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Review

A Brief Overview of Modeling Estimation of State of Health for an Electric Vehicle's Li-Ion Batteries

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Abstract: The current literature highlights several state-of-health (SOH) prediction models for lithium-ion (Li-ion) batteries used in electric vehicles (EVs). However, a thorough comparative analysis remains absent. This study addresses this gap by conducting a comprehensive evaluation of SOH prediction methods for Li-ion batteries in EV applications, encompassing direct measurement techniques, physics-based approaches, and data-driven methodologies. The analysis identifies the strengths, limitations, and applicability of each modeling method. Additionally, this study explores key indicators of SOH, influential variables affecting battery health, and publicly available datasets that support SOH modeling. By synthesizing these insights, the research provides recommendations for improving existing models and outlines prospective directions for enhancing the accuracy and efficiency of SOH estimation in EV applications. This work aims to contribute to the development of robust, accurate, and practical SOH models, thereby advancing the reliability and sustainability of Li-ion battery systems in the growing EV industry.

Keywords: data evaluation; electric vehicles; Li-ion batteries; modeling prediction; state of health (SOH)

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1. Introduction

Lithium-ion (Li-ion) batteries have fundamentally transformed energy storage, emerging as the leading technology in consumer electronics, electric vehicles (EVs) [1], and renewable energy systems. Their superior energy density, extended cycle life, and relatively low weight render them optimal for a broad spectrum of applications. In contrast to conventional batteries, Li-ion batteries operate by transferring lithium ions between the anode and cathode during charge and discharge cycles, facilitating efficient energy storage.

Predicting the state of health (SOH) of Li-ion batteries remains a significant challenge due to the complex interplay of capacity degradation, environmental sensitivity, and operational variability. Batteries experience diverse usage patterns, such as fluctuating charge/discharge rates, depth of discharge (DoD), and cycling frequencies, which directly impact degradation rates. For example, electric vehicle (EV) batteries endure rapid, dynamic load profiles, whereas grid storage batteries face slower, more consistent cycles. Environmental factors, particularly temperature fluctuations, further complicate SOH prediction, as high temperatures accelerate side reactions such as solid electrolyte interphase (SEI) growth, while low temperatures increase internal resistance. These variations hinder the development of generalizable models, often resulting in inaccurate predictions in real-world applications [2,3].

Additional challenges include data quality and availability, nonlinear degradation behavior, and real-world noise. High-quality datasets encompassing diverse operating conditions are often limited, restricting the accuracy and generalizability of data-driven models. Battery degradation is inherently nonlinear, with capacity fade occasionally accelerating abruptly after a specific number of cycles, complicating long-term SOH estimation. Real-world data are also susceptible to noise and uncertainties, such as measurement errors and sensor drift, which undermine the reliability of SOH estimates, particularly in online applications. Moreover, while high-fidelity models such as physics-based or hybrid approaches offer precision, their computational complexity often renders them unsuitable for real-time battery management systems (BMSs). These challenges underscore the need for robust, adaptive models capable of addressing variability, noise, and computational constraints while maintaining predictive accuracy [4,5].

Despite these challenges, ongoing research and development efforts are concentrated on enhancing their performance, safety, and sustainability, thereby enabling their further integration and adoption in the future [6,7].

The state of health (SOH) of Li-ion batteries refers to their current performance relative to their initial capacity. This critical metric assesses the battery's ability to store and deliver charge efficiently over time [8,9]. Several factors influence SOH, including aging, temperature fluctuations, charge cycles, and deep discharges. As Li-ion batteries age, their capacity progressively declines due to internal chemical changes, such as the degradation of the electrolyte and the formation of the solid electrolyte interphase (SEI) layer on the anode. The monitoring of the SOH is essential for predicting battery lifespan and optimizing its usage [8,10]. Techniques such as voltage-based methods and impedance spectroscopy are commonly employed to evaluate SOH. With the increasing demand for electric vehicles and renewable energy storage, understanding and improving SOH is vital for enhancing battery reliability and performance [11,12].

Despite the availability of several literature reviews on the evaluation of the state of health (SOH) of electric vehicle (EV) Li-ion batteries, they present certain limitations. For instance, ref. [10] reviewed strategies for monitoring Li-ion battery SOH [13], but this study is not exhaustive and primarily focuses on early generations of EVs. Additionally, ref. [14] classified battery SOH assessment techniques into experimental and physics-based approaches, yet a comprehensive analysis of the advantages and disadvantages of each method is lacking [15]. Studies by [16,17] explored methodologies for estimating battery SOH [18,19], but did not address the various factors influencing the SOH of Li-ion batteries. Furthermore, ref. [20] introduced data-driven approaches for estimating battery SOH, including machine learning and differential analysis; however, it did not consider alternative SOH prediction techniques, such as electrochemical models.

