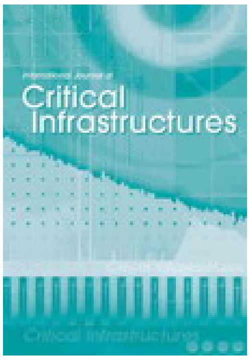
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Critical Infrastructures

ISSN online: 1741-8038 - ISSN print: 1475-3219
https://www.inderscience.com/ijcis

Design of an augmented unknown input estimator for the lithium-ion battery state of charge and sensor fault estimation

Li Fang

DOI: 10.1504/IJCIS.2028.10073260

Article History:

Received:	26 March 2025
Last revised:	12 June 2025
Accepted:	24 June 2025
Published online:	09 October 2025

Design of an augmented unknown input estimator for the lithium-ion battery state of charge and sensor fault estimation

Li Fang

Electronic Information Engineering College,
Jiangxi Institute of Engineering,
Xinyu City, Jiangxi Province,
338000, China
Email: 13755702667@163.com

Abstract: This research proposes a novel method to enhance the accuracy of state of charge (SoC) estimation in lithium-ion packs by utilising nonlinear battery models in combination with an estimator for the unknown input. It is crucial in optimising performance, ensuring safety, and increasing operational life in situations involving electric vehicles and renewable power systems. A key enhancement of this approach is the inclusion of sensing faults as state variables, allowing simultaneous estimation of both SoC and sensor faults. This improves system reliability by detecting and correcting sensor inaccuracies, ensuring stable battery management. The fault-tolerant design reduces errors and enhances real-world applicability. The methodology presented was validated through experimental tests, demonstrating a significant improvement in battery state estimation. The results verify the advancement in battery management systems and aim to develop efficient and reliable energy storage for diverse uses.

Keywords: lithium-ion battery; LIB; SoC and UIE estimator; electric vehicles; sensor fault; nonlinear model; terminal voltage; system reliability; energy efficiency; renewable energy; optimising battery operation.

Reference to this paper should be made as follows: Fang, L. (2025) 'Design of an augmented unknown input estimator for the lithium-ion battery state of charge and sensor fault estimation', *Int. J. Critical Infrastructures*, Vol. 21, No. 11, pp.30–54.

Biographical notes: Li Fang is graduated from Jiangxi Normal University of Science and Technology in 2006 with a Bachelor's in Engineering. She works at Jiangxi Institute of Engineering as a lecturer. She has published many excellent academic papers at the provincial level. Her main research field is electronic information engineering.

1 Introduction

Ever since energy efficiency and dependable energy storage systems have spiked in demand, lithium-ion batteries (LIBs) have been central in electric vehicles (EVs), renewable energy storage, and portable electronics. Correct estimation of the state of charge (SoC) is crucial for optimising battery operation throughout their life cycle and ensuring safety factors for various applications. SoC represents the remaining capacity of a cell compared to its maximum possible charge; thus, it provides a measure for energy management systems (He et al., 2020; Zhang et al., 2020). Unfortunately, the actual measurement of SoC is not possible due to the complex and electrochemical nature of LIBs. Hence, advanced battery management would require advanced means for estimation (Anand et al., 2024). It plays an important role in SoC estimation, enriching the functionality of battery management systems (BMSs) that minimise over-discharge and deep discharge of batteries, thereby preventing thermal runaway and optimising the consumption of energy by EVs and energy storage systems (Babu et al., 2024). Various methodologies have been used to estimate SoC, and they can be categorised into three main approaches: empirical, model-based, and data-driven (Zhang et al., 2015).

Empirical methods are those methods that measure directly observed parameters of the battery, utilising historical data (Ikwuagwu et al., 2024). These methods are generally straightforward, but they sometimes lack sufficient accuracy due to varying operational conditions (John Joseph et al., 2025). The second method is called the Coulomb counting method, which defines SoC by integrating the current over time (Kumar et al., 2024). However, this method is also affected by errors due to sensor drift, temperature variations, and initial SoC miscalculations (Du et al., 2016). The open circuit voltage method relates measurements of battery voltage with SoC levels according to predefined lookup tables, but it requires the battery to be left undisturbed for precise measurements (Kothuru, 2023). Impedance methods are based on the application of electrochemical impedance spectroscopy methods to evaluate cells under the analysed internal resistance and decay of the battery (Madhuranthakam, 2024). Still, they require sophisticated instrumentation and cannot be applied under dynamic conditions (Krishna Vaddy, 2023). Model-based SoC Reference techniques utilise mathematical representations of the battery's behaviour to predict the SoC by utilising various sensor inputs. Equivalent circuit models (ECMs) of battery behaviour represent the battery's behaviour using electrical components such as resistors, capacitors, and voltage sources. Examples of ECMs commonly used are Thevenin, Randles, and dual polarisation models (Mehta et al., 2023). The energies involved in ECM calculations necessitate the identification of parameters from one experiment for varying conditions, such as those affected by age and temperature, as in the case of SoC estimation from other sets of observations. Electrochemical models, such as the Doyle-Fuller-Newman (DFN) model, offer the highest accuracy as they describe internal physicochemical processes, including transport and reaction kinetics (Feng et al., 2021; Nath et al., 2020; Obeid et al., 2022).

