# Advanced Kalman Filter–Based Approaches for State-of-Charge Estimation in Lithium-Ion Batteries: Models, Techniques, and Applications

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**Abstract.** Lithium-ion batteries are pivotal in modern energy storage systems due to their high energy density and longevity, where accurate state-of-charge (SOC) estimation is critical for ensuring safe and efficient battery management. This paper reviews advancements in Kalman Filter (KF)-based SOC estimation methods, emphasizing their adaptability to nonlinear dynamics, parameter uncertainties, and aging effects. Classical KF demonstrates computational simplicity for mildly nonlinear systems, while Extended KF (EKF) and Unscented KF (UKF) address stronger nonlinearities via linearization or sigma-point propagation. Adaptive variants, such as the Model-Adaptive EKF (MAEKF), dynamically recalibrate resistance parameters using voltage-derivative analysis, reducing SOC errors below 4% in aged cells. Hybrid approaches integrating neural networks, such as LSTM-augmented UKF, achieve robust performance (1.1–2% RMSE) under dynamic loads and temperature fluctuations by leveraging temporal dependencies. However, challenges persist in computational complexity, temperature compensation, and chemistry-specific calibration. The study underscores the importance of balancing accuracy, adaptability, and computational efficiency for real-time battery management systems. These advancements enhance the reliability of SOC estimation in electric vehicles and grid storage, while future work should prioritize hybrid algorithms combining physical models with data-driven techniques and optimized embedded implementations for broader applicability.

**Keywords:** Lithium-Ion Batteries, State of Charge, Battery Management Systems, Kalman Filter, Neural Networks

## 1 Introduction

Lithium-ion batteries are widely recognized for their superior energy density, reduced mass, and extended cycle life relative to conventional battery technologies, rendering them a focal point of research and development in both industry and academia [1]. Accordingly, the accurate modeling, design, estimation, and deployment of battery management systems (BMS) for lithium-ion cells have become indispensable. Most current battery models rely on fundamental parameters, among which the state of charge—reflecting the internal condition of the battery—serves as a principal indicator [2].


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In recent years, substantial efforts have been directed toward enhancing the accuracy of SOC estimation. Among the proposed approaches, the Coulomb counting method remains one of the most widely employed techniques [3]. However, it is not without limitations, including a pronounced sensitivity to the initial SOC value, which may yield inaccuracies. In addition, reliance on integration-based calculations can cause errors to accumulate over time [4]. Hence, despite its simplicity and popularity, Coulomb counting often struggles to maintain reliable accuracy under fluctuating operating conditions or aging effects.

To overcome these shortcomings, researchers have explored a variety of complementary or alternative SOC estimation strategies. One approach involves open-circuit voltage (OCV)-based estimation, where the battery is assumed to rest for a sufficient period before measuring its terminal voltage [5]. Although theoretically straightforward, this method is difficult to implement in applications where continuous operation is required, since practical systems rarely permit lengthy rest intervals. Another significant thread of research has centered on model-based observers, which seek to incorporate dynamic battery models and feedback mechanisms to refine SOC estimates. Examples include sliding-mode observers, Luenberger observers, and various extended or robust state estimators. These approaches improve accuracy by fusing measurement data (such as voltage, current, and temperature) with a suitable system model, thereby mitigating reliance on a single estimation channel.

Among the observer-based techniques, Kalman filter-based methods have garnered particular attention. A Kalman filter recursively combines prior state estimates with real-time sensor measurements, yielding a statistically optimal solution under Gaussian noise assumptions [6]. In linear systems, the classical KF offers an elegant, computationally efficient framework. However, lithium-ion battery behavior frequently departs from strict linearity, prompting the development of variants such as the Extended Kalman Filter and Unscented Kalman Filter. Both methods aim to handle system nonlinearities—through either local linearization or sigma-point propagation—while retaining the recursive filtering properties that make KFs suitable for real-time BMS applications.

