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REVIEW

Research on State Evaluation Method of Energy Storage Lithium-Ion Batteries Based on Multi-Source Non-Invasive Big Data

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ABSTRACT

Lithium-ion batteries are the backbone of electric vehicles, renewable energy storage, and new emerging smart grid applications. However, the safety and the economic value of such batteries depend heavily on the proper assessment of State of Health (SOH). Conventional invasive measurements provide detailed information; however, they are difficult to apply to sealed or in-service battery packs. This makes non-invasive techniques such as voltage, current, temperature, impedance, and data-driven modeling better suited for battery management at scale. In this paper, three representative research directions, including comprehensive SOH characterization, fast impedance-based SOH estimation, and machine-learning diagnosis of degradation patterns from electrochemical impedance spectroscopy, are reviewed and synthesized. Rather than analyzing each study in isolation, the paper proposes a comparative framework to identify methodological strengths, data requirements, limitations, and potential for practical deployment. A unified SOH evaluation framework is proposed, which combines Gaussian Process Regression-Automatic Relevance Determination (GPR-ARD)-based feature selection, fast impedance calculation, lightweight Extreme Learning Machine (ELM)-based online estimation, and cloud–edge model updating. The practical feasibility is discussed in terms of computational cost, latency, bandwidth, temperature variation, data quality, cybersecurity, and real-time battery management constraints. The study concludes that, to support safer electric vehicles, second-life battery use and sustainable energy storage systems, future non-invasive battery diagnostics should

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combine physical interpretability, multi-source data fusion, and deployment-oriented model design.

Keywords: Lithium-Ion Battery; State of Health; Non-Invasive Diagnosis; Electrochemical Impedance Spectroscopy; Machine Learning; Battery Management System; Cloud–Edge Deployment

1. Introduction

Lithium-ion batteries have become one of the most important enabling technologies for the global transition to clean energy, electric transportation, and low-carbon industrial development. The lithium-ion battery has become the workhorse of electric vehicles, renewable energy storage stations, portable electronics, and smart-grid applications thanks to its high energy density, long cycle life, relatively low self-discharge rate, and mature manufacturing ecosystem. Of these applications, electric vehicles and large-scale energy storage systems are especially significant, as they directly help reduce fossil-fuel consumption and facilitate the integration of intermittent renewable energy sources such as wind and solar power. With the continuous expansion of the deployment scale of these systems, the safe, reliable, and intelligent management of lithium-ion batteries has become a critical technical and social issue [1,2].

The surge in electric vehicles has made the issue of battery safety and lifetime management more urgent than ever. Policy incentives, carbon neutrality goals, and industrial investment in many countries are accelerating the replacement of traditional internal-combustion vehicles with new energy vehicles. China has introduced purchase-tax exemptions and other supportive policies to encourage the adoption of electric vehicles. The global markets are also seeing steady growth in battery-powered transportation. But the large-scale use of lithium-ion batteries brings new risks. Battery packs are subjected to highly variable operating conditions, including varying temperatures, different charging rates, repeated fast charging, high-current discharge, vibration, and varying user behavior. These factors can accelerate aging, reduce available capacity, increase internal resistance, and, in severe cases, trigger safety problems such as overheating, thermal runaway, fire, or sudden performance failure. Thus, accurate assessment of battery health is important not only to enhance battery utilization but also to protect users, vehicles, and energy infrastructure [1,3,4].

State of Health (SOH) is one of the most important indicators for evaluating the condition of lithium-ion batteries [5]. Generally, SOH describes the degradation of a battery relative to its original or rated condition. It is generally associated with a loss of capacity, an increase in resistance, a decrease in power capability, or other electrochemical changes related to aging. A reliable SOH estimation method can help a Battery Management System (BMS) determine whether a battery can continue to operate safely, when it needs maintenance, and whether it is suitable for second-life applications after it is retired from vehicles. Accurate state-of-health estimation in electric vehicles can help with driving-range prediction, charging strategy optimization, warranty evaluation, and early warning of abnormal degradation. For stationary energy storage, it helps operators schedule charge-discharge cycles more efficiently, reducing maintenance costs and preventing unexpected system failures. Therefore, SOH evaluation is a core function for operational safety and lifecycle sustainability [6].