Given the knowledge gaps identified earlier, the aim of this study is to conduct a comprehensive literature analysis on various approaches used to predict the state of health (SOH) of electric vehicle (EV) Li-ion batteries. This paper will explore a range of methodologies, from traditional physics-based models to more modern data-driven techniques. Additionally, it will compile relevant data sources, key factors, and indicators related to Li-ion battery SOH. The findings from this study are expected to contribute to the development of enhanced models and applications for assessing SOH in EV-based Li-ion batteries.

2. Benchmark of Li-Ion Batteries SOH

Monitoring SOH is crucial for ensuring the longevity and performance of Li-ion batteries, particularly in EVs [21]. Below are several benchmarks used to assess the SOH of a Li-ion battery:

1. Capacity fade;
2. Internal resistance;
3. Voltage and voltage profile;
4. Cycle life;
5. Temperature behavior;
6. Self-discharge rate;
7. State of charge (SOC) accuracy.

Table 1 summarizes the key benchmarks for assessing the SOH of Li-ion batteries, their definitions, measurement methods, and significance in evaluating the SOH. By analyzing these benchmarks, researchers can assess battery health, detect potential failure types, and optimize battery management systems. This contributes to extended battery life and enhanced performance.

Table 1. Benchmarks for assessing the state of health (SOH) of Li-ion batteries.

Benchmark	Definition	Measurement	Significance	Pros	Cons
Capacity Fade	The battery's capacity reflects its ability to store and deliver energy. Over time, chemical degradation reduces capacity, signaling health deterioration [22].	SOH is calculated by comparing the current capacity relative to the initial rated capacity [23].	A significant capacity drop shortens battery life and reduces performance, making this a primary indicator of SOH [22,23].	Directly reflects the usable energy storage capability of the battery [22]. Easy to measure and widely used in SOH estimation [23].	Requires full charge/discharge cycles, which may not be practical in real-time monitoring. Sensitive to operating conditions (e.g., temperature, C-rate) [22].
Internal resistance	Refers to the opposition to current flow within the battery, which increases with aging and degradation [23–26].	Measured via Electrochemical Impedance Spectroscopy (EIS) or by observing the voltage drop under load [22].	Elevated internal resistance generates heat, reduces efficiency, and accelerates capacity fade, often correlating with decreased SOH [23–26].	Indicates power delivery capability and aging mechanisms (e.g., SEI growth). Can be measured without fully discharging the battery [23–26].	Measurement requires specialized equipment (e.g., impedance analyzers). Affected by temperature and SOC, complicating interpretation [23–26].
Voltage and Voltage Profile	Voltage is the potential difference between the battery's terminals, with characteristic charge/discharge curves that shift as the battery degrades [27,28].	Monitored under different charge/discharge conditions; deviations from typical voltage curves highlight potential issues [22,28].	Changes in nominal voltage or unusual fluctuations can indicate poor battery health or imbalanced cells [23,27].	Provides real-time insights into battery behavior during charge/discharge. Easy to measure using standard BMS sensors [27,28].	Voltage alone may not fully capture degradation mechanisms. Voltage profiles can vary significantly with load and temperature [23,28].
Cycle life	The number of full charge/discharge cycles before capacity drops below a specific threshold	Counted and compared against the manufacturer's expected cycle life under standard conditions [26–28].	Batteries exceeding expected cycles may exhibit reduced SOH due to material degradation [23,28].	Directly correlates with battery lifespan and degradation over time. Useful for predicting end-of-life	Requires long-term testing, making it impractical for real-time SOH estimation.

	(typically 80% of initial capacity) [23,26].			(EOL) conditions [27,28].	Cycle life can vary significantly depending on usage patterns [27,28].
Temperature behavior	Temperature significantly impacts performance and SOH, with elevated temperatures accelerating component degradation [24].	Monitored during operation; anomalies like excessive heat buildup indicate potential issues [24,28].	Abnormal temperature behavior can signal degradation, affecting battery health and safety [24].	Highlights thermal stability and safety concerns (e.g., thermal runaway). Helps identify abnormal heating, which can indicate degradation [24].	Requires precise temperature sensors and thermal management systems. Temperature effects are complex and may not directly correlate with SOH [28].
Self-Discharge Rate	The rate at which a battery loses charge when idle, increasing with age and degradation [27,28].	Measured over time; an elevated rate suggests internal issues [27].	High self-discharge rates can indicate internal shorts or rising resistance, both indicative of poor SOH [27,28].	Indicates internal leakage and potential aging mechanisms (e.g., SEI growth). Useful for identifying defective or degraded cells [27].	Difficult to measure accurately in real-world applications. Requires long periods of inactivity, which is impractical for active systems [28].
State of Charge (SOC) Accuracy	SOC represents the current charge level of the battery. Accurate SOC estimation is critical for effective battery management [22,27].	Evaluated by comparing the predicted SOC against actual charge levels [22,28].	Aging reduces SOC estimation accuracy, impacting performance and the reliability of battery management systems [23,27].	Reflects the battery's ability to accurately estimate remaining energy. Critical for real-time battery management and user feedback [23].	SOC estimation errors can mask true SOH degradation. - SOC accuracy depends on voltage and current measurements, which can be noisy [27].