In addition to handling nonlinearities, recent studies have explored adaptive or data-driven Kalman filters to address battery parameter variations arising from temperature changes, aging, and manufacturing discrepancies. For instance, adaptive EKFs periodically adjust process and measurement noise covariance matrices to better capture the evolving battery characteristics, and neural-network-augmented Kalman filters leverage machine learning to refine model parameters on the fly [7].

Overall, these research developments highlight the critical role of SOC estimation in maintaining safe, efficient, and long-lasting operation of lithium-ion batteries. By comparing different Kalman filter variants and other established methods, engineers and researchers can identify the most suitable balance between computational complexity, estimation accuracy, and robustness to parameter uncertainties. In the ensuing sections, this paper will review fundamental concepts of Kalman filter theory, assess their relevance to various SOC estimation methods, and examine prominent applications that illustrate both the effectiveness and the remaining challenges in lithium-ion battery management.

## 2 Overview of Kalman Filters

Kalman Filters are widely employed in dynamic state estimation problems where system and measurement uncertainties must be handled efficiently. Originally proposed for linear and Gaussian noise conditions, the Kalman Filter framework has been extended and adapted to cope with nonlinearities and time-varying parameters, thus giving rise to multiple variants such as the Extended Kalman Filter and the Unscented Kalman Filter [8]. This section provides an overview of these key variants, along with a brief discussion of how Adaptive Kalman Filtering differs in principle.

### 2.1 Classical Kalman Filter

The classical KF addresses discrete-time linear systems of the form:

$$X_{k+1} = AX_k + BU_k + \omega_k \tag{1}$$

$$Z_k = HX_k + \gamma_k \tag{2}$$

where $X_k$ is the state vector, $U_k$ Is the control input, and $Z_k$ is the measurement vector. The process noise $\omega_k$ and measurement noise $\gamma_k$ are typically assumed to be zero-mean Gaussian with known covariance matrices $Q$ and $R$, respectively. The KF recursively proceeds by predicting the state and covariance, then updating these estimates using incoming measurements. One of the core formulas in the update stage is:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1} \tag{3}$$

where $K_k$ is the Kalman gain, and $P_{k|k-1}$ is the predicted error covariance. This classical formulation performs optimally under linearity and Gaussian assumptions but may degrade when the system is significantly nonlinear. The versatility of Kalman Filters is exemplified in their widespread adoption for lithium-ion battery SOC estimation. For instance, Spagnol et al. [6] implemented a linear KF with a second-order equivalent circuit model (ECM), achieving 1–3% SOC error by balancing computational simplicity and moderate nonlinearity handling.

### 2.2 Extended Kalman Filter

When the state or measurement equations are nonlinear, the EKF performs a local linearization about the current estimate. Specifically, the system can be described by:

$$X_{k+1} = f(X_k, U_k) + \omega_k \tag{4}$$

$$Z_k = h(X_k) + \gamma_k \tag{5}$$

where $f(X_k, U_k)$ and $h(X_k)$ are differentiable functions. EKF computes Jacobian matrices of $f$ and $h$ at the estimated state to linearize these functions. This approach is relatively straightforward to implement but can suffer from inaccuracy if the actual system exhibits strong nonlinearities beyond the validity of a first-order expansion. Charkhgard and Farrokhi [7] integrated an Extended KF with a Radial Basis Function neural network, reducing dependence on precise battery models while maintaining 2% error robustness.

### 2.3 Unscented Kalman Filter

The UKF bypasses explicit Jacobian calculations by employing the Unscented Transform. It selects a set of "sigma points" around the mean and covariance to capture the spread of the state distribution. These sigma points are then propagated through the true nonlinear functions $f$ and $h$ . By recomputing a new mean and covariance from the transformed points, the UKF often yields higher accuracy than EKF for strongly nonlinear problems. However, it has a slightly higher computational demand due to the generation and transformation of multiple sigma points. For strongly nonlinear systems, Yang et al. [9] fused a Long Short-Term Memory (LSTM) network with UKF, leveraging sigma-point propagation to handle temporal dependencies in dynamic load profiles. This hybrid approach achieved RMSE values of 1.1–2% under temperature fluctuations (0–50°C), outperforming EKF in flat OCV-SOC regions typical of $LiFePO_4$ cells. UKF's avoidance of Jacobian calculations enhances stability but increases computational demands.

