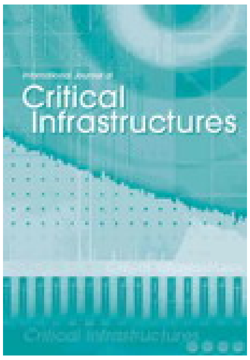

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Precise state-of-charge estimation for LIBs: a cutting-edge nonlinear model approach with enhanced robustness and reliability

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Precise state-of-charge estimation for LIBs: a cutting-edge nonlinear model approach with enhanced robustness and reliability

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Abstract: Precise state-of-charge (SoC) prediction is essential for optimising the performance, safety, and longevity of lithium-ion batteries (LIBs) in battery management systems (BMS). However, traditional prediction tactics, including Kalman filters and sliding mode observers (SMOs), struggle with sensor noise, model uncertainties, and external disturbances, leading to inaccuracies in real-world applications. This study proposes a nonlinear battery framework integrated with a Luenberger observer enhanced by H-infinity (H∞) optimisation to boost SoC prediction accuracy and robustness. The H∞ framework effectively mitigates disturbances, while sensor fault prediction enhances reliability under varying operational conditions. The recommended tactic is computationally efficient and suitable for real-time SoC prediction. Empirical outcomes validate the superior accuracy and stability of the recommended approach, achieving prediction errors that are up to 3.8% lower than those of conventional SMOs. The findings demonstrate potential for next-generation BMS applications, particularly in electric vehicles (EVs) and energy storage systems. Future work will focus on adaptive parameter prediction techniques to boost performance under real-world battery ageing conditions.

Keywords: lithium-ion battery; LIB; state-of-charge; SoC; Luenberger estimator; H-infinity theory; battery reliability; energy storage systems; battery management systems; BMS; electric vehicles.

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1 Introduction

1.1 Background and motivation

With the continuous advancement of sustainable energy technologies, the demand for efficient and high-performance rechargeable battery systems has surged significantly. As the world transitions toward renewable energy integration and electrified transportation, energy storage solutions are crucial for ensuring reliability, stability, and efficiency in power systems (Zhou et al., 2023). Among several energy storage technologies, LIBs are the most widely used due to their high energy density, long cycle life, and greater charge/discharge efficiency compared to traditional options, including lead-acid and nickel-metal hydride batteries. This growing demand is prominently observed in major markets such as EVs, grid-scale energy storage, portable electronics, and aerospace applications, where there is a need for lightweight, compact, and high-capacity power supplies (Kunatsa et al., 2024). The global LIB industry is experiencing rapid growth due to technological innovation, production cost reduction, and favourable policies promoting the adoption of clean energy (Srilakshmi et al., 2024). The LIB industry is said to grow exponentially with increasing investments in new-age battery chemistries, recycling technology, and enhanced manufacturing techniques. Additionally, with governments globally implementing aggressive carbon reduction regulations and electrification strategies, LIBs are seen as a key driver for decarbonising the energy infrastructure (Korneev et al., 2024). However, despite these advantages, capacity fading, thermal stability, and SoC prediction with precision remain fundamental research issues, demanding novel BMS and intelligent SoC prediction algorithms to achieve optimal performance and extend the life of batteries (Anand et al., 2024).

Accurate estimation of LIB SoC is among the most significant tasks of BMS since it can have direct implications on the overall energy efficiency, safety, and lifespan of a battery (Anushya et al., 2024). SoC refers to the available charge in a battery relative to its maximum capacity and thus is a key parameter for a battery's peak performance in applications like EVs, renewable energy storage, and consumer electronics (Ataseveri and Kose, 2024). However, SoC cannot be measured directly as it is intrinsically tied to the electrochemical reactions within the battery, a function of variables such as temperature variations, charge-discharge cycles, and aging (Babu et al., 2024). SoC estimation is therefore achieved using indirect methods that infer the charge level from the electrical variables such as voltage, current, and impedance, which can be measured (Shenbagavalli et al., 2024). Various SoC estimation techniques have been developed over the years, ranging from straightforward empirical techniques to complex machine learning-based techniques (Siddique et al., 2023). Some of the most cost-effective and straightforward techniques involve impedance measurement and ampere-hour (Ah) counting, which are favoured due to their ease of implementation and minimal computational overhead (Sundararajan et al., 2023). Impedance methods of prediction calculate the charge level of the SoC by analysis of the electrochemical impedance spectrum of the battery. At the same time, Ah counting integrates the charge/discharge currents over time to determine the battery's charge level (Singh et al., 2024). While straightforward, they have severe limitations, including vulnerability to external variability, measurement errors, and cumulative errors with repeated use over time (Kumar et al., 2024). Besides, Ah counting requires precise initial calibration, and impedance-based techniques are battery aging- and temperature-dependent, and therefore less desirable in practical applications (Sun et al., 2023). These intrinsic constraints have motivated researchers to explore more robust and agile SoC prediction techniques, such as model-based observers, Kalman filters (KFs), and artificial intelligence-based approaches for greater accuracy and robustness (John Joseph et al., 2025).

KF is a common recursive estimation approach that aims to produce the optimal state prediction in dynamic systems, especially where measurement noise and system uncertainty exist (Kothuru, 2023). Owing to its high computational efficiency in processing state-space models, the KF has been widely used in battery management systems (BMS) for real-time state-of-charge (SoC) estimation of LIBs (Li et al., 2025). Through the constant update of estimates based on the latest sensor measurements, the KF reduces forecast errors (Krishna Vaddy, 2023). It optimises SoC estimation accuracy to a level that makes it the choice for most applications in energy storage (Xing et al., 2022). To tackle the nonlinearity of LIBs, extensions of KF have been recommended, i.e., the extended KF (EKF) and the unscented KF (UKF) (Madhuranthakam, 2024). EKF linearises the system dynamics around a specific point using the first term of the Taylor series, but this approach may lead to inaccuracies, especially in systems with high nonlinearity (Ikwuagwu et al., 2024a). However, UKF utilises a method called unscented transformation, which handles nonlinearities more effectively at the expense of higher computational complexity (Feng et al., 2022). While effective, KF-based techniques are very sensitive to battery model errors and their accuracy can be compromised due to ambient environmental conditions, including temperature fluctuations, aging effects, and sensor noise. Such limitations underscore the need for more robust and flexible SoC prediction approaches, particularly for high-accuracy and real-time performance-sensitive applications operating in dynamic environments (Ikwuagwu et al., 2024b).

Accurate SoC estimation is a crucial need in BMS, as it maximises energy efficiency, prevents overcharge and deep discharge, and optimises the working life of LIBs (Mehta et al., 2023). Conventional SoC prediction schemes, nevertheless, are severely crippled in real applications by nonlinear battery behaviour, sensor inaccuracies, temperature fluctuations, and environmental noise (Panyaram, 2024). The need for better, more flexible, and stronger SoC schemes encouraged scientists to find novel observer-based strategies that can function in unfavourable conditions. Conventional SoC forecasting approaches, such as Ah counting and impedance spectroscopy, are hindered by elements that restrict their application. Ah, counting tactics accumulate charge/discharge current over time but are very sensitive to measurement errors and initial conditions, which cause huge cumulative errors. Electrochemical impedance-based techniques, although more sophisticated, rely on complex frequency-domain analysis and demanding laboratory conditions, and therefore are not viable for real-time BMS applications (Paramasivan et al., 2024). Similarly, KF-based tactics, such as EKF and UKF, are quite popular in SoC prediction but introduce additional computational complexity and depend strongly on accurate system modelling. EKF assumes linear approximations of the nonlinear dynamics, which can lead to prediction errors (Ramya et al., 2023). In contrast, UKF, although more suitable for nonlinear systems, is computationally more demanding and, hence, not suitable for embedded BMS applications (Xing et al., 2022).

To address these issues, this study proposes a hybrid method that combines the Luenberger observer and H∞ optimisation to improve SoC estimation accuracy, robustness, and stability (Mokdad, 2024a). The Luenberger observer is a deterministic state-space state estimator that utilises the real-time revision of estimated states based on system dynamics and sensory measurements (Mokdad, 2024b). Unlike Kalman-filter-based observers, the Luenberger observer is not probabilistically predictive of state or covariance matrix calibration, and hence, computation is simpler. Still, prediction accuracy is ensured to be high (Pierre et al., 2024). To further enhance the reliability of SoC prediction under real operating conditions, H∞ optimisation is integrated into observer design (Nomula et al., 2023). H∞ theory is a robust control technique that minimises the maximum prediction error, thereby making the system robust against model uncertainties, measurement noise, and external disturbances (Rezaei and Faghih, 2023). Incorporating the H∞ optimisation, the model presented herein possesses a mathematically rigorous basis for addressing uncertainty, as well as nonlinear battery dynamics, and is therefore of extremely high utility for industrial battery applications, grid energy storage, and electric vehicles (Sehrawat, 2024). Through merging the Luenberger observer with H∞ optimisation, a model for optimal, real-time, and very accurate SoC prediction can be established that excels standard tactics in terms of robustness, computational complexity, and adaptability under different working conditions (Senapati et al., 2023). The following sections present the mathematical formulation, experimental proof, and comparative study of the proposed tactic and its superiority compared to standard tactics.