3. Public Datasets for Li-Ion Batteries SOH

To construct a Li-ion battery SOH model, several publicly available datasets may be employed to evaluate battery deterioration and forecast the remaining usable life (RUL) of batteries. Some of these significant datasets are the following:

1. NASA battery dataset (battery aging data);
2. The CALCE battery dataset;
3. SELI dataset (Swedish Electric Vehicle Fleet);
4. UCI Machine Learning Repository: battery SOH dataset;
5. Battery Management System (BMS) battery dataset;
6. The G2 battery dataset;
7. ECOBATT dataset;
8. The LIB battery dataset.

Table 2 summarizes the description, usefulness, and access information for key datasets related to the SOH of Li-ion batteries. These datasets provide extensive information on battery performance and degradation, essential for developing SOH models and conducting prognostic analysis. Researchers can select a suitable dataset based on the specific requirements of electric vehicle (EV) applications. The available access links are given directly in Appendix A.

Table 2. Public datasets for Li-Ion batteries SOH analysis.

Dataset	Description	Usefulness	Applicability	Gaps	Limitations	Case Study	Access
NASA Battery	Provided by NASA's Prognostics Center of Excellence (PCoE), this dataset includes charge/discharge data, voltage, current, and temperature profiles for lithium-ion batteries under various operating conditions [29].	Commonly used for SOH modeling and degradation prediction tasks [29].	Detailed cycle-by-cycle data for SOH and RUL prediction [30].	Limited to 18,650 cells; lacks data from extreme conditions.	Controlled lab conditions; small sample size.	Used in [30] to develop an LSTM model for RUL prediction, achieving 95% accuracy in cycle life estimation.	NASA PCoE Dataset
CALCE Battery	Developed by the University of Maryland's CALCE, this dataset contains aging cycles, charge/discharge characteristics, and voltage variations for lithium-ion batteries [31].	Widely utilized for performance degradation analysis and developing thermal and voltage-based SOH models [31].	High-resolution data for capacity fade and impedance modeling [32].	Limited to LCO chemistry; lacks metadata on manufacturing.	Focuses on calendar aging; noisy impedance measurements.	Applied in [32] to study capacity fade using Gaussian Process Regression, with RMSE < 2% for SOH estimation.	CALCE Battery Data
SELI	The Swedish Electric Vehicle Fleet dataset provides SOC, temperature, voltage, and current data collected over months of EV operation, reflecting real-world conditions [33].	Useful for SOH estimation and condition monitoring in real-world EV scenarios [33].	Real-world EV battery data for practical SOH analysis [34].	Limited raw data availability; incomplete metadata.	Narrow operating conditions; potential inconsistencies in data collection.	Used in [34] to train a Random Forest model for SOH prediction in EVs, achieving 90% accuracy.	SELI Dataset
UCI Machine Learning Repository	Contains battery modeling datasets, including lithium-ion battery charge/discharge cycles, with variables such as current, voltage, and temperature [35].	Suitable for developing classification or regression models for battery SOH estimation [35].	Structured format for benchmarking ML models [36].	Limited cycle data; lacks impedance measurements.	Controlled conditions; small sample size and limited chemistries.	Employed in [36] to benchmark SVM and ANN models for SOH estimation, with SVM achieving 92% accuracy.	UCI Repository
BMS Battery	Focused on charge/discharge profiles, this dataset includes detailed current, voltage, and	Helpful for predicting battery health and identifying failure conditions [37].	Real-time BMS data for online SOH estimation [38].	Limited to specific battery packs; lacks metadata on usage history.	Noisy data due to real-world conditions; limited extreme scenario coverage.	Utilized in [38] to develop an online SOH estimation algorithm using	Kaggle BMS Dataset