SOH estimation is technically challenging but highly important. Lithium-ion battery aging is a complex process with multiple coupled mechanisms, including loss of lithium inventory, loss of active material, electrolyte decomposition, solid-electrolyte interphase growth, lithium plating, and impedance rise. These mechanisms are influenced by temperature, current rate, depth of discharge, state-of-charge range, storage conditions, and cell chemistry. In laboratory settings, battery degradation can be studied through controlled experiments such as full-charge/discharge capacity tests, electrochemical impedance spectroscopy, incremental capacity analysis, or post-mortem material characterization. However, a number of these approaches are difficult to apply directly to batteries already installed in vehicles or energy storage systems. Full-capacity tests are time-consuming and disrupt normal operation. Some analyses at the electrochemical or materials level require specialized equipment or destructive procedures. Therefore, there is still a long way to go to bridge the gap between accurate laboratory diagnosis and practical online health monitoring in real-world applications [7,8].

Existing methods for SOH estimation can be broadly divided into invasive and non-invasive methods. Invasive techniques monitor battery temperature, strain, pressure, or electrochemical signals inside the cell or pack using sensors or internal measurements [9]. These techniques can give detailed information with high sensitivity, but they often increase the system's complexity, cost, and potential reliability concerns. Sensors within cells could affect battery structure, packaging integrity, manufacturing consistency, and long-term durability. Invasive modifications are typically not practical for batteries in service. On the other hand, non-invasive methods estimate battery health using externally measurable signals such as voltage, current, temperature, impedance, charging curves, and operating history data. These methods are more suitable for large-scale deployment because they do not damage the cell structure and can be integrated into existing BMS platforms. Non-invasive and data-driven SOH estimation has thus been a promising direction for practical battery health management [10].

In recent years, progress in artificial intelligence, machine learning, cloud computing, edge computing, and Internet of Things technologies has created new opportunities to improve the evaluation of non-invasive battery health. Traditional model-based approaches, such as equivalent circuit and electrochemical models, can characterize battery behavior using physically meaningful parameters. Still, their accuracy depends heavily on the model structure, parameter identification, and operating conditions. Data-driven approaches such as neural networks, Gaussian process regression, support vector regression, and extreme learning machines can learn the non-linear relationships between measurable features and the SOH without relying on a complete electrochemical model. These techniques are particularly attractive when large-scale operational data are available from electric vehicles or energy storage systems. However, solely data-driven models may exhibit poor generalization when operating conditions differ from those in the training data. They may also lack physical interpretability, hindering trust in safety-critical applications. Thus, future SOH estimation frameworks will combine the merits of physics-based understanding and data-driven learning [11].

Electrochemical impedance spectroscopy and impedance-related features are particularly useful for non-invasive SOH estimation, since impedance is a more direct measure of internal electrochemical processes than simple voltage or capacity measurements [12]. Impedance variations can provide information about charge-transfer resistance, diffusion processes, electrolyte behavior, and interface degradation. However, conventional impedance measurement is often too slow or equipment-dependent for onboard use. Several studies in recent years have attempted to overcome this limitation by developing fast impedance-calculation methods, reducing measurement time, and extracting health-related impedance features for use by lightweight machine-learning models. Meanwhile, advanced machine-learning techniques such as Gaussian process regression with automatic relevance determination can find the most informative regions of the spectra in frequency space and provide uncertainty-aware predictions. These results indicate that impedance-based methods, appropriately simplified and integrated with BMS hardware, could represent a viable compromise between diagnostic accuracy and real-time feasibility [13–15].

Another key trend is the utilization of multi-source and multi-modal data. In real-world systems, battery health is not a single measurement. Voltage, current, temperature, impedance, charge behavior, driving conditions, environmental exposure and historical usage patterns all contain partial information about degradation. Combining multiple sources of non-invasive big data can provide a more complete picture of a battery's state than any single feature. For example, temperature data can be used to correct for thermal effects on impedance and capacity; charging curves can be used to detect changes in internal resistance and polarization; and fleet-level data can be used to detect degradation patterns across vehicles or storage units. The integration of these data streams through feature fusion, statistical learning, and cloud–edge collaboration lays the foundation for developing adaptive SOH estimation systems with high accuracy and scalability.

However, accuracy alone is not sufficient for practical deployment. A method that performs well in laboratory tests may face serious barriers in real applications. The onboard BMS hardware has limited computational resources, memory, and power budgets. The real-time SOH estimation should meet latency requirements and not affect the vehicle's normal operation. Cloud-based models can offer more computing power and facilitate continuous model updates. But they also raise concerns about data transmission bandwidth, communication reliability, cybersecurity, and user privacy. Making deployment more difficult are temperature variations, sensor noise, inconsistent charging behavior, battery pack imbalances, and differences among cell chemistries. Any proposed SOH framework must take into account not only the estimation performance but also the feasibility, robustness, interpretability, cost, and safety [16].