### 2.4 Relation to Adaptive Kalman Filters

Adaptive Kalman Filters adjust covariance matrices $Q$ and $R$, or even parts of the system model, on the fly. These adjustments can be integrated into either an EKF or a UKF framework, particularly in scenarios where system parameters (e.g., internal resistance or capacity in battery systems) change over time. Thus, AEKF is not a distinct type of filter in the same sense as EKF or UKF; rather, it is a mechanism that enriches existing Kalman formulations with real-time parameter adaptation. Adaptive variants like AEKF dynamically adjust noise covariances to counter parameter drift. For instance, Sepasi et al. [4] proposed a Model-Adaptive EKF that updates resistance parameters via voltage-derivative analysis. By optimizing model parameters at 92% and 15% SOC reference points, MAEKF reduced errors to below 4% in aged cells, demonstrating adaptability to capacity fade and aging effects.

## 3 SOC Estimation Methods Using KFs

Recent research on lithium-ion battery State-of-Charge estimation has explored a range of Kalman Filter approaches, often combined with data-driven or neural network methods to handle the nonlinearity and parameter uncertainties of real battery systems. Three representative studies illustrate the diversity of strategies in this domain, highlighting both traditional and more advanced techniques.

Spagnol et al. [6] propose a linear Kalman Filter framework anchored by a second-order equivalent circuit model (ECM). They linearize the open-circuit voltage (OCV) curve to accommodate the KF formulation and capture short- and long-term voltage transients via two RC networks. By judiciously tuning the process ($Q$) and measurement ($R$) covariances, their method successfully manages moderate parameter deviations across different cells. This Kalman Filter-based algorithm achieves rapid convergence (within 10 minutes) and robust noise rejection on the cell used for the identification process (Cell 1), maintaining SOC estimation errors below 4% under dynamic current profiles (Fig.1), while exhibiting adaptability to parametric dispersion across cells, as validated on a new battery (Cell 2) with ±3% accuracy under random loads and measurement uncertainties (Fig.2).

