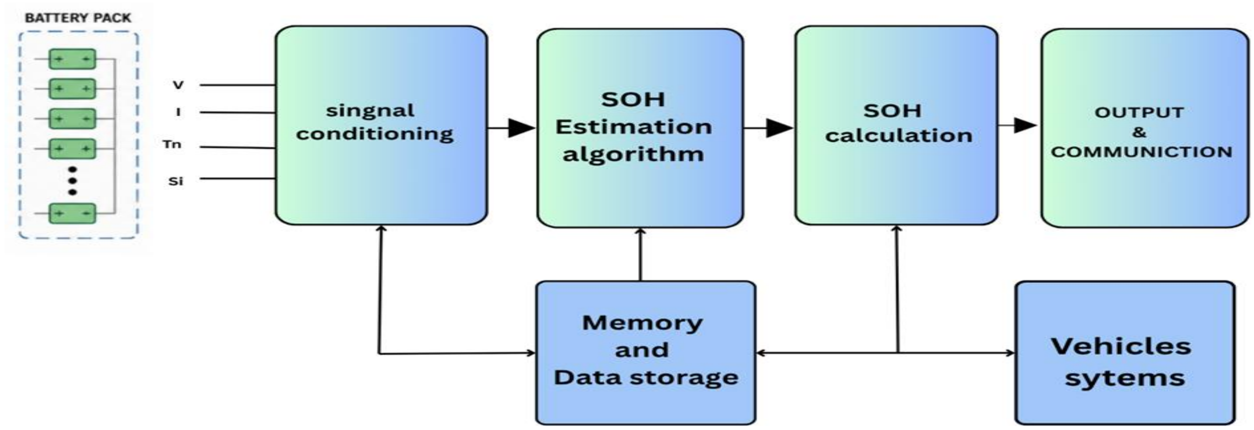
***Abstract*—The rapid global transition toward sustainable mobility has positioned Electric Vehicles (EVs) at the forefront of modern transportation. Central to EV performance, safety, and longevity is the Battery Management System (BMS), which acts as both a supervisor and caretaker for high-voltage battery packs. Among the critical parameters monitored by a BMS, the State of Health (SOH) stands out as a vital yet abstract metric that reflects battery degradation, remaining useful life, and overall operational reliability. Unlike voltage or current, SOH cannot be directly measured and must be inferred through advanced estimation techniques that correlate measurable physical quantities with internal battery aging. This paper presents a comprehensive framework for SOH monitoring in EVs, analysing model-based, data-driven, and hybrid estimation methodologies. It details the mathematical and algorithmic foundations of techniques such as Equivalent Circuit Models (ECMs), internal resistance and impedance tracking, Coulomb counting, Kalman filtering, neural networks, fuzzy logic, and ultrasonic wave detection. Furthermore, the study explores the integration of these SOH estimation methods within modern BMS architectures and examines how emerging EV platforms leverage artificial intelligence, cloud connectivity, wireless monitoring, and advanced thermal management to enhance battery health prognostics. By synthesizing experimental insights and contemporary industry practices, this work underscores the necessity of robust, multi-dimensional SOH assessment for optimizing EV performance, enabling predictive maintenance, extending battery lifespan, and supporting global decarbonization goals.**

***Index Terms*—Battery Management System (BMS), State of Health (SOH), State of Charge (SOC), Electric Vehicle (EV), Equivalent Circuit Model (ECM), Kalman Filter, Machine Learning, Ultrasonic Detection, Battery Degradation, Energy Storage Systems.**

I. INTRODUCTION

The automotive industry is undergoing a paradigm shift from internal combustion engines (ICEs) to electrified propulsion systems. Driven by stringent environmental regulations, fluctuating fossil fuel prices, and advancements in energy storage technologies, Electric Vehicles (EVs) have witnessed exponential growth over the past decade. At the core of every EV lies the high-capacity battery pack, typically composed of lithium-ion (Li-ion) cells, which dictates vehicle range, acceleration, charging speed, and overall operational cost.

