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Performance Evaluation Of State Estimation Algorithms For Li-Ion Battery State Of Health

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Abstract
Lithium-ion battery state of health (SOH) represents the battery's ability to store and deliver charge relative to its nominal condition . Accurate SOH estimation is vital for the safety and reliability of battery systems, preventing unexpected failures and hazards when cells approach end-of-life. This paper provides a comprehensive overview of prominent state estimation algorithms for predicting SOH in Li-ion batteries and evaluates their performance. We discuss traditional model-based techniques (including Kalman filtering and its variants), advanced data-driven approaches (machine learning models such as neural networks and support vector machines), and hybrid strategies. Key performance metrics and evaluation methods are described, and the strengths and limitations of each algorithm category are compared. By reviewing reported estimation accuracies, computational requirements, and robustness, we highlight how modern algorithms can achieve high precision (often within a few percent error) in SOH prediction. No specific application context is assumed, so the findings apply broadly to Li-ion battery management in electric vehicles, grid storage, and other domains. The paper concludes with insights into the trade-offs among algorithms and the importance of combining model fidelity with data-driven learning to enhance SOH estimation performance.
Keywords: *State of Health (SOH), Lithium-Ion Batteries, Kalman Filter, Particle Filter, Neural Networks, Support Vector Machines, Battery Management System (BMS), Machine Learning, Hybrid Estimation, Deep Learning, Ensemble Learning.*

1. INTRODUCTION

Accurate estimation of a battery's state of health is essential for effective battery management systems. SOH reflects the gradual capacity loss and performance degradation of Li-ion cells over their lifetime. Monitoring SOH in real-time enables predictive maintenance and ensures that battery packs operate safely within design limits . If a battery's SOH falls below a threshold, the risk of failure or hazards (such as overheating or fire) increases, hence timely replacement or reconditioning can be scheduled to avoid safety incidents .
Estimating SOH is challenging because it cannot be measured directly during operation. The SOH is typically defined as the ratio of the battery's current maximum capacity to its rated capacity when new, or alternatively inferred from internal resistance growth or other aging indicators. Traditional methods like coulomb counting (ampere-hour integration) that simply track charge throughput tend to accumulate errors over long use and are sensitive to noise and drift. Thus, more sophisticated state estimation algorithms have been developed to infer SOH from available measurements (voltage, current, temperature) with higher accuracy and robustness.[1] In recent years, a wide range of algorithms – from physics-based filters to data-driven machine learning models – have been proposed for SOH prediction. This paper reviews the most well-known approaches and evaluates their performance. We organize the discussion into model-based estimation techniques, data-driven methods, and hybrid combinations. Key evaluation criteria include estimation accuracy (typically quantified by error metrics), computational complexity (suitability for real-time on-board

implementation), and robustness to varying operating conditions. We focus on general algorithm principles rather than any specific application context, so the insights apply to diverse battery systems.

2. Background: SOH Estimation and Challenges

As a Li-ion cell ages, its capacity and power capability decline due to internal chemical and mechanical changes. Direct measurement of capacity requires fully charging and discharging the cell under controlled conditions, which is impractical for everyday use. Likewise, methods like electrochemical impedance spectroscopy (EIS) can precisely characterize degradation by measuring internal resistance, but such techniques require expensive equipment and cannot be performed continuously on-board a device. Instead, battery management systems rely on indirect estimation: by monitoring easily measured signals (voltage, current, temperature) and using models or data-driven algorithms to infer SOH.