To address the above problems, this paper proposes a state evaluation method for lithium-ion batteries in energy storage based on multi-source, non-invasive big data. Instead of viewing the existing studies as isolated contributions, this paper synthesizes three representative research directions, namely (i) comprehensive SOH characterization and application-oriented review, (ii) fast impedance-based SOH estimation using computationally efficient models, and (iii) machine-learning-based degradation diagnosis from impedance spectroscopy. By comparing their methodologies, data sources, merits, and shortcomings, this study proposes a unified framework that integrates GPR-ARD-based feature selection, fast impedance calculation, lightweight ELM-based online estimation, and cloud–edge collaborative deployment. The goal is to combine the interpretability and diagnostic richness of impedance analysis with the speed and practicality needed for real-time BMS applications.

The main contributions of this paper are threefold: first, it reorganizes existing SOH evaluation research into a comparative framework that focuses on the relationships among characterization, feature extraction, machine learning, and deployment; second, it offers a unified, non-invasive SOH estimation architecture that combines multi-source data, automatic feature selection, rapid impedance processing, and lightweight onboard modeling; third, it discusses the practical feasibility and deployment barriers of the proposed improvements, including computational cost, latency, bandwidth, temperature compensation, data security, and real-world robustness. This paper aims to consolidate and clarify the technical path toward developing safe, reliable, and scalable battery health evaluation systems for electric vehicles and stationary energy storage applications [17].

2. Literature Review

2.1. SOH Characterization and Application-Oriented Evaluation

Zhang et al. presented a comprehensive review on the SOH of lithium-ion batteries, including characterization, estimation, and application [18]. A key contribution of this work is the argument that SOH should not be limited to capacity fade or impedance growth. Instead, SOH should be considered a multi-parameter concept linked to degradation mechanisms such as Loss of Lithium Inventory (LLI), Loss of Active Material (LAM), and change of internal resistance. This broader perspective is important because it links the battery's measured performance to the fundamental electrochemical aging processes.

The review also distinguishes between SOH at the cell and pack levels, noting that pack health is affected by cell inconsistency, balancing strategy, and usage history. This is especially important for EVs and stationary energy storage systems, where thousands of cells might be connected in modules and packs. But the review remains largely qualitative. A quantitative comparison of estimation accuracy, computational cost, robustness to noise, and data requirement among various methods would improve their practical utility [19,20].

2.2. Fast Impedance-Based SOH Estimation

Fu et al. proposed a fast SOH estimation method based on impedance calculation to make electrochemical impedance spectroscopy (EIS) more applicable to online BMS implementation [11]. Traditional EIS is informative but time-consuming, which limits its application in real-time systems. To overcome this limitation, the study extracted some impedance-based health factors and estimated SOH using a regularized Extreme Learning Machine (ELM) model. The authors also improved computational efficiency by implementing a fast Fourier transform approach to process the current and voltage signals. The validation showed an estimation error of less than 1.12% within less than 35 s, indicating a promising online applicability.

The primary benefit of this method is that it provides a trade-off between accuracy and computational efficiency. As ELM models can be trained rapidly and run with relatively low computational burden, they are suitable for embedded BMS hardware. But the method has its limitations. The health features were handpicked, and the validation conditions were not sufficient to encompass the full range of real-world temperatures, charging patterns, and battery chemistries. Temperature sensitivity is particularly important, as impedance is highly dependent on temperature and state of charge [21].

2.3. Machine-Learning Diagnosis from Impedance Spectra

Zhang et al. identified degradation patterns from impedance spectroscopy using machine learning. The authors created a large EIS dataset from commercial lithium-ion cells that were cycled under multiple temperature conditions and used Gaussian Process Regression (GPR) to predict capacity and remaining useful life (RUL). An important methodological strength is the use of Automatic Relevance Determination (ARD), which allows the model to select the most informative frequency regions in the impedance spectrum. This reduces dependence on manually selected features and provides a path to a more interpretable diagnosis [17].

The full-spectrum impedance data have more information about the internal electrochemical processes than the simple discharge-curve features. The probabilistic nature of GPR also provides uncertainty estimates, which are useful for risk-aware BMS decision-making. But GPR models can be computationally expensive for onboard implementation, especially when the training dataset grows large. Therefore, their deployment requires either model compression, sparse approximation, or a cloud–edge architecture in which heavy learning tasks are offloaded to the cloud and lightweight models are deployed on the vehicle [22].