However, battery performance is inherently dynamic and degrades over time due to electrochemical aging, thermal stress, mechanical wear, and operational cycling. To ensure safe, efficient, and reliable battery operation, modern EVs employ a Battery Management System (BMS).



BLOC DIAGRAM FOR Battery Management System (BMS) in Electric Vehicles

A BMS is a multifaceted electronic control unit responsible for monitoring, regulating, and protecting battery cells. It continuously tracks critical parameters such as cell voltage, pack current, temperature distribution, State of Charge (SOC), and State of Health (SOH). While SOC indicates the remaining usable energy as a percentage of the current maximum capacity, SOH represents the battery's overall condition relative to its original factory specifications. SOH is typically expressed as a ratio of current maximum capacity or internal resistance to nominal values, often denoted as SOH_C(capacity-based) or SOH_R(resistance-based). Accurate SOH estimation is indispensable for predicting remaining useful life (RUL), optimizing charge/discharge strategies, preventing thermal runaway, scheduling maintenance, and enabling second-life applications for retired EV batteries.

Despite its importance, SOH cannot be measured directly using conventional sensors. It must be inferred through indirect indicators and computational models that correlate observable electrical, thermal, or acoustic signals with internal degradation mechanisms. Traditional approaches such as cycle counting or open-circuit voltage (OCV) tracking offer simplicity but lack precision under real-world driving conditions. Advanced methodologies, including electrochemical modelling, Kalman filtering, and machine learning algorithms, have emerged to address these limitations. However, challenges remain in computational complexity, sensor noise, real-time adaptability, and cross-chemistry generalization.

This paper systematically reviews and reframes the state-of-the-art SOH monitoring techniques applicable to EV battery packs. It provides a detailed exposition of model-based and data-driven estimation strategies, mathematical formulations for internal resistance and impedance assessment, and the integration of modern computational algorithms within BMS frameworks. Additionally, it explores how leading EV manufacturers and research institutions are deploying next-generation technologies to enhance SOH prognostics. By synthesizing theoretical foundations with practical implementation insights, this work aims to provide a comprehensive reference for researchers, engineers, and policymakers engaged in EV battery health management and sustainable mobility development.

II. LITERATURE SURVEY

Accurate SOH estimation has been a focal point of battery research for over two decades. The literature reveals a diverse array of methodologies, each with distinct advantages, limitations, and application domains. These techniques can be broadly categorized into model-based, empirical/data-driven, and hybrid approaches.

A. Model-Based Estimation Techniques

Model-based methods rely on mathematical representations of battery dynamics to infer SOH through parameter identification. Equivalent Circuit Models (ECMs) are among the most widely adopted due to their balance between accuracy and computational efficiency. ECMs simulate battery behaviour using combinations of voltage sources, resistors, and RC (resistor-capacitor) networks.

Parameters such as ohmic resistance, polarization resistance, and double-layer capacitance are extracted via system identification techniques (e.g., least squares, recursive algorithms) and tracked over time to quantify degradation. However, ECMs are phenomenological and do not capture underlying electrochemical mechanisms, limiting their extrapolation capability under extreme operating conditions.

Electrochemical models, such as the Pseudo-Two-Dimensional (P2D) model, offer higher fidelity by simulating ion transport, charge transfer kinetics, and solid-phase diffusion within electrodes. These models can precisely predict capacity fade and resistance growth but demand extensive computational resources and detailed cell-specific parameters, making them less suitable for real-time BMS implementation. Recent advancements have focused on reduced-order electrochemical models and physics-informed neural networks (PINNs) to bridge the gap between accuracy and real-time feasibility.

B. Voltage and Capacity Tracking Methods

Capacity fade monitoring remains a direct indicator of SOH. By periodically performing full charge-discharge cycles under controlled conditions, the actual available capacity can be measured and compared to the rated capacity. Voltage profile analysis complements this by identifying shifts in charge/discharge curves, such as plateau slope changes or hysteresis expansion, which correlate with active material loss and electrolyte decomposition. While highly accurate in laboratory settings, these methods are impractical for continuous onboard monitoring due to time constraints, operational disruptions, and dependency on ideal charging conditions.