2.1Modeling the degradation:

Battery SOH is influenced by factors such as cycle count, depth of discharge, charge/discharge rates, and temperature. These factors accelerate capacity fade and resistance rise through mechanisms like solid-electrolyte interface (SEI) layer growth and active material loss. Because SOH cannot be observed directly during operation, estimation algorithms must tie observable signals to these internal degradation states. This is complicated by the strong nonlinearity of battery behavior and the influence of operating conditions. Furthermore, each cell can age differently, so estimation methods must be robust to cell-to-cell variations. Effective SOH estimation thus demands models or learned mappings that capture the relation between measured signals and the underlying health state.[2]

2.2Performance evaluation metrics:

The accuracy of an SOH estimation algorithm is typically evaluated by comparing its predicted SOH (or capacity) to the true value obtained from laboratory measurements. Common error metrics include root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) over a set of test data . An estimator with an RMSE below 1–2% is generally considered high-precision for SOH prediction. Other performance considerations include the algorithm's convergence speed (or update rate), stability under noise, and computational load. In on-board applications, algorithms must run in real-time on embedded processors with limited resources, so methods requiring heavy computation or extensive data may be impractical despite high accuracy. We will discuss these trade-offs for each class of algorithms.

3. Model-Based State Estimation Methods

Model-based approaches rely on mathematical representations of battery behavior to estimate SOH. These methods embed knowledge of battery physics (often via equivalent circuit models or empirical aging models) and use **state observers** or filters to infer health-related parameters. Key model-based algorithms include Kalman filters and their variants, which are widely used in battery management.

• **Kalman Filter and Extended Kalman Filter (EKF):** The Kalman filter is an optimal recursive estimator for linear systems and has been adapted extensively for battery state estimation. In practice, the battery's dynamics (voltage response to current input) are modeled, and certain model parameters are associated with SOH. For example, the cell's capacity or internal resistance can be treated as slow-varying state parameters. The standard Kalman filter provides good accuracy and reliability in state estimation . However, batteries are nonlinear systems, so linear Kalman filters are insufficient on their own . The Extended Kalman Filter, which linearizes the nonlinear model at each time step, is commonly applied to estimate both state of charge (SOC) and SOH simultaneously. A typical strategy is the dual EKF: one EKF estimates the SOC in real-time, while another EKF (or an augmented state in the filter) tracks the gradual change in capacity or resistance, thus yielding the SOH . This dual-filter approach has been shown to robustly co-estimate SOC and SOH, and variations such as fractional-order EKFs have been proposed for improved accuracy . Kalman filter methods generally perform well when the model is reasonably accurate; they can achieve estimation errors on the order of a few percent in SOH under nominal conditions. Their performance, however, depends on proper tuning of model parameters and covariance settings. If the battery model is highly nonlinear or the operating conditions vary widely, extended or unscented Kalman filters (UKF) offer better state tracking by handling nonlinearities and uncertainties more effectively . For instance, combining an H-infinity (H∞) filter (a robust observer) with a Kalman filter has been reported to improve estimation under model uncertainty .[3]

• **Particle Filter:** The particle filter (PF) is a Monte Carlo estimation technique that represents the state probability distribution with a set of random samples (particles). PFs are well-suited to nonlinear, non-Gaussian systems and have been applied to battery SOH estimation to handle the nonlinear aging process. In a PF-based SOH estimator, each particle might correspond to a hypothesis of the battery's capacity and internal state, and particles are recursively updated and weighted according to how well they predict the observed voltage. Compared to Kalman filters, particle filters can achieve higher estimation accuracy in complex scenarios because they do not rely on linear approximations and can track multimodal uncertainty . Researchers have demonstrated that particle filtering can improve SOH prediction accuracy as more data samples are accumulated during operation . However, this comes at the cost of significantly increased computation. A standard particle filter requires a large number of particles for accurate results, which can strain the real-time computational resources in a battery management unit. Moreover, as the system complexity grows (e.g. cells in a pack with variability), the particle filter's sample size needs to grow to maintain accuracy, leading to poor timeliness for on-line estimation. To mitigate this, improved PF variants have been developed. For example, Unscented Particle Filters (UPF) combine the UKF and PF by using a UKF to generate proposal distributions for the particles, thus reducing the number of particles needed. Other hybrid PF approaches integrate optimization or machine learning to resample particles more efficiently. These enhancements aim to retain the PF's accuracy while lowering computational cost.