	temperature data for lithium-ion batteries [37].					Kalman filtering, with < 3% error.	
G2 Battery	Provided by General Electric, this dataset includes cell voltage, temperature, current, and resistance measurements for lithium-ion batteries used in grid applications [39].	Valuable for long-term battery degradation modeling and SOH prediction [39].	Grid storage data for stationary energy SOH analysis [40].	Limited to lithium iron phosphate (LFP) chemistry; lacks detailed cycle data.	Focuses on long-term aging; potential biases in data collection.	Applied in [40] to model capacity degradation using a physics-based approach, achieving 94% accuracy.	Not publicly available; access can be requested through GE or associated research projects.
ECOBATT	Real-world EV battery data, including voltage, current, and temperature, collected during routine operations [41].	Effective for investigating SOH and remaining useful life (RUL) in EV applications [41].	Recycled battery data for second-life SOH studies [42].	Small sample size; lacks detailed usage history metadata.	Inconsistent data due to recycling variations; limited operating condition coverage.	Used in [42] to evaluate second-life battery performance, showing 80% capacity retention after 500 cycles.	ECOBATT Dataset
LIB Battery	Focuses on lithium-ion battery performance, covering charge/discharge cycles, aging effects, and current/voltage/temperature profiles [43].	Highly useful for predicting battery degradation and supporting BMS research [43].	Multi-chemistry data for comparative SOH analysis [44].	Limited to lab conditions; lacks impedance data.	Small sample size; focuses on specific degradation mechanisms.	Employed in [44] to compare NMC and LFP degradation rates, identifying NMC as more susceptible to capacity fade.	Available via academic research platforms such as ResearchGate.

4. Li-Ion Batteries SOH Modeling Techniques

Accurate SOH modeling is vital for forecasting battery aging, optimizing performance, and estimating remaining useful life. Various methodologies have been proposed for SOH modeling, each differing in complexity, precision, and computational requirements. The key methodologies for SOH modeling include the following:

1. Empirical models;
2. Physics-based models;
3. Data-driven models;
4. Kalman filtering and extended Kalman filtering;
5. Hybrid models.

Figure 1 depicts an illustration of the Li-ion batteries SOH modeling techniques.

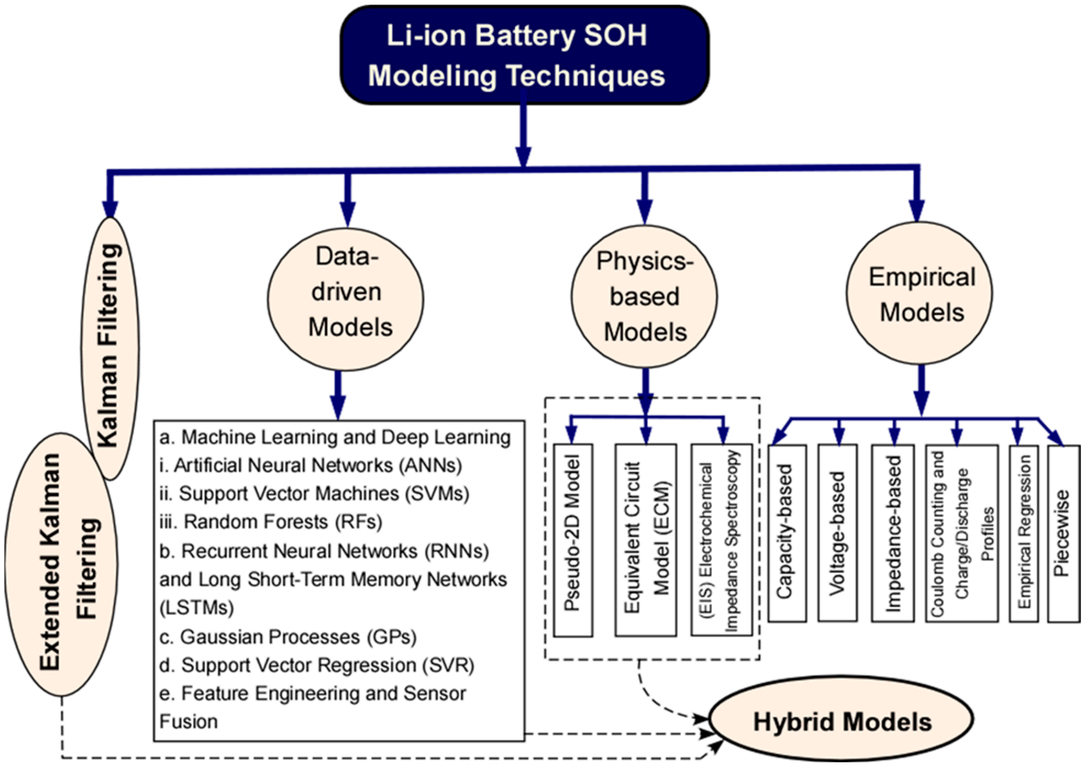

Figure 1. Illustration of Li-ion batteries SOH modeling techniques.

4.1. Empirical Models

Empirical models for SOH prediction are grounded in experimental data and aim to capture the relationships between a battery's internal state and its operational characteristics. These models are essential for estimating battery life and improving BMS. Below are key empirical approaches for SOH modeling:

1. Capacity-based models;
2. Voltage-based models;
3. Impedance-based models;
4. Coulomb counting and charge/discharge profiles;
5. Empirical regression models;
6. Piecewise models.