C. Internal State Indicators

Internal resistance (IR) and open-circuit voltage (OCV) are extensively used as SOH proxies. IR increases monotonically with aging due to SEI (Solid Electrolyte Interphase) layer growth, contact resistance degradation, and electrolyte dry-out. OCV-SOC curves also shift as electrode materials undergo structural changes. Cycle counting provides a rudimentary SOH estimate by tracking cumulative charge-throughput, but it fails to account for depth of discharge (DoD), temperature variations, and C-rate effects, leading to significant estimation errors in dynamic driving cycles.

D. Data-Driven and Machine Learning Approaches

The proliferation of high-frequency telematics data and edge computing has accelerated the adoption of data-driven SOH estimation. Kalman filtering techniques, particularly Extended Kalman Filters (EKF) and Unscented Kalman Filters (UKF), have become industry standards for real-time state estimation. By recursively updating state variables based on noisy measurements and process models, Kalman filters effectively mitigate sensor drift and nonlinearity. However, their performance heavily depends on accurate initial parameterization and noise covariance tuning.

Machine learning algorithms, including artificial neural networks (ANNs), support vector machines (SVMs), and gradient boosting models, have demonstrated remarkable predictive capabilities. ANNs can map complex, nonlinear relationships between historical charging profiles, temperature histories, and SOH without explicit physical modelling. Fuzzy logic systems excel in handling imprecise or incomplete data by applying rule-based inference engines, making them suitable for embedded BMS with limited computational overhead. Recent studies have also explored ultrasonic guided wave monitoring, where changes in acoustic wave amplitude, phase, and travel time correlate with internal structural degradation, gas generation, and electrode delamination.

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IV. METHODOLOGY

The accurate estimation of SOH requires a systematic methodology that integrates measurable electrical parameters, advanced algorithms, and real-time data processing. This section delineates the core techniques employed in modern BMS architectures, along with their mathematical foundations and implementation strategies.

A. Model-Based Methods

1. Equivalent Circuit Models (ECMs)

ECMs approximate battery terminal behaviour using an open-circuit voltage source $V_{OC}(SOC)$ in series with an ohmic resistance R_0 and one or more RC parallel networks (R_p, C_p) representing polarization dynamics. The terminal voltage V_t is expressed as:

$$V_t(t) = V_{OC}(SOC(t)) - I(t)R_0 - \sum_{i=1}^{n} V_{p,i}(t) \quad 4.1$$

where $V_{p,i}$ follows the differential equation:

$$\frac{dV_{p,i}}{dt} = \frac{I(t)}{C_{p,i}} - \frac{V_{p,i}(t)}{R_{p,i}C_{p,i}} \quad 4.2$$

SOH is estimated by tracking the gradual increase in R_0 and R_p over cycling. Parameter identification is typically performed using recursive least squares (RLS) or online optimization algorithms.

2. Electrochemical Models

Reduced-order electrochemical models simplify the P2D framework by assuming uniform electrolyte concentration and linearizing solid-phase diffusion. SOH is derived from estimated active lithium inventory loss and electrode thickness variation. While computationally intensive, these models enable early detection of degradation modes such as lithium plating and SEI thickening.

B. Voltage and Capacity Tracking

1. Capacity Fade Monitoring

SOH based on capacity is defined as:

$$SOH_C = \frac{C_{actual}}{C_{rated}} \times 100\% \quad 4.3$$

where C_{actual} is obtained by integrating discharge current over a full cycle. Real-time implementation relies on partial charge/discharge segments extrapolated using incremental capacity analysis (ICA) or differential voltage analysis (DVA).

2. Voltage Profile Analysis

Aging-induced shifts in voltage plateaus are quantified using feature extraction techniques such as peak identification in dQ/dV curves. Machine learning classifiers map these features to SOH labels trained on historical degradation datasets.