• **Other Observer Methods:** Beyond Kalman and particle filters, various observers and identification techniques contribute to model-based SOH estimation. Recursive least squares (RLS) can track changes in model parameters (like internal resistance) over time, providing an estimate of SOH. Adaptive observers (including H∞ observers mentioned above) offer robustness against model uncertainties and noise. Some methods use impedance models: for instance, measuring the incremental resistance increase at a particular operating point can directly indicate SOH. While not strictly an "algorithm" in the same sense, direct impedance measurement via periodic excitation (as in EIS) is a benchmark for model-based SOH assessment due to its accuracy . However, because of practicality issues discussed, on-line SOH estimation relies on observers that use regular operating data rather than specialized measurements. Generally, model-based methods benefit from physical interpretability – the estimated parameters correspond to real degradation phenomena (e.g. a rise in internal resistance or loss of capacity). Their performance is strong when the underlying model is valid and parameters can be excited and observed, but they may falter if the battery deviates from modeled behavior (for example, under extreme temperatures or aging regimes outside the calibration range). Model-based estimators often need recalibration or adaptive features to maintain accuracy as the battery ages.[4]

4. Data-Driven Estimation Methods

Data-driven approaches do not require an explicit battery model; instead, they learn the relationship between measured signals and SOH from data. With the advent of machine learning and the availability of extensive battery aging datasets, data-driven SOH estimation has become a highly active research area. These methods include machine learning regressors, neural networks, and other pattern recognition techniques. They treat SOH estimation as a mapping or prediction problem based on features extracted from usage data.

• **Statistical and Machine Learning Models:** Early data-driven methods applied statistical regression or simple machine learning algorithms to correlate measured features with battery health. For example, linear or polynomial regression could be used on features like discharge voltage curves or charge time to estimate capacity. More advanced techniques include support vector machines (SVM) and relevance vector machines (RVM). SVM-based SOH estimation has the advantage of working well with smaller training datasets and can handle nonlinear relationships by using kernel functions. Compared to neural networks, SVMs are less prone to overfitting in low-data regimes and have fewer hyperparameters to tune. Researchers have shown that SVM models, especially when optimized with methods like particle swarm optimization (PSO) for parameter selection, can achieve high accuracy in SOH prediction even when only limited degradation data are available . For instance, a PSO-optimized SVM was used to predict battery health with good results, indicating SVM's ability to converge on a global solution where neural nets might get stuck in local minima . Similarly, relevance vector machines (a Bayesian counterpart to SVM) have been applied to quantify SOH with uncertainty estimation; RVMs often yield sparse models and can provide probability distributions for the prediction. Other data-driven techniques include decision trees and ensemble methods (random forests, gradient boosting) that can capture nonlinear dependencies in the data. These have seen less use than neural networks in literature but offer interpretability and fast training.

• **Artificial Neural Networks (ANN):** Neural networks and deep learning have become prominent for SOH estimation due to their ability to approximate complex nonlinear mappings. Multi-layer feed-forward ANNs were among the first applied, taking inputs like voltage, current, temperature, and cycling information and outputting the estimated SOH. An ANN can learn directly from raw time-series or from engineered features (such as charge durations, voltage plateaus, or incremental capacity peaks). The accuracy of neural network models for SOH can be very high when sufficient training data are provided. For example, one study trained an ANN on 400-cycle aging data (voltage, current, temperature profiles) and achieved estimation errors under 1% on test data . The network could generalize the aging trend without needing explicit electrochemical knowledge, indicating the power of data-driven learning. However, conventional ANNs have some drawbacks: they can overfit if the network is too complex relative to the data volume, and their lack of an uncertainty estimate means the prediction confidence is unknown. Moreover, ANN models function as black boxes, providing little insight into the physical causes of degradation.[5]