2.4. Comparative Synthesis of Reviewed Approaches

Table 1 summarizes the three reviewed approaches in a comparative framework. This synthesis reduces repetition and clarifies how the studies complement each other.

Table 1. Comparative summary of reviewed SOH evaluation approaches.

Main Method	Input Data	Model/Algorithm	Key Contribution	Main Limitation	Proposed Improvement	Ref.
Review and SOH characterization	Literature on capacity, impedance, aging mechanisms, and applications	Conceptual classification and synthesis	Defines SOH as a multi-parameter and application-oriented concept	Mainly qualitative; limited quantitative benchmarking	Add meta-analysis and standardized comparison of accuracy, cost, robustness, and data needs	Yang et al. [10]
Fast impedance-based online estimation	Current/voltage response and selected EIS health factors	Improved FFT + regularized ELM	Achieves rapid SOH estimation suitable for BMS implementation	Temperature dependency and manually selected features limit generalization	Add temperature compensation, ARD-based feature selection, and richer excitation signals	Yang et al. [23]
Degradation-pattern identification from EIS	Large EIS dataset under different temperatures	GPR with ARD	Uses full spectral information and uncertainty-aware prediction	GPR may be computationally heavy for embedded systems	Use cloud–edge deployment, sparse GPR, and lightweight onboard model transfer	Zhang et al. [17]

3. Methodology and Proposed Unified Framework

In view of the reviewed studies, this paper presents a unified non-invasive SOH evaluation framework that integrates multi-source data acquisition, impedance feature extraction, data-driven feature selection, lightweight online estimation, and cloud–edge model updating. The framework is not intended to replace existing BMS functions, but to supplement them by offering adaptive and interpretable evaluation of battery health.

Data acquisition is the first layer. The BMS is responsible for collecting externally measurable signals, such as voltage, current, temperature, charging profile, and operating history. When appropriate operating conditions are available, impedance-related information can be obtained by current perturbation, step-response analysis, or converter-based excitation. The method applies to existing battery packs without altering the cell structure, thanks to non-invasive signals [24].

Layer 2: Fast impedance calculations and feature extraction. Inspired by fast EIS methods, the current and voltage responses can be processed using FFT-based algorithms to extract impedance features within a short time window. These may be the magnitude of impedance, phase angle, real and imaginary parts, and characteristic low-frequency or mid-frequency values associated with diffusion and charge-transfer processes.

The third layer is offline feature selection and model interpretability. GPR with ARD can be used on full impedance spectra and historical aging data to identify the most informative frequency points or derived health factors. This step reduces the dimensionality of the input data and avoids an over-dependence on manually selected features. Importantly, whenever possible, we want the selected frequencies to correlate with well-understood electrochemical processes, thereby transforming the black-box estimation model into a more interpretable grey-box diagnostic tool.

The fourth layer is lightweight on-board estimation. Once the most relevant features are identified, a computationally efficient model, such as a regularized ELM, can be deployed in the onboard BMS for frequent SOH estimates. This design combines the analytical power of the GPR-ARD with the real-time viability of the ELM. The onboard model provides SOH, uncertainty flags, and possibly RUL or degradation-risk indicators [20,25–27].

The fifth layer is cloud–edge update. Full fleet data can be uploaded periodically to a secure cloud platform, where models are retrained on larger, more diverse datasets. Then, the updated feature sets or lightweight model parameters can be sent back to vehicles or stationary storage systems. This architecture enables models to learn new chemistries, climates, and operating patterns while keeping time-critical decisions at the edge (**Figure 1**).

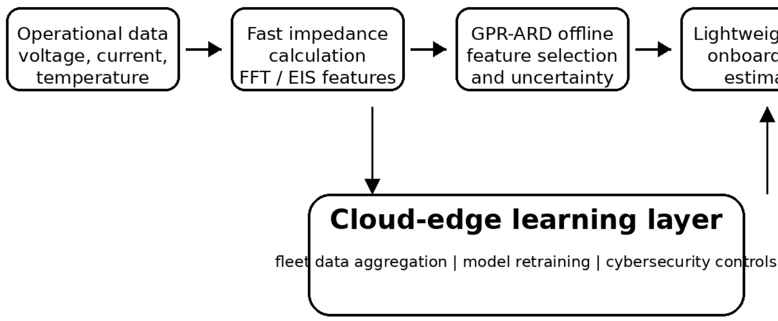

Figure 1. Proposed unified non-invasive SOH evaluation framework integrating fast impedance calculation, GPR-ARD feature selection, lightweight ELM online estimation, and cloud–edge model updating.