1.2 Literature review

Zhang and Li (2022) presented a discussion on the application of deep learning techniques in the prognostics and health management (PHM) of LIBs, focusing on data acquisition, model building, and performance evaluation. They presented varying architectures like autoencoders (AEs), deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), which have been successful in estimating key states of the battery like SoC and state-of-health (SoH). While deep learning schemes have demonstrated remarkable nonlinear feature extraction abilities, the research has also revealed drawbacks, including high computational expense, dependency on large amounts of labelled data, and a lack of interpretability, which necessitate enhancements in real-world applications. Bayani et al. (2022) noted that although EV adoption reduces carbon emissions and enhances energy sustainability, it also faces technical challenges, most notably, charging infrastructure capacity and high mile-per-hour charging rate. These issues underscore the need for more effective battery control and charging management, which is crucial for enhancing the performance and reliability of LIBs in EV systems. Xue et al. (2025) explored the impact of battery aging on SoC accuracy prediction. They identified that variations in electrochemical parameters and variations in internal resistance weaken the model with time. They compared GPR with aging conditions and LSTM networks and recommended a closed-loop correction policy along with active learning for robust prediction. They minimised errors in SoC prediction to below 1.5% via minimal retraining, highlighting the need for adaptive schemes in long-term battery management. Mao et al. (2023) presented a multi-sensor fusion approach to SoC prediction in LFP batteries through the fusion of voltage and expansion force (EF) signals. EF drift and non-monotonic EF-SoC relationships were addressed by applying normalisation and transformation techniques.

Their global optimal fusion approach outperformed single-sensor schemes with an RMSE below 3%, even in adverse conditions, demonstrating its reliability for use in smart battery applications. Shamarova et al. (2022) surveyed battery energy storage system (BESS) degradation modelling with an emphasis on its complexity due to nonlinear degradation trends, operational variability, and integration with renewable energy sources. They emphasised that oversimplified degradation schemes, i.e., linear depth of discharge (DOD) relation, can lead to misleading cost calculation and unreliable management policies. They surveyed existing BESS schemes, highlighting challenges in reflecting stochastic load variation, the impact of cyclic operation, and realistic environmental conditions, with a focus on the need for more accurate and adaptive degradation schemes to enhance the performance of BESS in microgrid operations. Approaches suggested in the literature for identifying SOC in LIBs involve formulating mathematical schemes to mimic battery dynamics. These schemes are then employed to predict SOC from sensor inputs. These tactics can be electrochemical, equivalent circuit, or empirical model-based, with accurate SOC predictions under various operating conditions. Yet, they may require a comprehensive understanding of battery chemistry and configuration, large computational efforts, and parameter calibration. Sliding mode observers (SMOs) have emerged as an effective approach for SOC prediction in LIBs. SMOs are robust observers with the capability to estimate system states amidst uncertainties and disturbances precisely.

Within the LIB framework, SMOs are effective in SOC prediction from voltage and current measurements. Their greatest advantage lies in their capability to handle nonlinearities and uncertainties within battery schemes, with adaptability to variations brought about by operating conditions, temperature, and aging effects, enabling precise SOC prediction. Additionally, SMOs are insensitive to measurement noise and disturbances commonly found in LIBs, enabling them to maintain the accuracy of SOC prediction. Literature highlights the effectiveness of SMOs for estimating SOC of LIBs accurately and reliably even under unfavourable conditions, with the added benefits of easy, real-time implementability and cost efficiency. Zhong et al. (2017) recommended a fractional-order SMO for SoC prediction of LIBs, with a fractional-order RC equivalent circuit model for better accuracy. The observer estimated SoC, polarisation voltage, and terminal voltage, and stability was verified using Lyapunov's theory. High robustness to modelling uncertainties and measurement noise was exhibited, making it a promising approach for BMS. Behnamgol et al. (2024) presented SoC prediction tactics through the comparison of direct (Coulomb counting) and indirect (observer/filter-based) tactics. Indirect tactics, despite their higher accuracy, are prone to sensor drift and computational issues. They focused on SMOs due to their robustness and fast convergence, and examined various types of SMOs through MATLAB-based simulations to assess their performance and applicability. He et al. (2017) developed a sustainable leaching process for the recovery of major materials from spent LIBs, solving the challenges in battery recycling and resource sustainability. Their approach facilitates efficient recovery of Mn, Li, Co, and Ni and assists in long-term battery lifecycle management. They were interested in material recovery. Lipu et al. (2022) introduced a better machine learning technique for SoC prediction of EV batteries utilising a differential search algorithm (DSA)-enhanced random forest regression (RFR). The method does not require data preprocessing filters and is independent of detailed battery chemistry knowledge, relying solely on sensor data for voltage and current measurements.

McCarthy et al. (2021) reviewed electrochemical impedance spectroscopy (EIS) for LIB state diagnosis, which has a growing significance in SoC, SoH, and internal temperature prediction. As the application of LIB is extended, faster charging, enhanced safety, and more effective energy management have stimulated research interest in more sophisticated diagnostic techniques. Their research highlighted EIS as a suitable tool for monitoring battery states, yet its sensitivity and complexity in response to environmental conditions pose limitations for real-time applications. Tahir et al. (2021) studied LIB electrical modelling using the modified Shepherd equation to estimate the voltage-current response at various loading conditions. Based on a 2RC model, they compared realistic uninterruptible power supply charge/discharge operations with the LIB life and cost efficiency, contrasting them with typical lead-acid batteries. Their findings highlight the benefits of LIBs in uninterruptible power supply applications, underscoring the need for effective SoC prediction strategies to optimise their performance and lifetime. Wang et al. (2021) elaborated on the up-to-date online SoC and SoH prediction tactics for LIBs, citing the importance of real-time battery management for EVs. They also pointed to the nonlinear electrochemical response of LIBs, making the prediction of SoC and SoH difficult. Their assessment compared various approaches introduced over the past five years in terms of their strengths, weaknesses, and overall predictive capabilities. The assessment requires more efficient real-time monitoring strategies to improve LIB performance, safety, and life in EV applications. Chaoui et al. (2017) demonstrated an intelligent SoC and SoH prediction method using a time-delayed neural network as input, eliminating the need for prior battery modelling. Their approach utilises ambient temperature variations and historical voltage-current data to predict battery states, accounting for nonlinear effects such as hysteresis and aging. Hsieh and Chen (2024) elaborated on the role of EVs in the circular economy, outlining key challenges in recycling batteries, charging infrastructure, and renewable energy incorporation. Their study emphasised the need for advanced battery management tactics to boost energy efficiency and battery life in EV applications.

Neural networks, intelligent systems, and artificial intelligence present alternative tactics for identifying SoC in LIBs. Their work explored multi-scale aging schemes at the particle, cell, and battery pack levels and highlighted the importance of thermal-electric battery management in extending LIB lifetime. They recommended a hybrid data-driven and multi-physics-based modelling framework for improved accuracy in aging simulation as well as in computational efficacy. As battery aging directly affects accuracy in SoC prediction, progress in robust prediction techniques can play a crucial role in increasing battery longevity as well as reliability. Fuzzy systems are also used either as a supporting method or for direct SOC prediction. Carrasco Ortega et al. (2023) reviewed the BESSs in renewable energy integration and electricity markets, emphasising the need for efficient battery management strategies to boost performance. They directed their efforts toward battery modelling, state prediction, and techno-economic aspects to improve the viability of storage systems. Fuzzy systems suffer from the limitation that they lack sufficient accuracy on their own and must be optimised to enhance their accuracy. The definition of rules in fuzzy systems relies on reliable and comprehensive knowledge. Recent advancements have included the prediction of battery SoC through the use of data-driven tactics, including ML, DL, and reinforcement learning. Kim et al. (2023) reviewed data-driven approaches for SoC, SoH, and remaining useful life (RUL) prediction in LIBs. Their study highlighted the growing reliance on open battery-cycling databases and ML schemes to boost predictive accuracy. By analysing various data-driven tactics, they highlighted the benefits of utilising large datasets and computational advancements for assessing battery health. However, the challenges associated with model generalisation, real-time adaptability, and dependence on extensive training data remain key limitations. Akram and Abdul-Kader (2024) examined the sustainability challenges of LIBs and the potential of end-of-life EV batteries for stationary applications, aiming to support the United Nations Sustainable Development Goals (SDGs). Their review examined battery aging mechanisms, including SoC, SoH, DOD, and RUL. Nonetheless, a significant drawback of these tactics, including neural networks, is their reliance on a complete and dependable dataset for training these intelligent systems. A comparative analysis of existing studies on SoC prediction and battery management strategies is summarised in Table 1, highlighting their strengths, weaknesses, and limitations in addressing real-world challenges.