Table 3 provides a detailed summary of these empirical models, including their types and representative examples. These approaches are critical for practical applications, enabling effective SOH estimation and optimization in various Li-ion battery systems.

Table 3. Empirical models, types, definitions, and examples.

Model Type	Definition	Example
Capacity-Based	Focuses on correlating capacity degradation over cycles with operational factors such as charge/discharge cycles, temperature, and current rates.	Cycling performance: Monitors discharge capacity over time and models deterioration using experimental data. For instance, ref. [45] developed a model to forecast capacity degradation across various operating conditions using cycle data.
Voltage-Based	Examines the voltage profile to correlate with the battery's residual health, capturing aging effects such as increased resistance or electrolyte loss.	Voltage profile monitoring: Utilizes voltage profiles during charge/discharge cycles to predict SOH. For example, ref. [46] used voltage measurements to estimate SOH and analyzed the impact of temperature variations on battery performance.
Impedance-Based	Leverages Electrochemical Impedance Spectroscopy (EIS) to assess SOH, as impedance rises with battery degradation.	Impedance monitoring: Collects impedance spectra at various frequencies to link impedance changes with degradation processes. In [47], the relationship between aging and impedance increases was analyzed to develop empirical SOH estimation models.
Coulomb Counting and Charge/Discharge Profiles	Measures total charge input/output to detect discrepancies indicating degradation.	Regression-based models: Construct equations linking parameters (e.g., capacity, voltage, resistance) with SOH [48]. For example, ref. [49] applied regression techniques to predict SOH from long-term cycling experiment data.
Piecewise	Segments the battery lifecycle into distinct phases with varying degradation rates for each phase.	Phase-based modeling: Captures degradation behavior in distinct lifecycle stages. For instance, ref. [50] employed a piecewise approach to model battery degradation, incorporating factors such as temperature and state of charge (SOC).

4.2. Physics-Based Models

Physics-based models for assessing SOH of Li-ion batteries focus on accurately representing the electrochemical and physical processes that drive performance degradation over time. SOH quantitatively reflects the battery's ability to store and deliver energy compared to its original state and encompasses critical parameters such as capacity loss, impedance growth, and reduced cycle life. The key methodologies within this modeling paradigm include the following:

1. Pseudo-2D Model—a detailed representation of electrochemical interactions and ion transport.
2. Equivalent Circuit Model (ECM)—A simplified electrical analog of battery behavior.
3. Electrochemical Impedance Spectroscopy (EIS)—A frequency-based diagnostic tool for identifying degradation mechanisms.

Table 4 provides an overview of the applications of these physics-based models in Li-ion battery SOH analysis:

Table 4. Applications of physics-based models.

Model Type	Definition	Example
Pseudo-2D Model	A widely utilized physics-based approach for evaluating battery performance, the pseudo-2D model employs differential equations to represent lithium-ion transport, potential distribution, and electrochemical reactions at the electrode/electrolyte interface.	Effectively simulates battery behavior over extended cycles and provides insights into degradation mechanisms under varying operational conditions (e.g., temperature, current rate) [51,52].
Equivalent Circuit Model (ECM)	ECM simplifies battery behavior into an electrical network of resistors, capacitors, and voltage sources. It captures battery degradation through simulated increases in	Widely applied in real-time battery health monitoring due to its computational

	impedance and decreases in capacity, with resistors representing internal resistance and capacitors mimicking charge storage dynamics.	efficiency and suitability for integration into BMS [53].
Electrochemical Impedance Spectroscopy (EIS)	A diagnostic technique for measuring battery impedance across a range of frequencies. Often integrated with physics-based models, EIS links changes in impedance to internal degradation mechanisms.	Highly effective in identifying solid electrolyte interphase (SEI) layer formation and evaluating its influence on battery aging and performance [54].

4.3. Data-Driven Models

Data-driven models for the estimation of the state of health (SOH) of Li-ion batteries have emerged as a critical area of research, providing an efficient approach for predicting battery health using real-time data and operational parameters. These models leverage various techniques from machine learning, artificial intelligence, and data analytics to improve the accuracy of SOH predictions. Notable methodologies include the following:

1. Machine learning and Deep Learning;
2. Recurrent neural networks (RNNs) and Long Short-Term Memory Networks (LSTMs)
3. Gaussian processes (GPs)
4. Support Vector Regression (SVR)
5. Feature Engineering and Sensor Fusion

Table 5 presents a detailed overview of these data-driven models, their definitions, and applications. These approaches have demonstrated substantial effectiveness in predicting battery SOH and are increasingly integrated into BMS. The performance of these models is primarily influenced by the quality and volume of the available data and their ability to capture the complex, nonlinear, and dynamic characteristics of battery aging.

Table 5. Data-driven models, definitions, and applications.