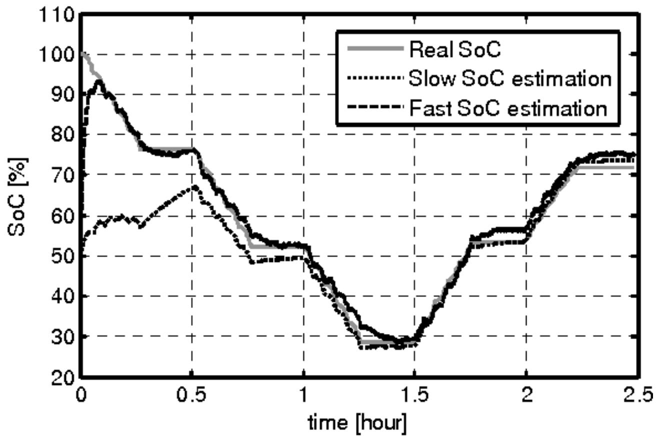


**Fig. 1.** Stair test on Cell 1 [6]

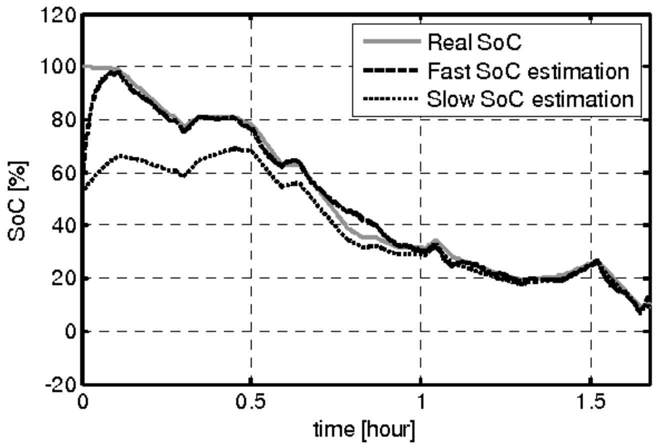


**Fig. 2.** Random test on Cell 2 [6]

Although they report convergence to roughly 1–3% error within minutes, their linear approximation inevitably imposes restrictions. For example, strongly nonlinear regimes or temperature-driven variations require either frequent model updates or complementary calibration steps. Nevertheless, the computational simplicity of a standard KF implementation is a clear strength for real-time Battery Management Systems.

In contrast, Charkhgard and Farrokhi [7] integrate a Radial Basis Function (RBF) neural network with an Extended Kalman Filter to better address the inherent nonlinearity of Li-ion batteries. Here, the RBF network approximates the voltage–SOC relationship offline, while the EKF corrects measurement noise and model discrepancies online. Their Adaptive EKF adjusts the process noise covariance to cope with battery aging or thermal effects, thereby reducing the dependence on precise a priori model knowledge. Experimental validation in Fig.3 shows around 2% SOC error across varying initial conditions, indicating a robust estimation scheme.

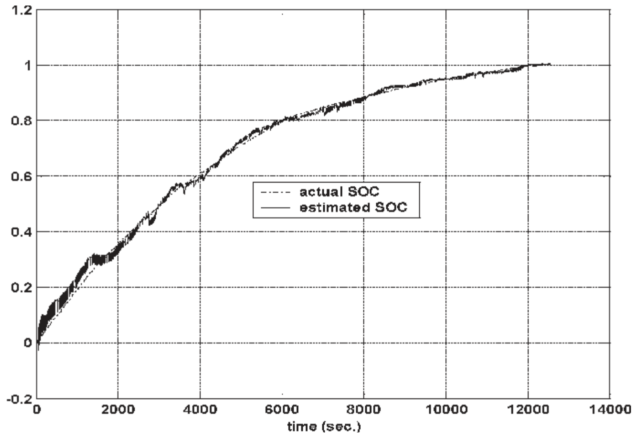


**Fig. 3.** (Dashed line) Desired SOC measured by the ampere–hour counting technique and (solid line) the estimated SOC using the EKF and the neural networks (NNs) [7]

However, the approach hinges on offline training data quality, and the neural network might require periodic retraining if the battery undergoes substantial aging or is operated in conditions not reflected in the training set.

A more recent contribution by Fangfang Yang et al. [9] further extends the data-driven paradigm by employing a Long Short-Term Memory recurrent neural network. Compared with simpler RBF or feedforward networks, LSTMs excel at capturing temporal dependencies, which is especially valuable under dynamic loads and temperature fluctuations. The authors fuse the LSTM's output into an Unscented Kalman Filter to refine SOC estimates in real-time, leveraging sigma-point propagation instead of linearization. Results from driving cycles (DST, US06, and FUDS) at temperatures ranging from 0°C to 50°C demonstrate RMSE values between about 1.1% and 2%. Notably, the LSTM–UKF framework manages "flat" OCV–SOC regions, typical of LiFePO4 cells, and adapts to temperatures unseen during training, underscoring the network's generalization ability and the UKF's noise mitigation.

Taken together, these three studies showcase the evolution of KF-based SOC estimation toward hybrid, data-informed solutions. While a classic linear KF with a well-identified ECM is sufficiently accurate for moderate nonlinearities, introducing an EKF or UKF and coupling it with a neural model can substantially improve performance across broader operating regimes. Each approach has trade-offs: standard KF or EKF methods are easier to implement and computationally lighter, yet they can struggle with severe nonlinearity or parameter drift. Neural-network-augmented filters offer superior adaptability but demand quality training data and add computational overhead. Looking ahead, integrating advanced learning architectures (e.g., deep RNNs, convolutional neural networks) with Kalman-based estimation may further enhance SOC estimation under real-world conditions characterized by temperature gradients, aging effects, and complex load patterns.