Table 1 Comparison of existing SoC prediction tactics and related studies

Study	*Focus of study*	*Strengths*	*Weaknesses*	*Limitations*
Zhang and Li (2022)	Deep learning for PHM in LIBs	High accuracy in complex datasets	High computational cost, requires large datasets	Requires extensive labelled datasets
Bayani et al. (2022)	EV adoption, carbon emissions, and charging infrastructure challenges	Emphasises sustainability and EV integration	Limited focus on technical solutions	Does not address battery modelling
Xue et al. (2025)	Battery aging effects on SoC prediction using LSTM and GPR	Robust under aging conditions	Requires retraining under new conditions	Limited to specific ML schemes
Mao et al. (2023)	Multi-sensor fusion for SoC prediction in LFP batteries	Improves accuracy using multi-sensor fusion	Complexity in integrating multiple sensors	High complexity in real-time applications
Shamarova et al. (2022)	BESS degradation modelling and impact on microgrid operations	Accounts for real-world degradation effects	Simplistic degradation schemes may not fully capture real-world behaviour	Real-world validation needed
Zhong et al. (2017)	Fractional-order SMO for SoC prediction	Handles modelling uncertainties well	Limited adaptability to aging effects	Limited real-world deployment
Behnamgol et al. (2024)	Comparison of SoC prediction tactics including SMOs	Comprehensive comparison of SoC prediction tactics	SMOs struggle with sensor noise	Computational overhead
He et al. (2017)	Sustainable battery material recovery from spent LIBs	An effective LIB material recovery process	Not directly related to SoC prediction	Focused on recycling, not SoC prediction

Table 1 Comparison of existing SoC prediction tactics and related studies (continued)

Study	*Focus of study*	*Strengths*	*Weaknesses*	*Limitations*
Lipu et al. (2022)	Machine learning-based SoC prediction with optimised RFR	Optimised for real-time implementation	Dependent on sufficient training data	Needs extensive sensor data
McCarthy et al. (2021)	EIS for SoC, SoH, and internal temperature prediction	Highly accurate in lab conditions	Sensitive to environmental conditions	Challenging for real-time deployment
Tahir et al. (2021)	Electrical modelling of LIBs using the 2RC model	Detailed LIB behaviour modelling	Limited application outside of UPS systems	Limited scalability for diverse LIBs
Wang et al. (2021)	Online SoC and SoH prediction for real-time BMS	A comprehensive review of real-time SoC/SoH tactics	Challenges in joint prediction tactics	Limited field validation
Chaoui et al. (2017)	Neural network-based SoC and SoH prediction	Adapts to nonlinearity and aging effects	Requires large labelled datasets	Requires real-time adaptation
Hsieh and Chen (2024)	EVs in the circular economy and battery recycling	A holistic review of battery sustainability	Policy-focused, lacks technical solutions	Lack of experimental validation
Carrasco Ortega et al. (2023)	BESS modelling for renewable energy integration	Techno-economic and modelling approach	Lacks real-time implementation details	Simplistic modelling assumptions
Kim et al. (2023)	Data-driven SoC, SoH, and RUL prediction	Leverages big data and machine learning	Limited generalisation to different LIB chemistries	Generalisation challenges
Akram and Abdul-Kader (2024)	Sustainability challenges of end-of-life EV batteries	Focuses on repurposing LIBs for sustainability	Requires structured datasets for analysis	Limited dataset dependency

1.3 Research gap and contributions

Accurate SoC estimation remains a fundamental challenge in BMS, as nonlinear battery dynamics, sensor noise, and environmental disturbances limit the effectiveness of existing approaches. Data-driven approaches, i.e., ML and DL-based techniques, require enormous amounts of labelled data and repeated retraining and are thus computationally intensive and less adaptable to real-time applications. On the other hand, model-based approaches, such as KFs and SMOs, are plagued by parameter uncertainties and sensor faults, which reduce their reliability in dynamic operating conditions. Furthermore, the effect of battery aging on SoC estimation remains an open issue, as demonstrated by recent research in the field (Vani et al., 2024a). To overcome these challenges, an adaptive, robust, and computationally efficient prediction technique must be developed that can provide high accuracy across varying operating conditions. In recent years, the growing utility of nonlinear methods for estimating SOC assessment in lithium-ion batteries has been noted (Vani et al., 2024b). These models are capable of accurately representing the nonlinear dynamics of battery behaviour and the variety of nonlinear electrochemical processes. Nonlinear methods may include the EKF (Zhang et al., 2024), UKF (Feng et al., 2022), and particle filter. A distinct advantage of these nonlinear methods is that they can model the nonlinearities in voltage behaviour to current behaviour, taking into account temperature and aging effects. A majority of nonlinear methods are built upon advanced mathematical or physics-based models that account for the battery's electrochemical characteristics in a more nuanced manner, ultimately producing more accurate SOC values under various operational circumstances. For example, the EKF linearises the model around the current estimate and then updates the SOC, whereas the UKF can perform nonlinear state estimation without linearisation, which can increase robustness.

In contrast, particle filters approximate the posterior distribution of SOC using a collection of weighted particles. These techniques provide good accuracy levels, particularly in highly nonlinear or non-Gaussian dynamics. A notable development is the incorporation of machine learning methods (for example, neural networks and fuzzy logic) into these nonlinear filtering techniques, which promotes data-driven SOC estimation that accommodates flexible adaptations for different battery chemistries and aging states (Kim et al., 2023). In general, nonlinear methods can improve the reliability and accuracy of SOC estimation, which is a critical aspect of BMS to monitor the safety, longevity, and performance of lithium-ion batteries, whether they are used as an energy source for electric vehicles or as grid storage for renewable energy (Victor Ikwuagwu et al., 2023). To overcome these constraints, in this study, a new nonlinear battery model is established for more accurate SoC estimation in LIBs. The new approach utilises a Luenberger observer, designed to achieve high-precision estimation in this nonlinear model, with enhanced flexibility to adapt to variations in battery states. Furthermore, sensor fault prediction mechanisms are also employed to enhance system robustness, compensating for measurement faults and sensor aging over time. To enhance the robustness of the prediction process, $H\infty$ optimisation is employed, which minimises external disturbances and model uncertainties.

Experimental outcomes validate the greater precision and effectiveness of the suggested approach and establish its feasibility for real-time application in BMS. The technique provides enhanced stability, flexibility, and computationally efficient performance, compared to the traditional approach, and therefore represents a suitable option for next-generation LIB-based technologies in EVs, renewable energy storage systems, and industrial power supply networks. This research contributes to advancing SoC prediction methodologies by enhancing predictive accuracy, improving robustness against real-world uncertainties, and ensuring long-term reliability in LIB performance. The key contributions of this study are:

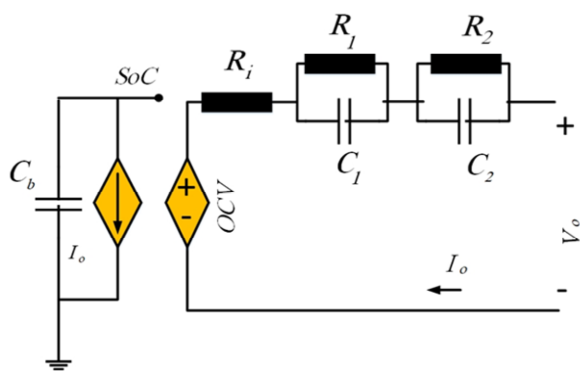
- Development of a nonlinear battery framework to boost the accuracy of SoC prediction.
- Implementation of a Luenberger observer tailored for precise state prediction in LIBs.
- Integration of sensor fault prediction to boost robustness against measurement errors.

- Application of H∞ optimisation to reduce the impact of disturbances and model uncertainties.
- Experimental validation demonstrating high accuracy and reliability in real-time SoC prediction.

2 Battery modelling

Different approaches have been recommended for simulating LIBs, including physical, electrical, thermal, electrochemical, and empirical schemes. Among these, electrical schemes have gained favour among engineers and designers for striking a balance between accuracy and simplicity in design.

Figure 1 Electrical battery model (see online version for colours)



In this investigation, an electrical scheme is employed to represent the battery, as illustrated in Figure 1. The model entails a resistor that symbolises the battery's internal resistance, as well as two capacitor/resistor loops that mimic the battery's transient behaviour throughout a range of periods, a dependent voltage resource that considers the OCV/SoC profile, a resistor that shows self-discharge, and a capacitor that represents the battery's total capacity. Kirchhoff's laws can be used to express the voltage at the terminal as:

$$V_o = V_{oc}(Soc) - V_1 - V_2 - I_o R_i \tag{1}$$

The equations of the SoC, together with V_1 and V_2, are:

$$\dot{S}oC = -\frac{1}{R_T C_T} SoC - \left(\frac{I_o}{C_T}\right) \tag{2}$$

$$\dot{V}_1 = -\frac{V_1}{R_1 C_1} + \frac{I_o}{C_1} \tag{3}$$

$$\dot{V}_2 = -\frac{V_2}{R_2 C_2} + \frac{I_o}{C_2} \tag{4}$$

V_1 and V_2 depict the voltages across (R_1C_1) and (R_2C_2), respectively. Generally, there is a nonlinear connection between SoC and V_{oc}:

$$V_{oc}(SoC) = L(SoC) \tag{5}$$

It describes the relationship between SoC and V_{oc}. Taking into account $dI_o/dt = 0$ as well as equations (2), (5), and (1) are used to construct the dynamic equation with relation to the delivered voltage V_o.

$$\begin{aligned} \dot{V}_o &= \frac{\partial V_{oc}}{\partial SoC}\dot{S}oC - \dot{V}_1 - \dot{V}_2 \\ \frac{\partial V_{oc}}{\partial SoC} &= \dot{L}(SoC) \end{aligned} \tag{6}$$