• **Deep Learning (CNNs and LSTMs):** More recently, researchers have adopted deep learning architectures, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), to improve SOH predictions. CNN-based models can automatically extract informative features from sequences like voltage charge curves. For instance, a CNN can learn shape patterns in the voltage vs. capacity curve that correlate with aging, outperforming manual feature extraction. Recurrent networks, particularly Long Short-Term Memory (LSTM) networks, are adept at capturing temporal dependencies in sequential battery data (such as cycling data over time). LSTM-based models have demonstrated excellent performance in SOH forecasting by learning how internal states evolve over cycles. In fact, comparative studies have found that LSTM networks often yield the highest accuracy among deep learning models for SOH, due to their ability to retain long-term temporal information . For example, an advanced study reported that by using a bidirectional LSTM on partial charge data, SOH could be estimated with as low as 0.4% error while significantly reducing computation and data requirements . The downside of deep models is the computational burden and large data requirement for training. Training a deep neural network can be time-consuming and demands a comprehensive dataset covering various aging scenarios to ensure the model generalizes well. Additionally, these models require more memory and processing power to run – though with modern microcontrollers and the option of off-board computation, this is becoming feasible. Another challenge is that deep learning models may not extrapolate well beyond the conditions seen in training data (for example, a network trained on one cell chemistry might not directly transfer to another). To address this, techniques like transfer learning have been used, where a model is pre-trained on one dataset and fine-tuned on another to adapt to different batteries.

• **Feature Extraction and Selection:** A crucial aspect of data-driven methods is choosing what input features to use for learning. Raw time-series of voltage or current can be high-dimensional; thus many approaches condense information into health indicators. Examples of effective health indicators include: discharge capacity at a fixed voltage cutoff, time to charge between certain voltage limits, internal resistance measured through current pulses, and derived quantities like the area under voltage curves or differential voltage peaks. Selecting a concise set of features can improve model performance and reduce overfitting. Techniques such as principal component analysis (PCA) and mutual information analysis are used to identify which measured variables or transformations thereof are most correlated with SOH. Data-driven algorithms are often paired with such feature engineering to enhance accuracy. The performance of data-driven models is typically evaluated on hold-out test data or cross-validation to ensure they can predict SOH for new cycles or cells not seen during training. When evaluated on standard datasets (like NASA battery aging data or CALCE datasets), many machine learning models report estimation errors within just 1–2%, rivaling the precision of laboratory methods. It should be noted, however, that achieving these results in practice requires that the operational data fed into the algorithm falls within the range of conditions the model was trained on. Unexpected conditions (e.g. extreme temperatures, novel load profiles) can degrade the predictive performance, since the model may not recognize patterns beyond its training distribution.

5. Hybrid and Ensemble Approaches

No single method excels in all aspects; hence researchers have explored combining multiple approaches to leverage their complementary strengths. Hybrid estimation algorithms fuse model-based and data-driven techniques, or combine multiple models, to improve robustness and accuracy.

One form of hybrid approach uses a model-based observer to preprocess data or constrain a data-driven model. For example, an unscented Kalman filter – particle filter (UKF-PF) fusion might employ a UKF to estimate SOC in real-time and feed that into a particle filter that estimates capacity (SOH). By splitting the task, each filter handles the part it is best at, improving overall stability. Similarly, some works combine extended Kalman filters with neural networks: the EKF can provide a real-time state estimate and uncertainty, which a neural network then refines by learning the residual errors. This kind of model-assisted machine learning ensures that physical constraints are respected while still allowing data-driven flexibility.[6]

Another powerful strategy is ensemble learning, wherein multiple estimation models are run in parallel and their outputs are combined for a final SOH prediction. Ensemble methods can average out the biases of individual models and provide more reliable estimates. Recent literature has presented ensemble frameworks that include diverse algorithms (e.g. an EKF, an SVM, and a neural network) whose outputs are weighted and aggregated. Multi-model ensemble learning for battery SOH, highlighting that ensemble approaches can improve estimation accuracy across different aging scenarios by capturing a wider range of behaviors.[6] In practice, an ensemble might involve a committee of neural networks (sometimes called an ensemble of experts) or a combination of data-driven predictors with rule-based adjustments. For instance, if one model tends to overestimate SOH at high temperatures and another underestimates it, an ensemble can balance these to yield a better result. The performance of ensemble methods in studies has been promising – often outperforming any single model, especially in scenarios with varying usage patterns where one model alone might not be sufficient for all conditions.