Model Type	Applications
Machine Learning and Deep Learning	**Artificial neural networks (ANNs)**: Widely utilized for SOH estimation due to their ability to capture complex, nonlinear relationships between battery parameters. ANN models, including feedforward neural networks, are trained on historical data to predict battery health degradation based on variables such as voltage, current, and temperature [55]. **Support Vector Machines (SVMs):** Applied in SOH forecasting by analyzing key features such as impedance, voltage, and temperature. SVMs are particularly effective with small datasets and are known for their superior classification accuracy [56]. **Random Forests (RFs):** A robust ensemble learning method, random forests have been successfully employed for SOH prediction by aggregating data from various sensors and conditions. The model constructs multiple decision trees to provide a reliable and precise evaluation of battery health [57].
Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)	These models are highly suited for sequence prediction tasks, making them ideal for battery SOH estimation where time-series data (historical performance) plays a significant role. LSTM networks are particularly adept at capturing long-term dependencies in the data, which is crucial for understanding battery degradation over time [58].
Gaussian Processes (GPs)	Gaussian processes offer a probabilistic approach to quantify uncertainty in SOH predictions. They are especially useful in scenarios involving sparse or noisy data, as they provide confidence intervals alongside predictions [59].

Support Vector Regression (SVR)	SVR is used to predict continuous values, making it suitable for SOH assessment based on historical battery performance data. It has shown promising results in accurately estimating the remaining useful life (RUL) of Li-ion batteries [60].
Feature Engineering and Sensor Fusion	The performance of data-driven models can be significantly improved by the careful selection and engineering of features derived from operational data. Additionally, sensor fusion, which integrates data from multiple sensors (e.g., temperature, voltage, current), provides a more comprehensive view of the battery's SOH [61].

4.4. Kalman Filtering and Extended Kalman Filtering

The assessment of the SOH for Li-ion batteries is crucial for evaluating their performance, longevity, and safety. Kalman filtering (KF) and Extended Kalman filtering (EKF) are widely used techniques for SOH estimation, utilizing system models to filter and assess the battery's internal condition based on noisy or corrupted measurements. In the typical application of KF for Li-ion battery modeling, a state-space model is employed to represent the dynamic behavior of the battery. This model incorporates various internal variables, such as voltage, current, and temperature, as part of the system's state. The measurement update in the Kalman filter adjusts the predicted state by incorporating actual measurements, such as voltage or current, with the Kalman gain determining the weight assigned to the forecast in relation to the measurements. KF is commonly used to simulate internal resistance over time by integrating voltage and current readings, which is a critical metric for estimating SOH. Additionally, SOH can be inferred from the variance between the predicted resistance and its original value [62].

While the Kalman filter is effective for linear systems, Li-ion batteries exhibit nonlinear dynamics due to complex electrochemical processes. To address these nonlinearities, the Extended Kalman Filter (EKF) is often employed. The EKF linearizes the nonlinear model through a first-order Taylor expansion around the current state estimate, allowing the application of Kalman filtering to nonlinear systems. A typical nonlinear model concerns the battery's capacity, which degrades over time. The EKF can estimate this capacity by monitoring the battery's terminal voltage and current throughout a charge/discharge cycle, refining the state estimation with the collected data [63].

4.5. Hybrid Models

Hybrid modeling approaches for SOH estimation in Li-ion batteries integrate physics-based and data-driven methodologies to enhance prediction accuracy. This synergistic approach leverages the strengths of both paradigms: physics-based models provide a fundamental understanding of electrochemical degradation mechanisms, while data-driven models capitalize on empirical observations and machine learning techniques.

For instance, integrating artificial neural networks (ANNs) with electrochemical models improves SOH prediction by capturing both real-time operational data and the underlying physics of battery operation. This enables the model to accurately represent nonlinear and dynamic behavior, including the effects of temperature fluctuations, charge/discharge cycles, and internal resistance, which are crucial for accurate remaining useful life (RUL) estimation and performance degradation prediction [64].

Hybrid models effectively address the limitations of individual approaches. When data are sparse or noisy, physics-based models provide a robust framework, while data-driven models enhance accuracy and adaptability in complex real-world scenarios with varying operating conditions. This hybrid approach has demonstrated significant potential in battery management systems (BMSs) for optimizing battery usage and extending operational lifespans [65,66].

Examples of successful hybrid approaches include the following:

1. EIS combined with machine learning algorithms: enables real-time SOH monitoring with improved accuracy and sensitivity [67].
2. Hybrid models integrated with prognostics: facilitate the accurate prediction of failure modes and maintenance schedules in electric vehicles [68].

These advancements underscore the growing importance of hybrid modeling in developing advanced BMSs and improving the sustainability and efficiency of battery systems across various applications, including electric vehicles and renewable energy storage.