$X = [SoC, V_1, V_2, V_o]^T$ is the notation for the state vector. I_o represents the input, as well as V_o represents the output of the battery model. By employing equations (2), (3), (4), and (6), the battery's state-space model is:

$$\begin{aligned} \dot{X} &= F(X, u) + \zeta \\ Y &= CX + \omega \\ C &= [0001] \end{aligned} \tag{7}$$

The noises are represented by terms ζ, ω that have zero mean. The matrix F is:

$$F(X, u) = \begin{bmatrix} -\dfrac{1}{R_T C_T}SoC - \left(\dfrac{I_o}{C_T}\right) \\ -\dfrac{V_1}{R_1C_1} + \dfrac{I_o}{C_1} \\ -\dfrac{V_2}{R_2C_2} + \dfrac{I_o}{C_2} \\ \dot{L}(SoC)\dot{S}oC + \dfrac{V_1}{R_1C_1} - \dfrac{I_o}{C_1} + \dfrac{V_2}{R_2C_2} - \dfrac{I_o}{C_2} \end{bmatrix} \tag{8}$$

Following the derivation of adaptive formulas for the battery representation, a series of examinations was performed to identify the parameters in the battery state-space representation. The methodology for extracting these parameters is detailed in He et al. (2017). Subsequently, after extracting and characterising the parameter values for the battery pattern, it is numerically modelled. In software surroundings, the battery model is numerically simulated.

$$\begin{aligned} \dot{X}_i &= \begin{bmatrix} -(14e-7)SoC - (1.5e-3)I_o \\ -(11e-5)V_1 + 0.05I_o \\ -0.01V_2 + (7.5e-3)I_o \\ (-30e-6)SoC^3 + \big((30e-7) - (3e-4)I_o\big)SoC^2 \\ +(31e-7)I_o \cdot SoC - \big(I_o + 1\big)(0.01)\exp(-39SoC) \end{bmatrix} \\ Y_i &= (0001)X_i + \omega_i \end{aligned} \tag{9}$$

If the input faults and disturbances are considered, the formula mentioned above can be reformulated in a manner suitable for the observer recommended in this research as follows:

$$\begin{aligned} \dot{X}_i &= AX_i + Z(X_i) + Bu + Ii + Er \\ Y_i &= (0001)X_i + \omega_i \end{aligned} \tag{10}$$

To confirm the accuracy of the determined battery model, the genuine terminal voltage from actual testing is compared with the simulated terminal voltage. Suppose the variance between the simulated and actual voltages falls below a specific threshold. In that case, battery model identification is considered successful, allowing for the continuation of the iterative prediction design process.

3 Recommended estimator

Take into account the dynamic pattern of the system, which consists of the formulas below:

$$\begin{aligned} \dot{x}(t) &= Gx(t) + Jv(t) + g(x(t)) + Ii(t) + Er(t) \\ o(t) &= Cx(t) \end{aligned} \tag{11}$$

In equation (11), $x(t) \in R^{n_x}$, $v(t) \in R^{n_v}$, $i(t) \in R^{n_h}$, and $o(t) \in R^{n_o}$ represent the states, inputs, faults, and outputs accordingly. $r(t) \in R^{n_r}$ incorporates the restricted fluctuation, treated as an unknown input. G, J, C, E, and I depict the state-space matrices, and the nonlinear term is referred to as g(x(t)). It is frequently assumed that i(t) remains constant to simplify the fault prediction process. However, the system fault may vary over time, as this work assumes that the second derivative over the concerned time is zero. To estimate the fault, the system's state variables are supplemented as:

$$S(t) = \begin{pmatrix} x(t) \\ i(t) \\ i(t) \end{pmatrix} \in R^{n_x + 2n_i} \tag{12}$$

When considering the additional enhanced states mentioned above, the dynamic model described in equation (11) undergoes the following modifications:

$$\begin{aligned} S(t) &= \bar{G}S(t) + \bar{J}v(t) + \bar{g}(S(t)) + \bar{E}r(t) \\ o(t) &= \bar{C}S(t) \end{aligned} \tag{13}$$

where

$$\bar{G} = \begin{pmatrix} G & 0 & I \\ 0 & 0 & 0 \\ 0 & I_n & 0 \end{pmatrix}, \bar{J} = \begin{pmatrix} J \\ 0 \\ 0 \end{pmatrix}, \bar{g}(S(t)) = \begin{pmatrix} g(x(t)) \\ 0 \\ 0 \end{pmatrix}, \bar{E} = \begin{pmatrix} E \\ 0 \\ 0 \end{pmatrix}, \bar{C} = \begin{pmatrix} C & 0 & 0 \end{pmatrix} \tag{14}$$

Remark 1: In equations (11) and (14), if I = J, the fault present in the model will be of the sensor fault type because the input channel and the fault channel will be the same.

Assumption 1: Taking into account the Lipschitz property of $\overline{g}(S(k))$, there is:

$$\left\|\overline{g}\left(S(t)\right)-\overline{g}\left(\hat{S}(t)\right)\right\| \leq \overline{n}\left\|\overline{N}\left(S(t)-\hat{S}(t)\right)\right\| \tag{15}$$

where $\overline{n}$ and $\overline{N}$ are Lipschitz coefficients.

To develop the recommended observer, certain initial stages need to be taken into account.

Lemma 1: When considering matrices S and Z, as well as a scalar t > 0, the subsequent relationship holds:

$$S^T Z + Z^T S \leq tS^T S + t^{-1} Z^T Z \tag{16}$$

Here, a Luenberger estimator is presented. Due to the battery's state-space model in equation (13) and its state-space matrices, including $\overline{G}, \overline{J}, \overline{E},$ and $\overline{C},$ the proposed estimator is given as follows:

$$\begin{aligned} &\hat{S}(k+1) = \overline{G}\hat{S}(k) + \overline{J}v(k) + \overline{g}\left(\hat{S}(k)\right) + P\left(o(k) - \hat{o}(k)\right) \\ &\hat{o}(k) = \overline{C}\hat{S}(k) \end{aligned} \tag{17}$$

where $\hat{S}$ and $\hat{o}$ display the estimated values of S and o, respectively. Due to equation (17), the input and output of the battery model are considered as inputs to the estimator. In equation (17), parameter P is unknown and must be determined such that the estimation error dynamics have H∞ performance. Therefore, the dynamics of the estimation error are first derived. Then, based on these estimation error dynamics, the H∞ condition is transformed into a linear matrix inequality (LMI) optimisation problem. Finally, by solving this LMI optimisation problem, the parameter P is obtained.

The estimation error dynamics are determined below:

$$\begin{aligned} &e(k+1) = \left(\overline{G} - P\overline{C}\right)e(k) + \tilde{g}\left(x(k)\right) + \overline{E}r(k) \\ &e(k) = S(k) - \hat{S}(k), \ \tilde{g}\left(x(k)\right) = \overline{g}\left(x(k)\right) - \overline{g}\left(\hat{x}(k)\right) \end{aligned} \tag{18}$$

Also, the H∞ condition is written as follows:

$$\sum_{k=0}^{\infty} e^T(k)e(k) \leq \gamma^2 \sum_{k=1}^{\infty} r^T(k)r(k) \tag{19}$$

Equation (19) shows that the ratio of the L2-norm of estimation error signal to the disturbance signal is less than γ^2. Now, the smaller γ^2 the less the disturbance affects the estimation error, the more robust the estimation is. Therefore, the parameter gamma plays a crucial role in the robustness of the estimator. Accordingly, the best performance of the estimator is achieved based on the following optimisation problem.

$$\min \gamma \sum_{k=0}^{\infty} e^T(k)e(k) \leq \gamma^2 \sum_{k=0}^{\infty} r^T(k)r(k) \tag{20}$$

It is proven that if equation (21) holds, then equation (20) also holds:

$$\min \gamma \ \upsilon\left(e(k+1)\right) - \upsilon\left(e(k)\right) \leq \sigma_s \upsilon\left(e(k)\right) - e^T e + \gamma^2 r^T r \tag{21}$$

where υ is the Lyapunov function, now, we attempt to convert the optimisation problem in equation (21) into an LMI optimisation problem. Therefore, Theorem 1 is presented.

Theorem 1: Suppose the prediction error dynamics in equation (18) hold under Assumption 1. Additionally, the values of $\sigma_s < 0$ and $t > 0$ are given. If there exist matrices $Q > 0$ and Z, as well as a scalar $\Pi > 0$, such that the subsequent enhancement issue is feasible:

$$\min \gamma \begin{pmatrix} (1+\sigma_s)Q & \sqrt{1+2t^{-1}}\bar{n}Q^T\bar{N}^T & Q & 0 & \sqrt{1+t}\left(Q^T\bar{G}^T - Z^T\right) \\ * & \prod I_n & 0 & 0 & 0 \\ * & * & I_n & 0 & 0 \\ * & * & * & \gamma^2 I_n & \sqrt{1+t}\bar{E}^T \\ * & * & * & * & Q \end{pmatrix} \geq 0 \tag{22}$$

$$Q - \prod I_n \geq 0$$

Then for a switched observer in equation (7) with $P = ZQ^{-1}\bar{C}^{\dagger}$ the prediction error dynamic in equation (18) has the $H\infty$ performance.