4. Practical Feasibility and Deployment Challenges

Although the proposed unified framework is a promising approach toward non-invasive SOH assessment, its practical implementation for electric vehicles and stationary energy storage systems requires careful examination of multiple engineering, computational, and operational constraints. A battery diagnostic method cannot be judged solely by its laboratory accuracy, but also by real-time requirements, changing environmental conditions, compatibility with the existing Battery Management System (BMS) hardware, data security, and user privacy. Therefore, this section critically discusses the feasibility of applying the proposed GPR-ARD, fast impedance calculation, ELM-based online estimation, and cloud–edge collaborative framework in real-world applications [28,29].

4.1. Computational Cost and Onboard Hardware Constraints

The primary challenge is the limited computing capabilities of the onboard BMS hardware. BMS units are currently widely used for basic functions such as voltage monitoring, temperature monitoring, cell balancing, overcurrent protection, and basic state estimation. In general, they have limited processing power, memory capacity, and energy budget in comparison to cloud servers or laboratory computers. This means that computationally intensive algorithms may not be directly suitable for onboard implementation.

For example, Gaussian Process Regression with Automatic Relevance Determination (GPR-ARD) is relevant because it can automatically identify the most relevant impedance frequencies and produce uncertainty-aware predictions. However, the computational cost of GPR models is high, especially as the training dataset grows. The computational complexity grows dramatically with the number of training samples, which makes full GPR training unsuitable for frequent execution on embedded BMS hardware. This is a critical limitation as large-scale EV fleets will generate large amounts of impedance, voltage, current, and temperature data [30].

On the other hand, the Extreme Learning Machine (ELM) models are more suitable for the onboard real-time estimation due to their fast inference speed and relatively simple structure. However, ELM models may not have the same level of interpretability or uncertainty quantification as GPR models. Hence, the proposed framework should not attempt to deploy all the algorithms directly on the vehicle. A more practical strategy is to adopt a two-layer architecture, where the computationally demanding GPR-ARD analysis is performed offline or in the cloud to select robust health features, and the lightweight ELM models are deployed onboard for frequent real-time SOH updates.

This division makes it more practical, but it does come at a cost. A simple onboard model may become inaccurate under unfamiliar operating conditions. If the model is too complex, it might be beyond the capability of low-cost BMS hardware. Therefore, model compression, feature reduction, and embedded-system benchmarking need to be included in future implementations. The proposed method should be evaluated not only on accuracy metrics like the RMSE or MAE but also on inference time, memory consumption, processor load, and energy consumption [31,32].

4.2. Real-Time Latency and Diagnostic Frequency

The other important feasibility issue is latency. In real EV operation, not all diagnostic decisions require the same response speed. Some safety-related warnings, such as risk of thermal runaway or severe internal short-circuit indications, should be addressed immediately, in seconds or even milliseconds. In contrast, SOH estimation typically reflects long-term degradation and does not need to be continuously updated at high frequency. This difference is important since it determines the acceptable computational and communication delay of the proposed framework [33].

Fast impedance-based methods are attractive because they reduce the time required to extract impedance-related health features. However, even a 30-s diagnostic window may be difficult to implement in all driving or charging situations. For example, estimating impedance typically requires relatively constant operating conditions or controlled input signals. Current and voltage signals during aggressive acceleration, regenerative braking, or unstable fast charging can be too dynamic or noisy to perform reliable impedance extraction. Therefore, the system must identify appropriate diagnostic windows, such as during charging, parking, low-load operation, or quasi-steady-state conditions [34].

A critical point is that real-time feasibility must not be confused with continuous real-time impedance measurement. Event-triggered or condition-triggered diagnosis is a more practical approach. The onboard BMS can verify the battery's appropriateness for impedance extraction. Under sufficiently stable operating conditions, the system can perform fast impedance calculations and update the SOH estimate. This avoids unreliable measurements and saves unnecessary computations. But it also means the frequency of diagnosis may differ between users, depending on driving behavior and charging habits. Less frequent vehicle charging under stable conditions might mean fewer opportunities for high-quality diagnostics [35].

Further research is needed to determine the accurate criteria for diagnostic timing. Such criteria can include present stability, temperature range, State of Charge (SOC) range, signal-to-noise ratio, and minimum data window length. If the criteria are not met, the proposed framework may yield inconsistent outcomes in real-world scenarios.