# 4 Application

## 4.1 Application of AEKF

Accurate state-of-charge estimation is paramount for optimizing the performance and reliability of lithium-ion batteries in real-world applications, particularly in compact electric vehicles (EVs) utilizing 1.2-Ah Li-ion cells. These batteries are integral to urban EVs, where precise energy management ensures extended range, safe operation, and longevity. Charkhgard and Farrokhi's hybrid methodology, which synergizes radial basis function (RBF) neural networks with an adaptive extended Kalman filter, addresses the inherent nonlinearities and noise challenges in dynamic operating environments. This approach was rigorously validated under practical charging protocols, including reflex charging and pulse charging, demonstrating robust applicability in EV battery management systems.

## 4.2 Implementation in Urban EV Battery Systems

The proposed framework was experimentally tested on a 1.2-Ah Li-ion battery, representative of those used in compact EVs like Nissan Leaf's auxiliary power modules or Tesla's urban mobility prototypes. The RBF NN, trained offline using data from full charging cycles, effectively modelled the nonlinear relationship between terminal voltage, current, and SOC. The adaptive EKF dynamically adjusted process noise covariance matrices to mitigate uncertainties arising from sensor inaccuracies and aging effects. As illustrated in Fig. 3, the estimated SOC (solid line) exhibited a tight alignment with the reference SOC (dashed line) derived from Coulomb counting, achieving an RMS error of 2% under steady-state conditions. This precision persisted even during abrupt load transitions, such as shifts from 70% to 20% charging duty cycles, mimicking real-world urban driving patterns with frequent acceleration and deceleration.

## 4.3 Robustness Under Real-World Scenarios

The algorithm's resilience was further validated in scenarios emulating practical disruptions. For instance, when the battery was disconnected mid-charge and reconnected after a 30-minute interval, the adaptive EKF converged to the true SOC within 2.5 minutes (Fig. 4), showcasing rapid recovery from initialization errors—a critical feature for EVs encountering sudden power interruptions in traffic or grid instability. Additionally, the method maintained a 3% RMS error across varying ambient temperatures (5 ° C–45°C), underscoring its adaptability to diverse climatic conditions typical of global urban environments.

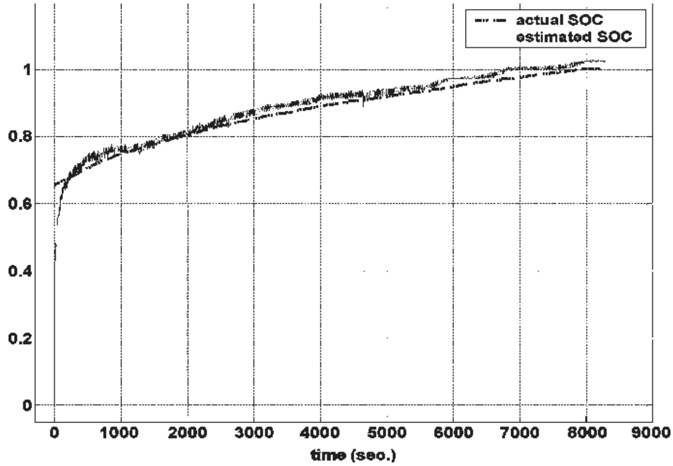


**Fig. 4.** Testing the proposed SOC estimator with different initial conditions for state variables of EKF (disconnecting the power supply for 30 min) [7]

## 4.4 Computational Efficiency and Scalability

The hybrid NN-EKF framework's computational efficiency enables seamless integration into embedded BMS hardware. By employing adaptive noise covariance updates, the algorithm minimizes processing overhead while retaining accuracy, making it suitable for resource-constrained EV systems. For example, in BYD's electric buses or Renault's city EVs, this method ensures real-time SOC tracking without necessitating high-end processors, thereby reducing production costs.