Proof: Take the candidate Lyapunov function and the stability condition given below:

$$\upsilon(e(k)) = e(k)^T He(k),\ H > 0 \tag{23}$$

$$\upsilon(e(k+1)) - \upsilon(e(k)) \leq \sigma_s \upsilon(e(k)) - e^T e + \gamma^2 r^T r \tag{24}$$

The resilience requirement for the trajectory of the anticipation error dynamic is expanded as:

$$\begin{aligned} \upsilon(e(k+1)) - \upsilon(e(k)) &= e^T(k+1)He(k+1) - e^T(k)He(k) \\ &= \left((\bar{G} - P\bar{C})e + \tilde{g}\bar{E}r\right)^T H\left((\bar{G} - P\bar{C})e + \tilde{g} + \bar{E}r\right) - e^T He \end{aligned} \tag{25}$$

Utilising Lemma 1, there is:

$$\begin{aligned} &\upsilon(e(k+1)) - \upsilon(e(k)) \leq (1+t)e^T\left(\bar{G} - P\bar{C}\right)^T H\left(\bar{G} - P\bar{C}\right) \\ &+e^T\left(\bar{G} - P\bar{C}\right)^T H\bar{E}r + (1+t)r^T\bar{E}^T H\bar{E}r + r^T\bar{E}^T H\left(G - P\bar{C}\right)e \\ &+\left(1+2t^{-1}\right)\tilde{g}^T H\tilde{g} - e^T He \end{aligned} \tag{26}$$

Considering:

$$H \leq \lambda I \tag{27}$$

And utilising Assumption 1:

$$\begin{aligned} &\upsilon(e(k+1)) - \upsilon(e(k)) \leq (1+t)e^T\left(\bar{G} - P\bar{C}\right)^T H\left(\bar{G} - P\bar{C}\right) \\ &+e^T\left(\bar{G} - P\bar{C}\right)^T H\bar{E}r + (1+t)r^T\bar{E}^T H\bar{E}r + r^T\bar{E}^T H(G - PC)e \\ &+\left(1+2t^{-1}\right)\lambda\bar{n}^2 e^T\bar{N}^T\bar{N}e - e^T He \end{aligned} \tag{28}$$

Substituting equation (28) into equation (21), we get:

$$\begin{aligned}&(1+t)e^{T}\left(\overline{G}-PC\right)^{T}H\left(\overline{G}-P\overline{C}\right)+e^{T}\left(\overline{G}-P\overline{C}\right)^{T}H\overline{E}r+(1+r)r^{T}\overline{E}^{T}H\overline{E}r\\&+r^{T}E^{T}H\left(\overline{G}-P\overline{C}\right)e+\left(1+2t^{-1}\right)\lambda\overline{n}^{2}e^{T}\overline{N}^{T}\overline{N}e-e^{T}He-\sigma_{s}e^{T}He+e^{T}e\\&-\gamma^{2}r^{T}r\leq 0\end{aligned}\tag{29}$$

Equation (29) is rephrased in the following manner:

$$\begin{pmatrix}e\\r\end{pmatrix}^{T}\begin{pmatrix}\begin{matrix}(1+\sigma_{s})H-(1+t)\left(\overline{G}-P\overline{C}\right)^{T}H\left(\overline{G}-P\overline{C}\right)\\-\left(1+2t^{-1}\right)\lambda\overline{n}^{2}\overline{N}^{T}\overline{N}+I_{n}\end{matrix} & -\left(\overline{G}-P\overline{C}\right)^{T}H\overline{E}\\ * & \gamma^{2}I_{n}-(1+t)\overline{E}^{T}H\overline{E}\end{pmatrix}\begin{pmatrix}e\\r\end{pmatrix}\geq 0\tag{30}$$

It can be inferred that if equation (31) is satisfied, then equation (30) is also satisfied.

$$\begin{pmatrix}\begin{matrix}(1+\sigma_{s})H-(1+t)\left(\overline{G}-P\overline{C}\right)^{T}H\left(\overline{G}-P\overline{C}\right)\\-\left(1+2t^{-1}\right)\lambda\overline{n}^{2}\overline{N}^{T}\overline{N}+I_{n}\end{matrix} & -\left(\overline{G}-P\overline{C}\right)^{T}H\overline{E}\\ * & \gamma^{2}I_{n}-(1+t)\overline{E}^{T}H\overline{E}\end{pmatrix}\geq 0\tag{31}$$

Equation (31) is rephrased in the following manner:

$$\begin{aligned}&\begin{pmatrix}(1+\sigma_{s})H-\left(1+2t^{-1}\right)\lambda\overline{n}^{2}\overline{N}^{T}\overline{N}+I_{n} & 0\\ 0 & \gamma^{2}I_{n}\end{pmatrix}-\begin{pmatrix}\sqrt{1+t}\left(\overline{G}-P\overline{C}\right)^{T}\\ \sqrt{1+t}\overline{E}^{T}\end{pmatrix}\\&H\left(\sqrt{1+t}\left(\overline{G}-P\overline{C}\right)\quad\sqrt{1+t}\overline{E}\right)\geq 0\end{aligned}\tag{32}$$

By applying the Schur complement lemma, there is:

$$\begin{pmatrix}(1+\sigma_{s})H-\left(1+2t^{-1}\right)\lambda\overline{n}^{2}\overline{N}^{T}\overline{N}+I_{n} & 0 & \sqrt{1+t}\left(\overline{G}-P\overline{C}\right)^{T}\\ * & \gamma^{2}I_{n} & \sqrt{1+t}\overline{E}^{T}\\ * & * & H^{-1}\end{pmatrix}\geq 0\tag{33}$$

By utilising the change of variables $Q = H^{-1}$ and $\lambda = \Pi^{-1}$, and multiplying both sides of the inequality as mentioned above by bdiag(Q^T, I, I) and bdiag(Q, I, I), in that order:

$$\begin{aligned}&\begin{pmatrix}(1+\sigma_{s})Q-\left(1+2t^{-1}\right)\Pi^{-1}\overline{n}^{2}Q^{T}\overline{N}^{T}\overline{N}Q+Q^{T}I_{n}Q & 0 & \sqrt{1+t}Q^{T}(G-PC)^{T}\\ * & \gamma^{2}I_{n} & \sqrt{1+t}\overline{E}^{T}\\ * & * & Q\end{pmatrix}\\&\geq 0\end{aligned}\tag{34}$$

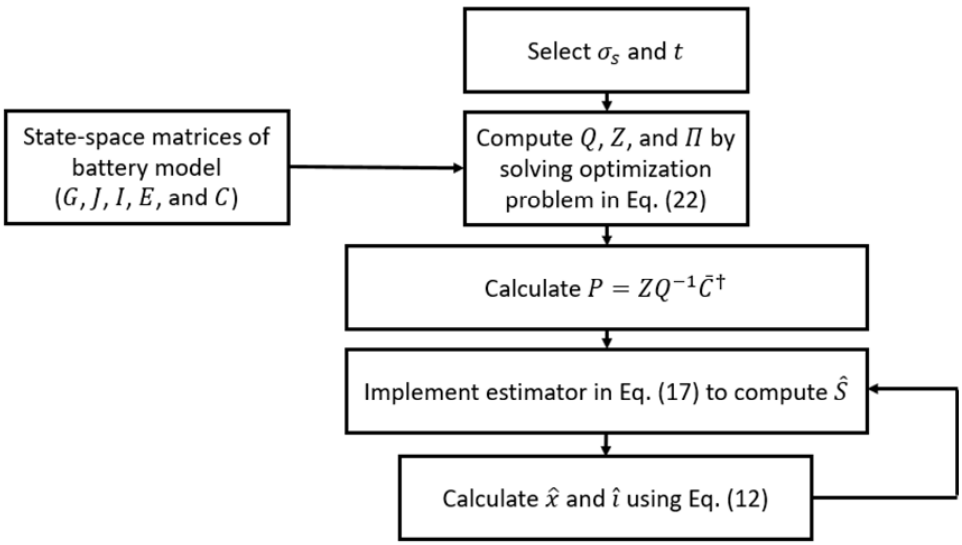
By employing variable transformations, $Z = P\overline{C}Q$ and the Schur complement lemma, there is:

$$\begin{pmatrix} (1+\sigma_s)Q & \sqrt{1+2t^{-1}\bar{n}}Q^T\bar{N}^T & Q & 0 & \sqrt{1+t}\left(Q^T\bar{G}^T - Z^T\right) \\ * & \Pi I_n & 0 & 0 & 0 \\ * & * & I_n & 0 & 0 \\ * & * & * & \gamma^2 I_n & \sqrt{1+t}\bar{E}^T \\ * & * & * & * & Q \end{pmatrix} \geq 0 \tag{35}$$

Equation (35) verifies the validity of equation (22), thereby concluding the proof.

The implementation algorithm of the proposed Estimator is shown in Figure 2.

Figure 2 The implementation algorithm of the proposed estimator



Remark 2: The Luenberger estimator generally has the lowest computational complexity since it involves straightforward linear matrix operations. The sliding mode estimator, although nonlinear, typically requires moderate computational effort due to discontinuous functions such as sign or saturation functions, but is still manageable for real-time use. The KF is the most computationally intensive, especially in high-dimensional systems, because it involves complex matrix operations, such as covariance predictions, updates, and matrix inversions, which make it more demanding in terms of processing power. Overall, the complexity order is Luenberger estimator < sliding mode estimator < KF.