4.3. Data Transmission, Bandwidth, and Cloud–Edge Trade-Offs

The proposed cloud–edge architecture can improve model performance by leveraging analysis of large-scale fleet data on cloud servers and periodically updating the onboard models. But this architecture assumes that data can be transmitted reliably. Full impedance spectra, high-frequency voltage and current signals, temperature records, and operational histories can produce large volumes of data. If all vehicles upload raw battery data continuously, the bandwidth and storage costs may be too much.

A practical solution is to reduce the amount of data being transmitted. The onboard BMS can instead extract selected health features, compressed impedance parameters, statistical summaries, or records of abnormal events, rather than uploading all raw signals. For example, the vehicle may send impedance values only at the frequencies GPR-ARD determines to be most relevant, rather than across the entire spectrum. This reduces bandwidth requirements and enhances scalability [36].

But data compression also has its downsides. Raw data may contain information that is useful later if new degradation mechanisms are found or models are retrained. If only selected features are stored, potentially useful diagnostic information may be lost. So, the cloud–edge system should strike a balance between data efficiency and future analytical value. A hierarchical data approach might be possible, with routine operations uploading compressed features and abnormal cases, rapid degradation events or safety alerts uploading richer raw data [37].

Another weakness is communication reliability. Vehicles can be used in locations where network coverage is poor, and stationary storage may have varying connectivity, depending on the location. Therefore, the onboard BMS cannot fully rely on cloud connectivity. Local models must work when the network is down. The cloud-based updates should improve performance, but should not be required for basic safety monitoring. This requirement enables a lightweight on-board ELM model to serve as the main real-time estimator, while the cloud-based GPR-ARD is used as a periodic optimization tool [38,39].

4.4. Temperature Variation and Environmental Robustness

Temperature is one of the most influential factors for lithium-ion battery behavior. The temperature dependence of capacity, internal resistance, impedance response, charge-transfer kinetics, and diffusion processes is reported. Therefore, an SOH model trained under limited thermal conditions may be inaccurate when applied to real vehicles in hot summers, cold winters, or during fast charging [40].

This is a major disadvantage of many laboratory-based SOH estimation studies. If the training dataset is collected at room temperature, the model may mistake a temporary, temperature-dependent change for a permanent, aging-dependent change. For example, the impedance can increase at low temperatures even if the battery has not degraded significantly. The model may overestimate aging under cold conditions without temperature compensation. On the other hand, high temperature can improve some kinetic responses, but this can be temporary, and long-term degradation can be accelerated. This makes interpretation more complex.

For greater robustness, temperature should be a primary input rather than a secondary correction factor. The model should be trained and validated at a wide temperature range and different thermal histories. Also, pack-level temperature gradients must be accounted for, as cells at different positions may experience different thermal conditions. A single temperature sensor may not accurately represent the thermal state of the whole pack [41,42].

However, incorporating temperature information also makes the model more complex. The more input variables there are, the more diverse the training data needs to be, and the temperature-degradation relation is non-linear. Thus, temperature compensation is not just a matter of adding one temperature value to the model. A more robust approach could combine thermal modeling, impedance feature normalization, and multi-temperature validation. The proposed framework may achieve high accuracy in controlled experiments but may not generalize well to real-world applications without systematic thermal validation.

4.5. Data Quality, Sensor Noise, and Pack-Level Complexity

Non-invasive SOH estimation depends strongly on the quality of measured voltage, current, temperature, and impedance-related signals. In laboratory studies, measurements are usually collected using precise instruments under controlled conditions. In actual vehicles or energy storage systems, sensor noise, calibration drift, electromagnetic interference, sampling-rate limitations, and communication errors may reduce data quality. These practical issues can directly affect feature extraction and model accuracy [14].

Battery-pack complexity creates another challenge. Many SOH estimation methods are developed and validated at the single-cell level, but practical systems contain hundreds or thousands of cells connected in series and parallel. Pack-level behavior is not simply the average of individual cell behavior. Cell inconsistencies, imbalances, local temperature differences, uneven aging, and variations in manufacturing quality can cause cells to degrade at different rates. A model trained on individual cells may not accurately represent a full battery pack.

The proposed framework must therefore distinguish between cell-level and pack-level SOH. Cell-level diagnosis provides detailed information but requires more sensing and data processing. Pack-level diagnosis is easier to implement but may hide weak or rapidly degrading cells. This raises a safety concern because a single abnormal cell can reduce pack reliability, even when the average SOH appears acceptable [43,44].