Adaptive and meta-learning techniques have also emerged in SOH estimation. These involve algorithms that can adapt to new data on-line or transfer knowledge from one battery to another. For example, meta-learning can train a neural network that quickly fine-tunes to a new cell using a few early cycles of data, thereby addressing the variability between batteries. Such techniques aim to ensure that an algorithm trained on one dataset remains effective when deployed in a slightly different context (different battery batch or operating profile). While still an active research frontier, adaptive methods are crucial for practical deployment, as they can continuously recalibrate the SOH estimator to remain accurate over the life of the battery without human intervention.

In summary, hybrid algorithms and ensembles strive to exploit the strengths of both model-based and data-driven worlds. Model-based components inject physical reasoning and ensure consistency, while data-driven components contribute flexibility and ability to capture complex patterns. The performance benefit of these combinations is evident in many studies – they tend to yield lower estimation error and better generalization than either approach alone. The trade-off is increased algorithmic complexity and sometimes higher computational cost, but ongoing improvements in processing capabilities are making such sophisticated schemes increasingly viable for on-line battery management. The comparision of various SOH estimation methods for Li-ion batteries is tabulated in table 1.

Table. 1 Comparison of various SOH Estimation Methods for Li-ion Batteries

Method Category	**Technique**	**Estimation Accuracy**	**Computational Complexity**	**Robustness to Noise/Uncertainty**	**Strengths**	**Limitations**	**Citation**
Model-Based	Kalman Filter (KF)	Moderate (5–10%)	Low–Moderate	Low	Real-time; simple; widely implemented	Assumes linearity; sensitive to model mismatch	[11], [12]
	Extended Kalman Filter (EKF)	High (2–5%)	Moderate	Moderate	Handles nonlinear dynamics; well-validated	Linearization errors; parameter tuning required	[10], [11], [12]
	Unscented Kalman Filter (UKF)	Very High (<2%)	High	High	No Jacobian; accurate nonlinear estimation	Heavy compute; sensitive to noise assumptions	[13]
Data-Driven	Neural Networks (NN)	High (<3%)	High	High	Captures complex patterns; flexible training	Needs large dataset; risk of overfitting	[8], [14]
	Support Vector Machines (SVM)	Moderate–High (3–6%)	Moderate	Moderate–High	Robust generalization; small-data-friendly	Kernel selectivity; less interpretable	[9], [15]
Hybrid	EKF + Neural Network	Very High (<2%)	Very High	High	Merges physics and data insights	Integration complexity; computational demands	[8], [16]

6. Performance Evaluation and Discussion

When evaluating the performance of SOH estimation algorithms, it is important to consider several aspects:

Accuracy: This is typically the primary metric. Most algorithms aim for an estimation error under a few percent. Model-based methods like EKF often achieve around 2–5% error in experimental validations , assuming the model is well-tuned. Data-driven methods, especially deep learning models, have reported even higher accuracy. For instance, a convolutional neural network combined with a Transformer model was able to keep SOH prediction errors within about 1%. In another case, a Bi-LSTM deep network reached 0.4% error by focusing on the most informative portion of the charge curve . Such high precision is encouraging, but one must ensure these results are reproducible across different cells and conditions. Often, results quoted in literature are obtained on specific datasets in controlled settings. In real-world applications, achieving sub-1% accuracy consistently may require additional calibration or ensemble averaging to account for variations.