4 Outcomes and discussion

In this section of the article, the analysis of practical test outcomes is detailed. Several practical tests were conducted to evaluate the recommended tactic's ability to accurately estimate battery charge levels, using the setup depicted in Figure 3. These tests utilised a programmable resistance reservoir to simulate various battery discharge scenarios. A

2.4 Ah battery with the 18650 model from Samsung was used in these tests. The battery has a health level of 95%. The battery cell has a cut-off voltage of 3.6 volts and a nominal voltage of 4.2 volts. A DSP microprocessor is used to implement the estimation algorithms, and Hall effect sensors are used to measure current and voltage. The effectiveness of the suggested approach was compared with the widely employed SMO method for battery charge level prediction in industrial settings. The experiments were conducted in two distinct scenarios: one where the battery was discharged by a resistive load producing a regular pulse in terminal current, and another where a resistor variation resulted in a complex pulse shape with a non-uniform frequency in terminal current.

Figure 3 Test setup (see online version for colours)

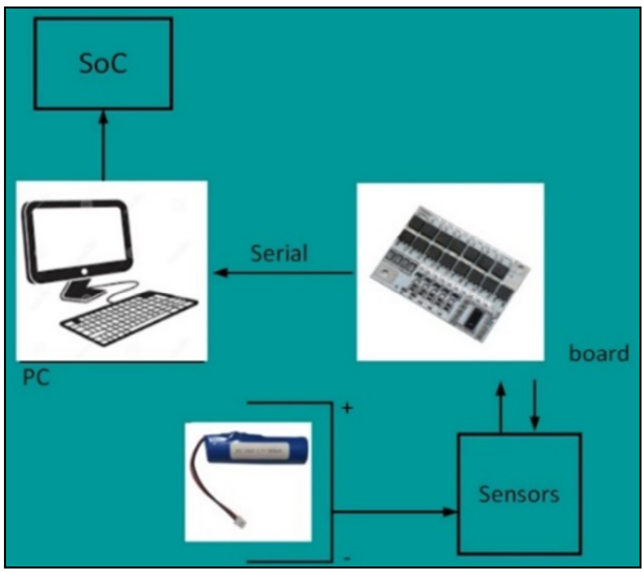


Figure 4 Battery current (first scenario) (see online version for colours)

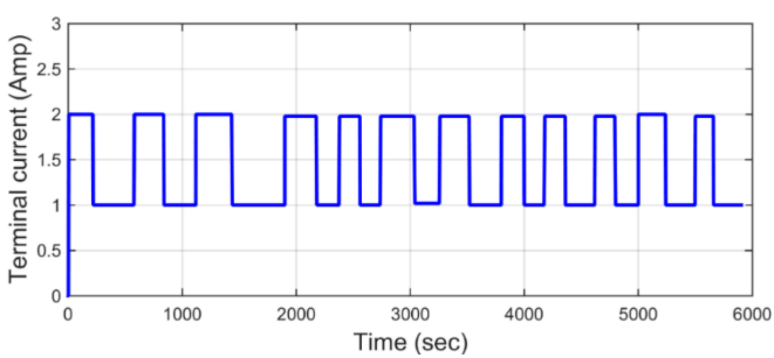


Figure 5 SOC prediction (first scenario) (see online version for colours)

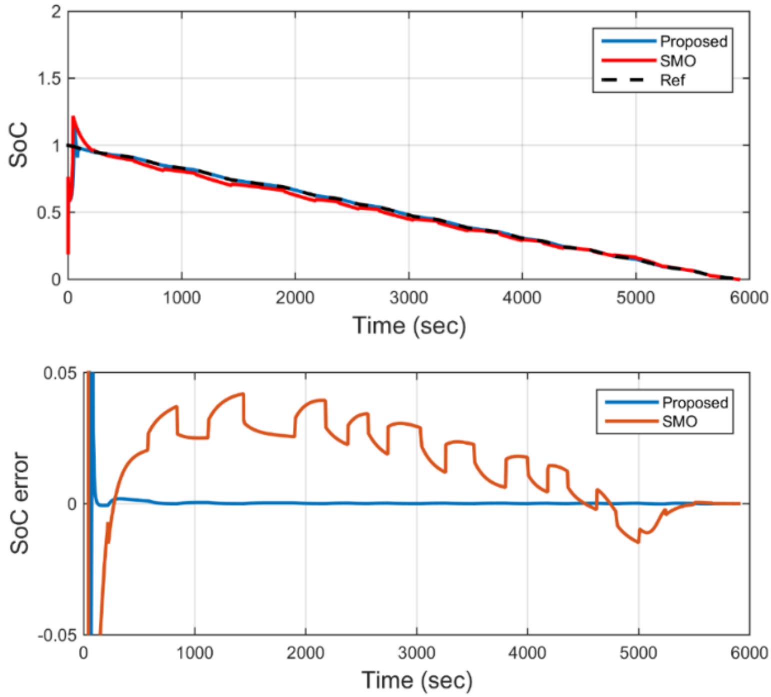


Figure 6 Voltage prediction (first scenario) (see online version for colours)

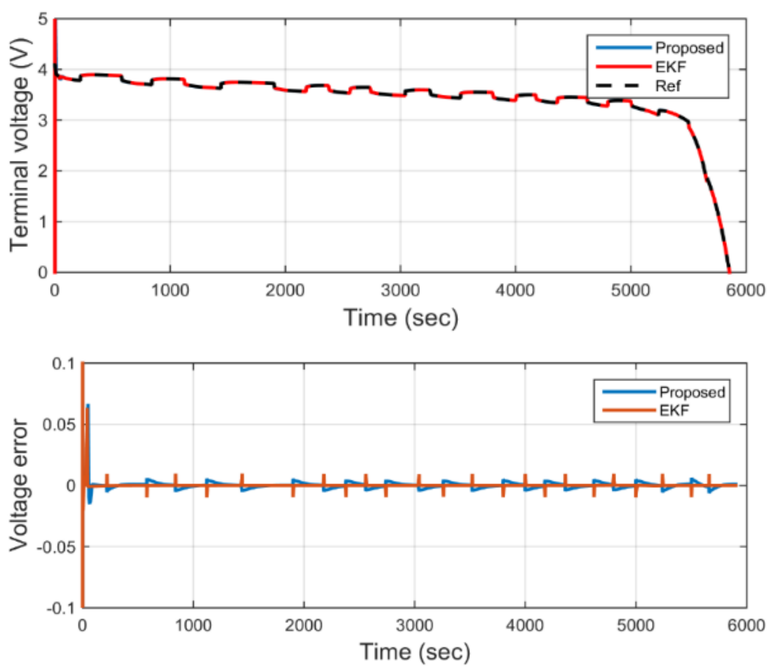


Figure 7 Battery current (second situation) (see online version for colours)

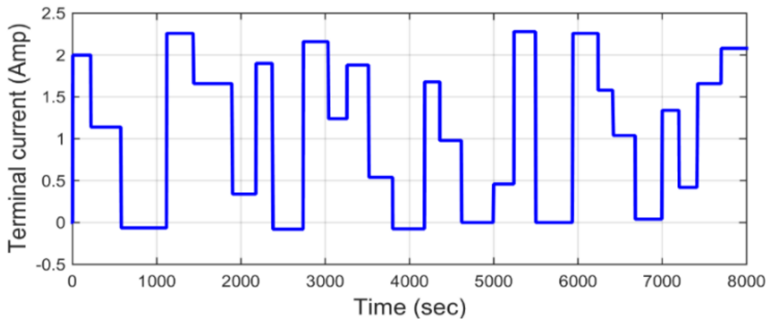
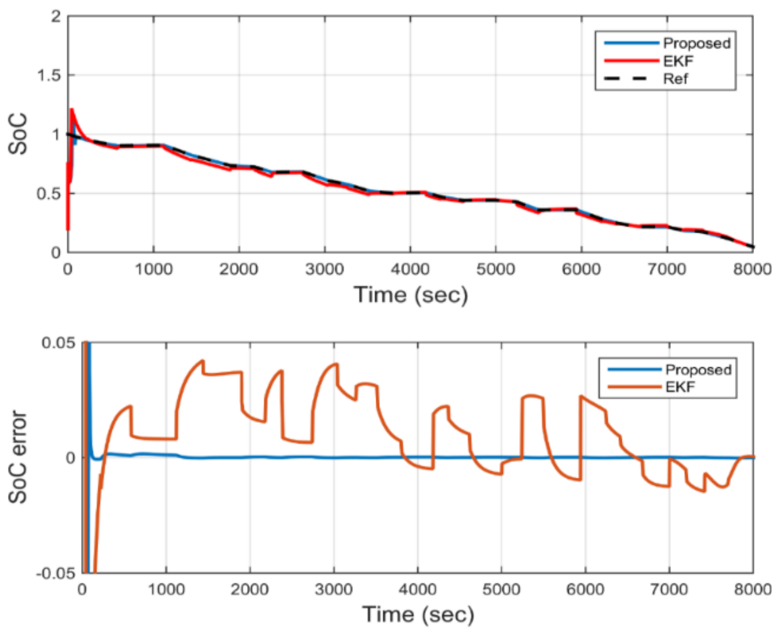


Figure 8 SOC prediction (second situation) (see online version for colours)



In the first case, a resistor is configured to create a consistent pulse pattern in the battery terminal current at a steady rate. The graph in Figure 4 displays this current pattern. Figure 5 compares the accuracy of estimating the battery's charge status using the suggested method against the SMO method, showing that the recommended tactic outperforms the SMO method with a nearly 1.2% error rate, compared to the SMO method's nearly 4.8% error rate. Additionally, in Figure 6, the accuracy of estimating the terminal voltage utilising the recommended strategy is compared to the SMO method, revealing that the suggested method achieves almost zero error. In contrast, the Kalman method has an error of about 0.019 volts in estimating the terminal voltage.