C. State Indicators

1. Internal Resistance Measurement

DC internal resistance R_{DC} is calculated using Ohm's law during load transients:

$$R_{DC} = \frac{V_{OC} - V_{load}}{I_{load}} \quad 4.4$$

where V_{OC} is measured after a relaxation period, V_{load} is the terminal voltage under current I_{load}. SOH inversely correlates with R_{DC}.

2. Open Circuit Voltage (OCV) and Cycle Counting

OCV-SOC hysteresis expansion and cycle accumulation provide supplementary SOH indicators. Cycle counting requires DoD normalization and temperature correction factors to improve accuracy.

D. Coulomb Counting

SOC is updated via:

$$SOC(t) = SOC(t_0) - \frac{1}{C_n}\int_{t_0}^{t} \eta I(\tau)d\tau \quad 4.5$$

where η is Coulombic efficiency. SOH degradation manifests as a reduction in C_n, which can be estimated by comparing integrated charge to known capacity fade trends. Sensor drift necessitates periodic recalibration using OCV or model-based correction.

E. Data-Driven Methods

1. Kalman Filtering

EKF linearizes nonlinear battery models around operating points. The state vector $x = [SOC, R_0, V_{p1}, \ldots]^T$ is updated recursively:

$$x_{k|k-1} = f(x_{k-1|k-1}, I_k) \quad 4.6$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \quad 4.7$$

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \quad 4.8$$

$$x_{k|k} = x_{k|k-1} + K_k(V_{meas,k} - h(x_{k|k-1}, I_k)) \quad 4.9$$

SOH is extracted from tracked parameter trajectories.

2. Neural Networks

Feedforward or recurrent neural networks (RNNs/LSTMs) process time-series voltage, current, and temperature data to predict SOH. Training involves minimizing mean squared error (MSE) between predicted and experimentally validated SOH values. Transfer learning enables cross-chemistry adaptation.

3. Fuzzy Logic
Fuzzy inference systems (FIS) map input variables (e.g., ΔR, temperature variance, charge time) to linguistic SOH categories (e.g., Excellent, Good, Fair, Poor). Membership functions and rule bases are tuned using expert knowledge or optimization algorithms.

4. Ultrasonic Detection
Ultrasonic guided waves propagate through battery cells, with amplitude attenuation and phase shift correlating with internal gas accumulation, electrode cracking, and electrolyte depletion. Time-of-flight (ToF) and frequency-domain analysis enable non-invasive SOH assessment, particularly valuable for solid-state and high-energy-density cells.

F. Hybrid Integration Strategy
Modern BMS architectures employ multi-sensor fusion and algorithmic blending. A typical pipeline includes:
1. Real-time data acquisition (voltage, current, temperature, acoustic sensors)
2. Preprocessing (noise filtering, outlier rejection, synchronization)
3. Parallel SOH estimation via ECM-Kalman, ANN, and fuzzy logic modules
4. Confidence-weighted fusion using Dempster-Shafer theory or Bayesian averaging
5. Cloud synchronization for fleet-wide degradation modelling and predictive maintenance alerts

This methodology ensures robustness, adaptability, and compliance with automotive functional safety standards (ISO 26262).

V. LATEST TECHNOLOGIES IN VARIOUS ELECTRIC VEHICLES

The integration of advanced SOH monitoring techniques has evolved alongside rapid innovations in EV architectures, battery chemistries, and digital infrastructure. Leading manufacturers and technology providers are deploying next-generation solutions to enhance battery health prognostics, optimize energy utilization, and extend vehicle lifespan.

A. Advanced Battery Chemistries and Platforms
Lithium Iron Phosphate (LFP) batteries, popularized by BYD's Blade Battery architecture, exhibit exceptional cycle life and thermal stability, reducing SOH degradation rates under high-temperature operation. Nickel Manganese Cobalt (NMC) and Nickel Cobalt Aluminium (NCA) chemistries, utilized by Tesla, Rivian, and General Motors, prioritize energy density but require sophisticated BMS algorithms to mitigate capacity fade and lithium plating. Emerging solid-state batteries promise enhanced safety and higher SOH retention by eliminating flammable liquid electrolytes, though manufacturing scalability and interfacial resistance management remain challenges.