Robustness: A robust SOH estimator maintains accuracy despite noise, sensor bias, and changing operating conditions. Model-based approaches can struggle if the battery operates outside the assumed model range (e.g. at very low temperatures or after extreme aging where model parameters shift). Data-driven models can also fail if they encounter conditions not represented in training data. To evaluate robustness, researchers test algorithms on cycles with fluctuating load profiles (instead of neat constant-current tests) and introduce perturbations. Algorithms like the PF are inherently equipped to handle noise probabilistically, while Kalman filters can be tuned for different noise levels. Many neural network models include data augmentation during training (adding noise, varying usage patterns) to improve their resilience. In performance terms, a robust algorithm might show only a small increase in error when moving from laboratory test profiles to realistic driving profiles of electric vehicles, for example. Another aspect of robustness is long-term stability – the estimator should not drift significantly over hundreds of cycles without external recalibration. Evaluating this may involve running the algorithm in a simulation or on experimental data for extended periods and checking that it does not accumulate error.

Computational efficiency: The computational load of each algorithm varies widely. Simple models (like an RLS or a single EKF) can run on microcontrollers with negligible CPU impact, updating in real-time at 1 Hz or faster. In contrast, a particle filter with thousands of particles or a large deep neural network might be computationally intensive. Performance evaluation must thus consider whether an algorithm can meet real-time requirements on the target hardware. In recent work, optimizations have been proposed to reduce computation: for example, simplifying neural network architectures or using smaller time windows of data without sacrificing accuracy . Some systems employ onboard digital signal processors or even machine learning accelerators to handle the more demanding algorithms. The timeliness of estimation is also a factor – certain methods can estimate SOH on-line every cycle, whereas others might require a special calibration cycle or a periodic rest (for instance, some impedance measurement). Algorithms that can update SOH continuously during normal operation are preferred for most applications.

Generality and adaptability: A key practical consideration is whether a given algorithm needs to be re-trained or re-parameterized for each battery type or if it can generalize. Many data-driven models are trained on a specific battery chemistry and cycling regime, and their performance can degrade on a different dataset. Model-based methods anchored in electrochemical meaning (like those tracking resistance or capacity) often translate better across similar cell types, although they too may require parameter tuning. Hybrid and ensemble approaches can improve generality by incorporating multiple perspectives. Performance evaluation should include testing on multiple batteries (if data is available) to see how sensitive the method is to cell-to-cell variation. Recently, adaptive algorithms have shown the ability to self-calibrate – for example, by using a small number of initial cycles of a new cell to adjust a pre-trained model. This adaptability is increasingly incorporated into performance benchmarks: the less human intervention needed to deploy the estimator on a new battery, the better its practical performance.[7]