In the second situation, the test poses greater challenges. Here, the resistive load is adjusted to create varying battery terminal currents, illustrated in Figure 7. At times, the battery is discharging, while at others it is charging, and the frequency of these changes is not constant. Performance comparisons between the recommended tactic and the SMO tactic in estimating the charge level and terminal voltage are depicted in Figures 8 and 9. Figure 8 reveals that even in this more complex scenario, the recommended tactic accurately determines the battery charge level. Similar to the earlier scenario, the SMO method exhibits a 3.8% higher error rate compared to the suggested method for assessing the battery's charge level. Furthermore, the prediction of terminal voltage in Figure 9 showcases that the recommended tactic achieves an almost negligible error, while the SMO method has an error of around 0.029 volts. Figure 10 indicates the prediction of the sensor fault, which is estimated using the recommended Estimator. However, the SMO method fails to estimate this fault, impacting the prediction of other state variables.

Figure 9 Voltage prediction (second situation)

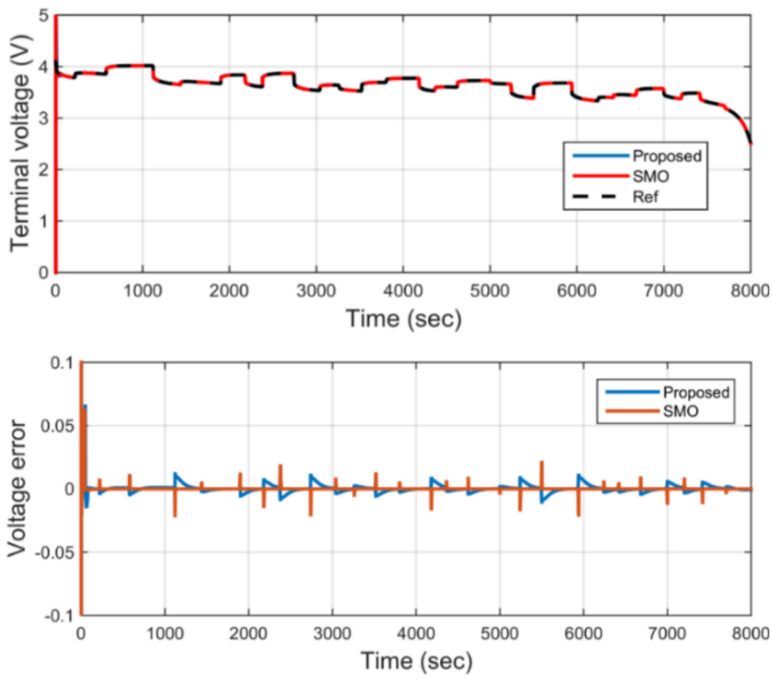
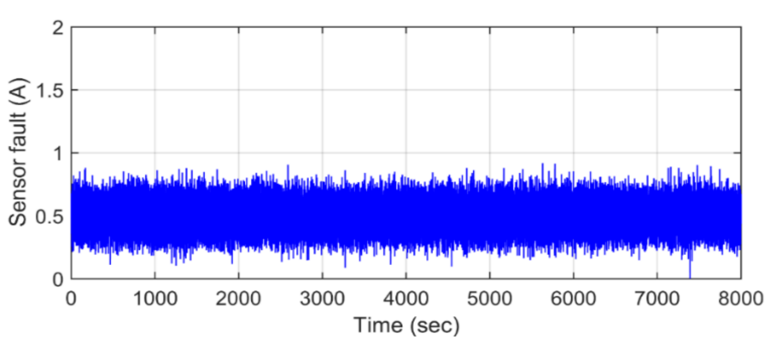
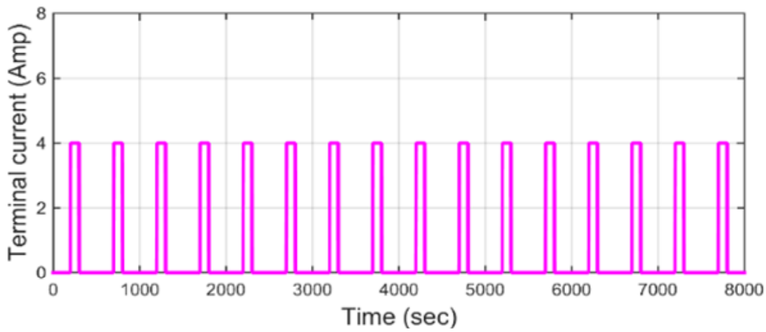


Figure 10 Fault prediction (see online version for colours)

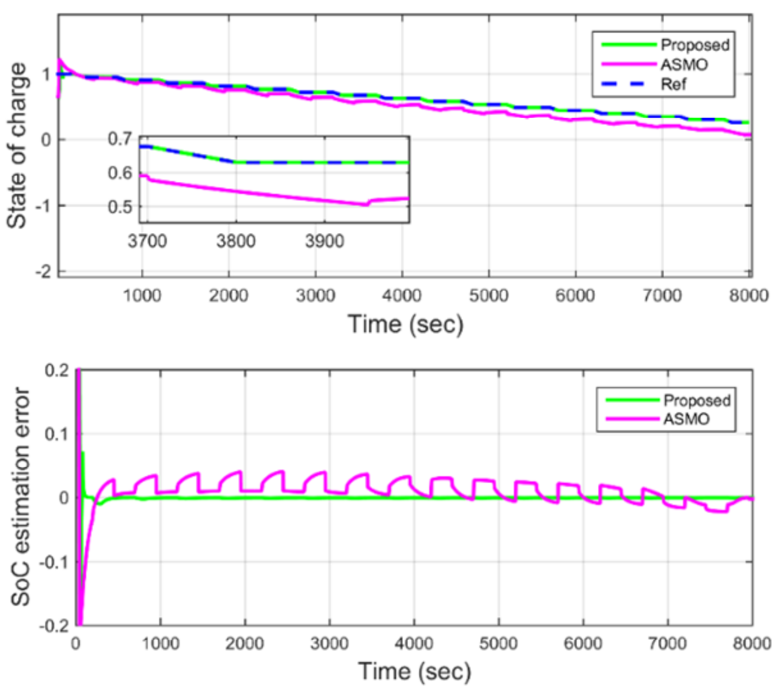


To better and more extensively investigate the performance of the proposed method, a series of practical experiments was conducted using the flow profiles shown in Figures 11 and 12. The performance of the proposed method was then compared with that of new methods, such as adaptive SMO (ASMO) and adaptive UKF (AUKF). In parts B and C, the performance of these two methods for estimating the charge level and terminal voltage is compared. As is clear from these figures, the proposed method exhibits significantly better accuracy and converges to the original value in a shorter convergence time.

Figure 11 Comparison to ASMO (see online version for colours)

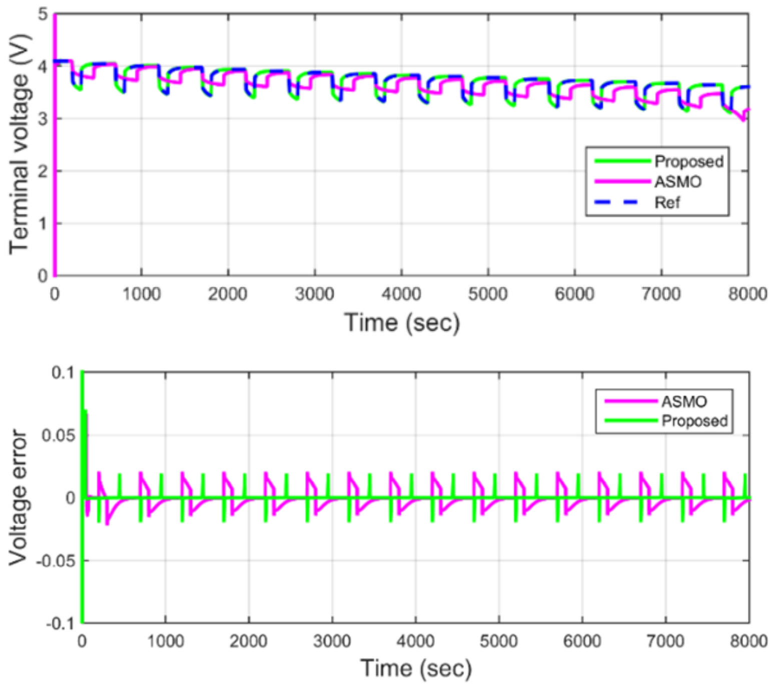


(a)



(b)

Figure 11 Comparison to ASMO (continued) (see online version for colours)