5. Strength and Weakness of Li-Ion SOH Modeling Estimation Techniques

Table 6 outlines the estimation methodologies employed for modeling the SOH of Li-ion batteries. These five techniques are effective at uncovering complex relationships between operational parameters and SOH, enabling the development of prediction models that can be applied across various battery chemistries and usage scenarios. Data-driven approaches, for instance, are particularly adept at learning intricate, nonlinear patterns from large datasets. They can adapt to evolving conditions and account for nonlinear degradation processes, making them well suited for real-time applications. However, such methods are heavily reliant on vast and diverse datasets for effective training, with the quality and variety of data being crucial for accurate predictions. Additionally, data-driven models often lack the interpretability of physics-based models, making it challenging to understand the underlying mechanisms driving the degradation processes.

On the other hand, physics-based models simulate the internal thermal and electrochemical dynamics of the battery, providing outputs that are often more interpretable compared to those generated by data-driven methods. This interpretability allows for a deeper understanding of the battery's degradation mechanisms, such as capacity fade, impedance growth, and internal resistance variations. However, while these models offer valuable insights into battery behavior, they may not capture the full complexity of real-world scenarios, especially under dynamic and varied operating conditions. Therefore, hybrid approaches that combine the strengths of both data-driven and physics-based models have been proposed to improve both the predictive accuracy and interpretability of SOH estimation, addressing the limitations of each individual methodology [69–79].

The integration of multiple modeling methodologies presents a promising avenue for future research on the state of health (SOH) of electric vehicle (EV) batteries. However, the hybrid approach often demands substantial computational resources, which can hinder its applicability in real-time SOH monitoring applications [72–80].

Table 6. Strengths and weaknesses of Li-ion SOH modeling estimation techniques.

Model Type	Strengths	Limitations and Weaknesses	Practical Applicability
Pseudo-2D Model	- Simple implementation - Fast computation - Low computational demand - Widely applicable - Less complex	- Poor adaptability - Limited accuracy - Lack of physical insight - Risk of overfitting - Limited predictive power - Calibration requirements Computationally expensive Limited to lab-scale validation	Simulates electrochemical processes (e.g., lithium-ion diffusion) for detailed degradation analysis [81]. **Example**: Used to study capacity fade in NMC batteries under high C-rates [81].

Physics-based Models	- High accuracy and precision - Well-established model principles - Predictive capability - Adaptability - No need for extensive data	- Not suitable for real-time applications - Highly complex - Depends on assumptions and simplifications - Parameter sensitivity - Limited to specific conditions - Inability to handle uncertainty - Struggles with real-world variability and noise in data - Requires extensive experimental data for calibration	Captures degradation mechanisms (e.g., SEI growth, lithium plating) for long-term SOH prediction [82]. **Example**: Applied to predict capacity loss in LFP batteries at varying temperatures [82].
Data-driven Models	- Flexibility in learning complex relationships - Adaptability - Real-time monitoring - Accuracy in predictions - Reduced need for physical testing - Scalability - Predictive maintenance	- Dependent on data quality - Risk of overfitting - Complexity in model interpretation - Limited data in critical cases - Need for regular updates - Computational overhead - Challenges in generalizing models - Limited physical insight - Requires large, high-quality datasets for training - Limited interpretability may lead to failure under unseen operating conditions	Uses machine learning (e.g., ANN, SVM, Random Forest) for SOH estimation from operational data [83]. **Example**: Random Forest used to predict SOH in EV batteries with 95% accuracy [83].
Kalman Filter (KF) and Extended Kalman Filter (EKF) Models	**KF:** - Real-time operation - Recursive updates - Optimal estimation - Low computational cost - Error minimization - Widely understood **EKF:** - Nonlinear system support - Real-time estimation - Flexibility - Noise filtering - Improved accuracy	**KF**: - Sensitive to modeling errors - Assumes linear dynamics - Requires accurate sensors - Struggles with nonlinear degradation processes (e.g., SEI growth) **EKF**: - Computational complexity - Nonlinear approximation challenges - Convergence issues	**KF:** Estimates SOH in real-time using voltage and current measurements [84]. **Example:** KF used for online SOH estimation in BMS applications, achieving < 3% error [85]. **EKF**: Handles nonlinear battery dynamics for improved SOH estimation [86]. **Example**: EKF applied to estimate SOH in Li-ion batteries under dynamic load conditions [86].

Hybrid Models	- Combines strengths of various techniques - Enhances accuracy - Better generalization - Robust against parameter changes and uncertainties - Faster real-time estimation - Enhanced predictive power	- Dependence on model quality - Requires accurate system models and parameter initialization. - Complex implementation - Data dependency - Risk of overfitting - Lack of interpretability - Requires more computational resources for training and real-time applications - Challenges in integrating and coordinating different components - May not scale well for large datasets	Combines physics-based and data-driven approaches for robust SOH estimation [87]. **Example**: Hybrid model used to predict RUL in grid storage batteries with 90% accuracy [87].