B. Cloud-Connected and Wireless BMS
Traditional wired BMS harnesses are being replaced by Wireless Battery Management Systems (W-BMS), as demonstrated in General Motors' Ultium platform. W-BMS reduces wiring complexity, weight, and failure points while enabling seamless over-the-air (OTA) updates. Coupled with cloud connectivity, telematics data from millions of vehicles is aggregated to train fleet-wide machine learning models that predict SOH degradation patterns, optimize charging schedules, and issue early fault warnings. Digital twin technology creates virtual replicas of physical battery packs, simulating aging trajectories under real-world usage and environmental conditions.

C. AI and Edge Computing Integration
Modern EVs incorporate edge-AI processors within the BMS to execute real-time SOH estimation without cloud dependency. Tesla's onboard neural networks analyse charging curves, thermal gradients, and driving habits to dynamically adjust power limits and recommend optimal charging thresholds (e.g., limiting charge to 80% for daily use). Hyundai and Kia's 800V ultra-fast charging architecture integrates predictive SOH algorithms that modulate charge current to minimize lithium plating and electrolyte oxidation during high-C-rate sessions.

D. Thermal Management and Fast Charging Optimization
Effective thermal management directly influences SOH degradation. Liquid cooling plates, phase-change materials (PCM), and heat pump systems maintain cell temperatures within optimal ranges (20–35°C), slowing SEI growth and capacity fade. Advanced fast-charging protocols employ SOH-aware current profiling, reducing peak currents as internal resistance

increases. Vehicle-to-Grid (V2G) and vehicle-to-home (V2H) systems require bidirectional SOH monitoring to assess degradation impact from grid cycling and schedule maintenance accordingly.

E. Standardization and Regulatory Frameworks
Industry consortia are working toward standardized SOH metrics and reporting protocols. The Society of Automotive Engineers (SAE) and International Electrotechnical Commission (IEC) are developing guidelines for SOH disclosure, second-life certification, and battery passport documentation. These initiatives ensure transparency, facilitate recycling, and support circular economy models for EV batteries.

The convergence of advanced materials, intelligent algorithms, and cloud-edge architectures is transforming SOH monitoring from a reactive diagnostic tool into a proactive, predictive health management system. This paradigm shift enhances EV reliability, reduces total cost of ownership, and accelerates the global transition to sustainable transportation.

VI. CONCLUSION

The State of Health (SOH) of electric vehicle batteries is a critical determinant of performance, safety, longevity, and economic viability. As EV adoption accelerates worldwide, the demand for accurate, real-time, and adaptive SOH monitoring has become paramount. This paper has presented a comprehensive overview of SOH estimation methodologies, ranging from model-based equivalent circuit and electrochemical frameworks to data-driven Kalman filtering, neural networks, fuzzy logic, and ultrasonic detection techniques. Each approach offers distinct advantages, yet standalone implementations are inherently limited by sensor noise, computational constraints, and operational variability. Hybrid architectures that integrate physics-based interpretability with machine learning adaptability have emerged as the most promising pathway for robust SOH prognostics.

Modern EV platforms are increasingly leveraging cloud connectivity, wireless BMS architectures, edge-AI processing, and advanced thermal management to enhance SOH tracking capabilities. These technologies enable predictive maintenance, optimized charging strategies, and extended battery lifespans, directly contributing to reduced greenhouse gas emissions and sustainable mobility ecosystems. Standardization efforts and digital twin implementations further pave the way for fleet-level health management and circular battery economies.

Future research should focus on cross-chemistry SOH generalization, real-time validation under extreme fast-charging and sub-zero conditions, integration of quantum-inspired optimization for parameter identification, and development of open-source benchmark datasets for algorithm validation. As battery technologies evolve toward solid-state and sodium-ion architectures, SOH monitoring frameworks must remain agile, scalable, and interoperable. By continuing to refine estimation methodologies and embed intelligent diagnostics within BMS architectures, the automotive industry can ensure safer, longer-lasting, and more efficient electric vehicles, ultimately accelerating the transition to a zero-emission transportation future.

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