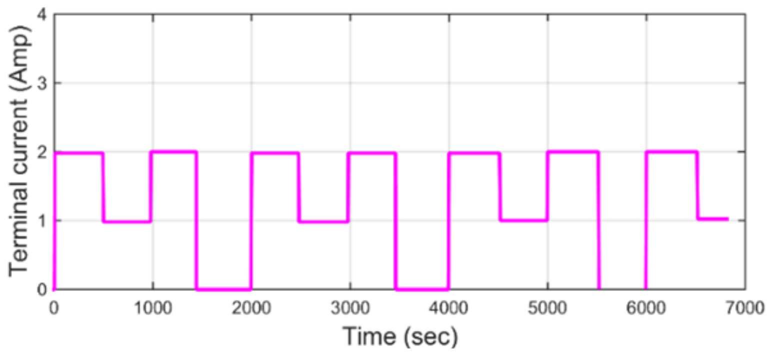
(c)

In all practical tests conducted, the parameters as mentioned above were taken into account, and as is clear from the results, the method in question was able to resist them well. In other words, the presence of parameters such as disturbance and measurement errors has caused other comparative methods to be less accurate and even to suffer from bias in their estimates. This is, although the method in question has been able to perform well in the presence of these destructive factors. In future generations of BMS, due to the scale of current in applications such as electric vehicles, destructive factors will have a direct impact on the accuracy of estimating the charge level. Therefore, estimation methods must be such that they can provide appropriate and reliable performance in these applications, so that a reliable new generation BMS can be offered to the market. The method proposed in this article can have good accuracy in the presence of these destructive factors, and the result of other functions available in the BMS can also be performed with good accuracy and reliability.

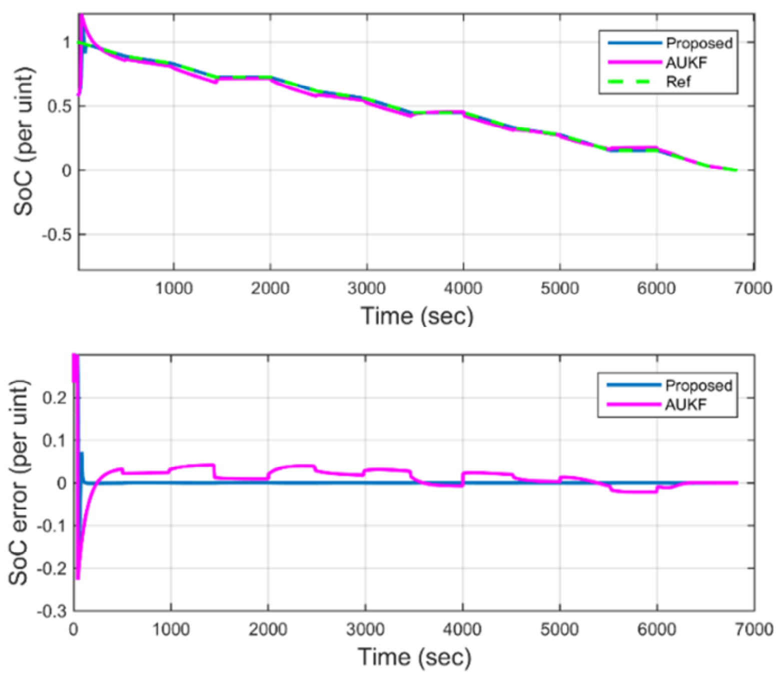
4.1 Discussion

The outcomes of the recommended Luenberger observer with $H\infty$ optimisation for SoC prediction demonstrate substantial enhancements in accuracy, robustness, and adaptability over traditional tactics. The experimental findings confirm that the recommended approach reduces prediction error and maintains stability under varying load conditions and sensor noise. In the first scenario, where the battery operated under a steady pulse current, the recommended tactic achieved an SoC prediction error of approximately 1.2%, compared to 4.8% for the SMO. Similarly, in the second scenario with a more complex current profile, the method exhibited a 3.8% lower error than SMO, reinforcing its reliability in real-world applications. In addition, the terminal voltage prediction was more accurate, with a close to zero error margin, compared to traditional tactics like Kalman filtering, which resulted in minor errors.

Figure 12 Comparison to AUKF (see online version for colours)

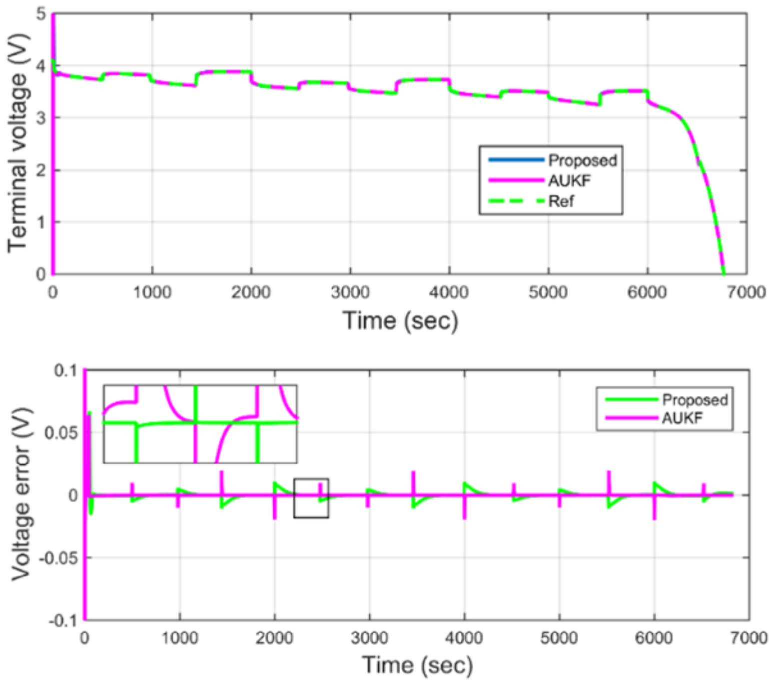


(a)



(b)

Figure 12 Comparison to AUKF (continued) (see online version for colours)



(c)

The reported gains in performance from this study align with the findings in the literature. For instance, Zhong et al. (2017) and Behnamgol et al. (2024) demonstrated how SMOs provide good robustness in the face of uncertainties but lack resistance to chattering effects as well as sensitivity to noise, which degrades their accuracy under dynamic conditions. Similarly, Kim et al. (2023) and Lipu et al. (2022) have worked on machine learning-based SoC prediction techniques. Still, the algorithms are too computation-intensive and data-intensive, and need to be retrained at periodic intervals, which makes them inappropriate for real-time embedded systems. On the other hand, the Luenberger observer provides a computationally more efficient solution with precision maintained. The addition of H∞ optimisation further enhances model uncertainty resilience, making this method superior to Kalman-based estimators, which require precise covariance tuning and are sensitive to model errors.

Even in the presence of these promising outcomes, a few limitations need to be kept in mind. Firstly, while the technique is first-rate in standardised laboratory tests, some verification is needed with actual driving and grid-storage modes. Secondly, the model simulates an optimal internal battery parameter set, while real degradation phenomena may result in long-term discrepancies from this operation. Adaptive prediction of parameters integrated within the system would yield further improved long-term performance. For future research, this method can be extended by combining it with machine learning algorithms to develop a hybrid method, leveraging data-driven flexibility with observer-based resilience. Future studies should also explore multi-sensor fusion techniques for fusing other state indicators like SoH and RUL to develop an all-inclusive battery management solution.

5 Conclusions

Accurate SoC prediction is crucial for enhancing the efficiency, safety, and lifespan of lithium-ion batteries in commercial BMS. This study proposes a novel nonlinear battery model and a Luenberger observer optimised using H∞ control to improve both the accuracy and robust estimation of SoC. The proposed solution reduces the impact of both sensor noise and model uncertainty along with unknown disturbances, providing a computationally efficient solution for real-time, integrated BMS platforms in the commercial sector. The experimental results showed that the proposed solution can reduce SoC prediction errors to less than 3.8% compared to conventional techniques using SMOs, offering better stability under dynamic conditions. Furthermore, the H∞ optimisation process was effective in managing sensor drift, as well as disturbance effects, to enhance the reliability of the estimation process. These characteristics show that the proposed framework is a potential solution for future commercial BMS for electric vehicles and grid energy storage applications. However, additional considerations are needed to enable practical implementation. Most importantly, the current work assumes that the battery parameters are constant and does not accurately model the long-term degradation due to aging. Future work should investigate adaptive parameter estimation methods that take into account aging over time. It is also crucial to validate the approach under various and diverse real-world operating conditions (e.g., EV driving cycles and grid storage), thereby confirming its wider applicability. Additionally, exploring hybrid diagnostic schemes that link machine learning with observer-based models would provide real-time adaptability and more accurate long-term predictions. Extending the framework to include the estimation of state of health (SoH) and RUL would also significantly enhance holistic battery diagnostics, further supporting more reliable and maintenance-friendly energy storage systems.

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Declarations

Competing interests: The scholars assert no competing interests.

Authorship contribution statement: Xiaowei Zhang: writing-original draft preparation, conceptualisation, supervision and project administration.

Availability of data and materials: Data is accessible upon demand. The investigators claim no competing interests.

Conflicts of interest: The authors declare no conflicts of interest in connection with the release of this article.

Author statement: All scholars have reviewed and endorsed the manuscript, meeting the authorship requirements. Each scholar affirms that it portrays honest work.

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