6. Future-Estimation Techniques for the SOH of Li-Ion Batteries

6.1. Future Research Directions

Future advancements in SOH estimation will likely involve the integration of diverse techniques, including advanced machine learning algorithms, sophisticated electrochemical models, and hybrid approaches [88]. This multi-pronged approach aims to enhance predictive accuracy, improve adaptability to dynamic operating conditions, and more precisely account for aging phenomena, such as capacity fade and impedance growth [89]. Hybrid models, combining the strengths of physics-based and data-driven approaches, offer a promising avenue, providing both interpretability and adaptability to real-world battery usage scenarios [90].

The integration of advanced sensor data with sophisticated predictive algorithms is crucial for real-time SOH monitoring and early detection of performance degradation, enabling proactive maintenance and extending battery lifespan in practical applications [91]. These advancements will contribute to the development of more intelligent battery management systems (BMSs), facilitating the transition towards sustainable and reliable energy storage solutions for electric vehicles and other applications [91,92].

6.2. Current Limitations

The limited availability of high-quality, diverse datasets poses a significant challenge, hindering model generalization and restricting the scope of research. Many machine learning models exhibit a black-box nature, limiting interpretability and hindering trust in their predictions. Adapting models to different battery chemistries and operating conditions remains difficult. Moreover, the high computational demands of some algorithms limit their applicability in resource-constrained environments. Finally, the lack of reliable uncertainty estimates hinders robust decision-making in safety-critical applications [93,94].

6.3. Potential Solutions

Transfer learning can mitigate data scarcity and improve model adaptability by leveraging knowledge from one battery type to another. New techniques in explainable AI can enhance model interpretability and build trust. Combining data-driven and physics-based approaches in hybrid models can improve both accuracy and interpretability. Edge computing and model compression techniques can enable real-time SOH estimation on embedded systems. Developing models that provide reliable uncertainty estimates, such as Bayesian neural networks, is crucial for improved decision-making. Federated learning enables collaborative model training across multiple devices while preserving data privacy [93,95].

6.4. Resolving Limitations

Overcoming data scarcity requires employing data augmentation and synthetic data generation techniques. Developing flexible and adaptable model architectures can improve generalizability and reduce retraining needs. Collaborative research and open data initiatives are essential for building comprehensive and diverse datasets. Establishing standardized battery aging protocols will facilitate the generation of consistent and comparable datasets, enabling the development of more robust and generalizable models [96,97].

7. Conclusions

This comprehensive review critically analyzes current research on the SOH estimation for Li-ion batteries in EEVs. A key focus lies in defining and evaluating relevant SOH benchmarks, assessing their significance in assessing battery performance. Furthermore, this review examines publicly available datasets used for SOH estimation, evaluating their utility, accessibility, and data quality, which are crucial for the development and validation of accurate SOH estimation models.

This review investigates a range of SOH estimation methodologies, including empirical, physics-based, data-driven (including machine learning), Kalman filtering (including the Extended Kalman Filter), and hybrid models that combine data-driven and electrochemical approaches. Each technique is critically assessed for its strengths, limitations, and practical applicability.

Finally, this review explores future directions for SOH estimation in EV batteries, emphasizing the need for integrating diverse modeling techniques, developing comprehensive battery lifecycle datasets, and utilizing advanced predictive algorithms. These advancements aim to enhance real-time SOH monitoring capabilities and extend the operational lifespan of batteries in practical applications.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial neural network
BMS	Battery management system
ECM	Equivalent Circuit Model
EIS	Electrochemical Impedance Spectroscopy
EKF	Extended Kalman filter
EV	Electric vehicle
GP	Gaussian process
KF	Kalman filter
Li-ion	Lithium-ion
LFP	Lithium iron phosphate
LSTM	Long Short-Term Memory
RF	Random Forest
RNN	Recurrent neural network
RUL	Remaining useful life
SEI	Solid Electrolyte Interphase
SOH	State of health
SVM	Support vector machine
SVR	Support vector regression

Appendix A

Table A1. Access to available data.

Number of Accesses	Data Availability
1	https://www.nasa.gov/content/prognostics-center-of-excellence-data-set (accessed on 15 December 2024.)
2	https://calce.umd.edu/battery-data (accessed on 15 December 2024.)
3	https://www.svenskaelektriska.se/ (accessed on 15 December 2024.)
4	https://archive.ics.uci.edu/ml/datasets (accessed on 15 December 2024.)
5	https://www.kaggle.com/ (accessed on 15 December 2024.)
6	Not publicly available but can be accessed upon request from GE or associated research projects.
7	https://www.ecobatt.eu/ (accessed on 15 December 2024.)
8	Available via academic research groups on platforms like ResearchGate.

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