A practical solution is a multi-resolution diagnostic strategy. The BMS can perform routine pack-level SOH estimation while using abnormal voltage deviations, temperature deviations, or impedance inconsistencies to identify suspicious modules or cells. More detailed analysis can then be applied selectively to these high-risk components. This approach reduces computational burden while improving safety. However, it requires reliable thresholds and validation across different battery chemistries and pack designs.

4.6. Cybersecurity, Privacy, and Data Governance

Cybersecurity and privacy issues come with cloud-connected battery diagnostics. Battery data can reveal sensitive user behavior, such as driving patterns, charging locations, charging frequency, vehicle usage intensity, and energy consumption habits. Such data, if transmitted to cloud platforms without proper protection, may compromise user privacy. In commercial fleets or grid-scale storage, battery data may include operational strategies and business information [45].

Cybersecurity is just as important. Cloud-connected BMS are potential attack surfaces. If attackers tamper with battery data, model updates, or diagnostic commands, the system may produce erroneous SOH estimates, inhibit safety warnings, or trigger unnecessary maintenance. In extreme cases, compromised diagnostic systems could affect decisions on charging control or thermal management. Therefore, cybersecurity is not an external issue but must be included in the design of the diagnostic framework.

For practical deployment, encrypted communication, secure authentication, data anonymization, access control, and model update verification are needed. Another perspective is that federated learning is a privacy-preserving approach in which vehicles or storage systems can contribute to model improvement without uploading raw data. Federated learning faces its own set of challenges, such as heterogeneous data distributions, communication overhead, and susceptibility to malicious model updates. Therefore, data governance should be a fundamental part of the design of future SOH frameworks [45,46].

4.7. Generalization across Battery Chemistries and Operating Conditions

Another major limitation is the model's generalization. Lithium-ion batteries vary in chemistry, format, manufacturer, electrode design, electrolyte composition, and pack configuration. A model trained on one cell type may not work well on another. Lithium iron phosphate and nickel-rich layered oxide batteries may have different aging mechanisms and impedance signatures. Manufacturing differences can lead to variations in degradation behavior, even within a single chemistry.

The revised studies provide useful methodological insights, but their datasets remain limited relative to the variability of batteries in real systems. A model that performs well on a given dataset may, to some degree, learn dataset-specific patterns rather than universal indicators of degradation. This is a common drawback of data-driven SOH estimation. Reported accuracy should thus be taken with caution. High accuracy in controlled validation does not guarantee reliable operation in different vehicles, climates, charging protocols, and battery suppliers [47,48].

Future work should include cross-dataset validation, cross-chemistry testing, and long-term field data to improve generalization. Models should be tested on batteries that have not been used in training and that differ in operating conditions. It's also important to quantify the uncertainty. When the model receives data that it has not seen before, it should indicate low confidence rather than output an apparently precise but unreliable SOH value. In this respect, GPR-based methods have an advantage as they can provide predictive uncertainty. However, lightweight onboard models such as ELM may require additional uncertainty-estimation schemes.

4.8. Economic Feasibility and Standardization

The proposed method is not only technically feasible, but also economically feasible. Automakers and energy storage operators will not adopt diagnostic systems that impose significant increases in hardware costs, software complexity, maintenance burden, or certification difficulty. If impedance measurement requires additional circuits, higher sampling rates, or more precise sensors, the cost-benefit ratio must be justified. The method should provide measurable value, such as increased safety, longer battery life, lower warranty costs, better second-life evaluation, and lower maintenance costs.

Standardization is another obstacle. The manufacturers use different BMS architectures, data formats, sampling rates, safety protocols, and battery-pack designs. Without common data interfaces and validation procedures, it will be difficult to compare SOH algorithms or deploy them widely. The comparative table and unified framework presented in this paper offer a conceptual foundation, but practical adoption requires common benchmark datasets, shared evaluation metrics, and standardized testing protocols [31,49].

A critical problem is that many studies report SOH estimation accuracy with different definitions of SOH, different datasets, and different validation methods. Some define SOH as residual capacity, while others include resistance, power capability, or degradation mechanisms. This inconsistency complicates direct comparison. Future research should thus clarify the SOH definition used and report multiple performance indicators, including accuracy, robustness, computational time, uncertainty, and deployment cost [18].