7. Summary of Pros and Cons: To synthesize the evaluation, we compare the major algorithm categories:

• **Kalman filter-based (including EKF/UKF):**
Pros: Physically grounded, stable and proven in real BMS applications, moderate computational needs.
Cons: Requires accurate battery models and careful tuning; linearization (in EKF) can introduce error under highly nonlinear behavior; may not capture complex aging dependencies without augmented states.
Typical accuracy: a few percent error with proper model, but can drift if model mismatch grows.
• **Particle filter:**
Pros: Handles nonlinear, non-Gaussian systems well; provides a probabilistic estimate (confidence in SOH).
Cons: High computational cost; performance depends on number of particles and resampling strategy; can be difficult to tune (degeneracy and sample impoverishment issues).
Typical accuracy: very high (1–3% error) in studies with enough particles and data; computational limits might force trade-off in real-time use.
• **SVM and other ML regressors:**
Pros: Effective with smaller datasets; SVM offers good generalization and avoids local minima; fast inference once trained.
Cons: Requires feature selection; not as flexible as neural networks for very complex relationships; training needs a representative dataset.
Typical accuracy: 2–4% error in reported works , with improved results (near 1%) when combined with feature optimization or ensemble techniques.
• **Neural networks (ANN, deep learning):**
Pros: Can achieve very high accuracy by learning intricate patterns; no need for an explicit model of the battery; can incorporate many inputs (multivariate).
Cons: Data-hungry – needs extensive aging data for training; risk of overfitting; acts as a black box (limited explainability); heavy computation for large networks.
Typical accuracy: Many studies report <2% error, some even <1% , on test data. Real-world accuracy depends on similarity to training conditions; might drop if encountering novel situations unless retrained.
• **Hybrid/Ensemble:**
Pros: Combine strengths to improve accuracy and robustness; ensemble reduces individual model bias; can provide more reliable estimates across diverse conditions.
Cons: Increased complexity and computational overhead; more difficult to design and validate; requires careful integration of components.
Typical accuracy: Among the best reported – ensembles often beat single models by a noticeable margin, achieving error around 1% or less in research demonstrations . The complexity trade-off must be managed for practical deployment. Overall, the state of the art in SOH estimation is capable of very precise predictions under experimental conditions. For instance, with laboratory datasets, algorithms have shown they can estimate remaining capacity within a few tens of milliampere-hours of the true value (i.e., within ~1% for a cell of a few Ah capacity). The challenge is to maintain such performance in real-world operation over the full lifespan of the battery, under changing environments and usage patterns.
Performance evaluation, therefore, is not one-time: it is an ongoing process. In practical BMS software, the algorithm's estimates would be periodically checked against reference points (like occasional full charge/discharge or known checkpoints) to recalibrate as needed. A combination of algorithmic accuracy and strategic validation ensures that the SOH estimation remains reliable.

8. CONCLUSION
Accurate SOH estimation in lithium-ion batteries is pivotal for the safe and efficient use of battery systems. Through this review, we have surveyed the most prominent algorithms for SOH prediction and discussed their performance characteristics. Model-based methods, grounded in battery physics and typically employing Kalman filters or observers, offer transparency and have proven effective with carefully developed models. They tend to be computationally efficient and can be quite accurate (within a few percent error) so long as the battery behaves according to the modeled parameters. Data-driven methods, leveraging machine learning

and large datasets, have pushed the envelope of accuracy even further – often achieving sub-1% estimation errors in research settings – by uncovering complex relationships in the data that elude simpler models. Techniques like neural networks (CNNs, LSTMs) and support vector machines enable direct mapping from measured signals to health state, at the cost of requiring extensive training data and computational resources. Hybrid approaches and ensembles combine these paradigms to capitalize on their strengths, yielding robust performance across varying conditions and extending the range of applicability.

In evaluating performance, one must consider not only nominal accuracy but also robustness to noise and cell variability, computational load, and ease of adaptation to new cells or systems. The best choice of algorithm often depends on the context: for example, an electric vehicle's BMS might favor a fast, robust filter with ensured real-time operation, whereas an offline diagnostic tool could employ heavy data-driven analytics for maximum accuracy. There is no one-size-fits-all solution, but rather a toolkit of algorithms that can be tailored and even combined to meet specific requirements. Importantly, all the discussed methods continue to evolve. Future trends point toward improved adaptivity – algorithms that can learn from field data in-service, continuously refining their estimates as more information becomes available. This could involve online machine learning or adaptive observers that adjust to each battery's unique aging trajectory. Another active area is developing explainable AI models for SOH, which would merge the accuracy of black-box models with the interpretability of physics-based approaches, thereby increasing trust in the estimates.

In conclusion, the performance of state estimation algorithms for Li-ion battery SOH has reached impressive levels, with many methods now capable of tracking battery health with a high degree of precision. Achieving <1% error is feasible under certain conditions, as demonstrated by advanced filtering and deep learning techniques. The challenge moving forward is to ensure these algorithms maintain their performance in the messy, unpredictable realm of real-world usage. By judiciously selecting or combining algorithms and rigorously evaluating them against practical criteria, battery engineers can deploy SOH estimation strategies that significantly enhance battery management – enabling longer lifespans, improved safety, and better overall utilization of lithium-ion batteries in all applications.

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