## 4.5 Practical Implications

This hybrid approach revolutionizes SOC estimation in aging-sensitive applications. By combining voltage-current dynamics modelling with adaptive filtering, it mitigates the limitations of traditional EKF in aged batteries, where parameter drift (e.g., increased internal resistance) degrades accuracy. For automakers like Tesla or NIO, adopting this method enhances BMS reliability, prolongs battery lifespan, and reduces maintenance costs. Furthermore, its scalability to larger battery packs—common in electric trucks and grid storage systems—positions it as a universal solution for next-generation energy storage technologies.

## 5 Challenges and Future Directions

Despite significant advancements in Kalman Filter-based SOC estimation methods, several challenges persist, particularly in addressing real-world operational complexities. First, model parameter drift due to aging remains a critical issue. While adaptive frameworks like MAEKF mitigate this by updating resistance parameters, the reliance on fixed reference points (e.g., 92% and 15% SOC) introduces sensitivity to cell chemistry variations. For example, different Li-ion chemistries (e.g., NMC, LFP) exhibit distinct voltage-SOC characteristics, necessitating generalized or chemistry-specific calibration strategies. Second, computational constraints limit the feasibility of complex algorithms, such as brute-force optimization or neural-network-augmented KFs, in low-cost embedded BMS hardware. Real-time execution of these methods under dynamic load profiles demands further optimization to balance accuracy and computational efficiency.

Third, temperature dependency complicates SOC estimation, as both battery dynamics and Kalman filter parameters (e.g., noise covariances) vary with thermal conditions. Existing studies often validate algorithms under controlled temperatures, but real-world applications require adaptive frameworks that integrate temperature compensation without excessive calibration. Fourth, data-driven approaches, while promising, face challenges in generalization. Neural networks trained on limited datasets may fail to capture aging trends or unseen operating conditions and ambient temperatures, necessitating robust transfer learning or online adaptation mechanisms [10].

Future research should focus on hybrid architectures that synergize physical models with machine learning. For instance, physics-informed neural networks (PINNs) could embed electrochemical principles into data-driven models, enhancing interpretability and reducing training data requirements. Additionally, edge computing advancements may enable lightweight implementations of UKF or AEKF variants on low-power BMS hardware. Exploring multi-scale estimation frameworks, where SOC is co-estimated with state-of-health and state-of-power, could further improve BMS reliability. Finally, standardization of aging protocols and open-access datasets would accelerate algorithm benchmarking and foster reproducibility across studies.

## 6 Conclusions

This article systematically reviews the state of charge estimation methods for lithium-ion batteries based on Kalman filtering, with a focus on analysing the performance and limitations of classical KF, extended KF, unscented KF, and adaptive KF variants in dealing with nonlinear dynamics, parameter uncertainty, and aging effects. It also explores the progress of their hybrid architecture with neural networks such as radial basis function networks and long short-term memory networks in improving estimation accuracy and robustness. The study revealed the core advantages of the KF method in real-time battery management systems: classical KF achieves 1-3% error with low computational complexity, EKF handles moderate nonlinearity through local linearization, UKF optimizes strong nonlinearity problems using traceless transformation (RMSE

1.1-2%), and adaptive KF (such as MAEKF) reduces SOC error of aged batteries to below 4% by dynamically calibrating resistance parameters. Experimental verification shows hybrid methods such as LSTM-UKF have excellent generalization ability under dynamic loads and temperature fluctuations. However, existing technologies still face challenges such as computational complexity, temperature dependence, chemical specificity calibration, and insufficient generalization of data-driven models. In the future, it is necessary to integrate physical models with machine learning (such as physical information neural networks), optimize embedded algorithms to achieve low-power BMS, and promote standardization of ageing protocols and open datasets. This article provides a theoretical framework and technical roadmap for high-precision and high-reliability SOC estimation, encouraging the intelligent development of battery management technology in electric vehicles and grid energy storage systems.

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