4.9. Overall Critical Assessment

Overall, the unified framework is feasible in principle but requires careful engineering before real-world deployment. The main strengths are the integration of impedance data richness for diagnosis, the automatic feature selection of GPR-ARD, the fast online inference of ELM, and the scalability of cloud–edge cooperation. This mix directly tackles the limitations of a single method. GPR-ARD can enhance feature reliability; fast impedance calculation can shorten measurement time, and ELM can facilitate onboard implementation.

However, there are also some weaknesses in the framework. First, it is heavily dependent on high-quality, representative training data. Without diverse datasets that cover different temperatures, chemistries, aging modes, and operating conditions, the model may not generalize well. Second, cloud–edge deployment enhances scalability, but also entails communication, privacy, and cybersecurity risks. Thirdly, impedance-based diagnosis may be difficult under highly dynamic operating conditions. Suitable measurement windows have to be identified. Fourth, estimating pack-level SOH is more complicated than estimating cell-level SOH due to cell-level inconsistencies and thermal gradients [23,50].

Therefore, the proposed framework should be considered a practical research direction rather than a fully mature deployment solution. Future work should focus on embedded system testing, multi-temperature and multi-chemistry validation, field data collection, cybersecurity design, and the standardization of SOH evaluation metrics. The multi-source, non-invasive, big-data-based SOH estimation can only be moved from laboratory demonstration to reliable application in electric vehicles and stationary energy storage systems once these issues are resolved.

5. Discussion

The trend in the studies reviewed is clear: future SOH estimation needs to move beyond single-signal and single-model approaches. Capacity-based SOH is easy to understand but difficult to measure under normal operating conditions. Impedance-based SOH gives more detailed internal information but needs careful excitation, signal processing, and temperature compensation. Machine learning models can capture nonlinear degradation behavior, but they may suffer from limited interpretability, dataset bias, and deployment constraints. A practical solution should thus combine the benefits of physical insight, impedance diagnosis, and computationally efficient learning.

The proposed framework induces cross-study synergy in three aspects. The multi-parameter SOH concept from the review paper provides the theoretical basis for evaluating the battery health beyond capacity retention. Secondly, the fast impedance calculation and the ELM model in the second study provide a possible approach to online estimation. Third, the GPR-ARD method in the third study enables automated feature selection and uncertainty-aware diagnosis. These elements combined offer a more complete path from data acquisition to real-world deployment.

Another promising direction is multi-modal data fusion. Future systems could include thermal imaging, acoustic signals, mechanical strain, and charging behavior in addition to voltage, current, temperature, and impedance. Such data can help with early detection of localized heating, lithium plating, cell swelling, or abnormal mechanical changes. But more data sources come with more cost and complexity. Hence, the value of each modality should be judged on its contribution to accuracy, robustness, and actionable safety decisions.

The proposed non-invasive SOH framework also has other implications besides vehicle operation. Accurate SOH estimation can enable second-life battery screening, residual value assessment, recycling decisions, and battery passports.

Reliable prediction of SOH and RUL for stationary storage systems enables maintenance scheduling, optimization of charge-discharge strategies, and grid services such as peak shaving and renewable energy buffering. Thus, battery health monitoring is not only a safety technology but also a driver for the circular economy and smart energy systems.

6. Conclusion

This paper reorganized and synthesized the research on non-invasive SOH estimation for energy-storage lithium-ion batteries. To create a clearer academic structure, the manuscript was divided into the following sections: introduction, literature review, methodology, feasibility, discussion, and conclusion. The three studies reviewed were not presented as separate summaries, but their contributions and limitations were integrated within a comparative framework.

The analysis shows that the full SOH characterization, fast impedance-based estimation, and machine-learning diagnosis from EIS are not competing but complementary. We propose a unified framework that utilizes GPR-ARD to identify informative impedance features offline, uses fast FFT-based methods to calculate impedance-related health factors, uses ELM for lightweight onboard SOH estimation, and uses cloud–edge learning to update models under diverse operating conditions.

For practical deployment, technical accuracy must be balanced against computational cost, latency, bandwidth, temperature robustness, data security and validation standards. Future work should focus on standardized datasets, multi-temperature and multi-chemistry validations, interpretable grey-box modeling, cybersecurity-aware cloud BMS design, and pack-level SOH estimation. These improvements will enable non-invasive state-of-charge assessment of batteries, making electric vehicles safer, stationary storage more reliable, and battery lifecycle management more sustainable.

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Data Availability Statement

No new data were created or generated in this study. As this is a review, it is based on data and information from previously published sources, which are cited in the reference list.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

The authors declare that no artificial intelligence (AI) tools were used in the preparation of this manuscript.

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