However, complex sets of partial differential equations are used, and simulation tools require considerable computing resources; hence, these models are not suited for real-time applications (Nomula et al., 2023). Kalman filtering (KF) techniques, such as the extended Kalman filter (EKF) and unscented Kalman filter (UKF), are state-of-the-art State estimation techniques that recursively apply updates to the estimates of states based on real-time sensor data. These techniques are robust against noise and uncertainty and are therefore widely adopted in BMS applications. Sliding mode observers (SMOs) enhance the SoC estimation accuracy by accommodating the nonlinearities and disturbances of LIBs, making the approach particularly suitable for applications with strongly varying operating conditions (Cui et al., 2022b; Ma et al., 2021).

After training with historical data, the ANN would be able to make accurate SoC predictions under various operating conditions (Mokdad, 2024a). An example is support vector machines (SVMs), which classify and estimate the SoC based on a nonlinear relationship mapping between battery parameters using supervised learning (Mokdad, 2024b). Random forests (RFs) comprise multiple decision trees that enhance the robustness of SoC estimation while maintaining accuracy. GPR can provide probabilistic SoC estimation because it models the input-output relationship as a distribution, enabling the quantification of uncertainty in battery management decisions. RNNs and long short-term memory (LSTM) networks are ideal for SoC estimation because they can capture temporal dependencies that exist in time series. Significant progress has been made in advancing methods of estimating SoC, but many aspects remain unresolved. Aging in LIBs causes internal resistance, capacity, and voltage response to change over time. Adapting the SoC estimation models to these modifications is necessary to maintain the accuracy of such estimations over time. Temperature change influences SoC estimation because different thermal conditions under which a battery operates cause it to perform differently; hence, compensating techniques are required to minimise errors due to temperature influences (Paramasivan et al., 2024). Advanced SoC estimation methods require large computational resources and may not be suitable for real-time use in embedded systems. AI-powered SoC estimation requires massive, high-quality datasets for training; however, gathering large, labelled battery datasets is a daunting task (Wei et al., 2020; Xu et al., 2022).

Research on SoC estimation increasingly pursues hybrid approaches that combine various estimation methods into a single framework to alleviate current challenges. Several potential avenues include coupling physics-based models with AI techniques to improve accuracy while minimising computational burden (Pierre et al., 2024). Several scenarios involving hybrid KF and deep learning models can ensure robust real-time SoC estimation (Shenbagavalli et al., 2024). Continuous learning frameworks for updating SoC estimation models in real-time, based on battery usage patterns and environmental conditions, can provide improved long-term reliability (Panyaram, 2024). Physics-informed machine learning integrates traditional battery modelling with ML techniques to retain interpretability (Srilakshmi et al., 2024). Cloud-based BMSs help collect large-scale data needed for real-time SOC estimations using AI algorithms, facilitating better battery monitoring over distributed energy storage networks (Ramya et al., 2023). Sociological estimation of SOC is crucial for LIBs in terms of their efficiency in real-time application areas (Sehrawat, 2024). Each of the three basic methods of SOC estimation has its merits and limitations: traditional empirical, model-based, and AI methods. On the one hand, empirical methods are straightforward and computationally inexpensive, maintaining flexibility under static conditions. Model-based approaches rely heavily on parameter identification and can therefore be highly accurate (Senapati et al., 2023).

In contrast, AI methods offer flexibility and accuracy in varied environments, but require extensive datasets and substantial computing power (Sundararajan et al., 2023). The hybrid methodologies would, therefore, be the future of SOC estimation, aiming to incorporate many techniques with high accuracy, efficiency, and adaptability (Siddique et al., 2023). Battery modelling, machine learning, and innovations in real-time adaptive estimation will surely foster the revolution of BMSs for the reliability and sustainability of LIB-based energy solutions (Guo and Ma, 2023; Liu et al., 2022; Zhang et al., 2022).

In this study, a novel approach is presented to boost the precision of SoC testing in LIB packs. In this work, a considerable improvement has been achieved by utilising nonlinear battery models, which have enabled a significant increase in precision

(Victor Ikwuagwu et al., 2023). Moreover, an unknown input estimator is implemented to further increase the level of precision. The introduction of sensing faults as extra state variables is one of the most significant innovative features of this method, enabling the simultaneous estimation of SoC and sensor faults. Extensive experimental tests, which have demonstrated superior performance in battery state estimation, have successfully validated the productivity of our method. These findings have a significant impact on the development of BMSs and could also lead to potentially substantial improvements in reliability and efficiency for energy storage devices. The present research truly lays a powerful foundation for future developments in battery management and energy retention systems (Shi et al., 2021; Zhao et al., 2020).

This method will significantly enhance the safety of the entire system, as it detects and corrects sensor faults in real-time to prevent unsafe conditions, such as overcharging or thermal runaway, particularly in EVs and renewable energy systems. It also enables the early identification of faults, helping to minimise maintenance costs by taking mitigations early through timely repairs, thereby reducing service interruptions and expensive repairs. The fault-tolerant design provides stable and reliable performance that can accommodate various and uncertain real-world conditions and challenges, such as temperature fluctuations and aging, making it ideal for critical applications. Additionally, the methodology supports predictive or preventive maintenance through continuous battery health monitoring and assessment of sensor integrity, enabling speedy or timely intervention to ensure optimal battery health and prolong its lifespan. Therefore, the coupled fault tolerance can enhance the reliability and longevity of battery energy storage systems under various operating conditions, assisting sustainability in connection with other sectors globally. All in all, this new approach to working will lead to safer, more controlled, reliable, and cost-efficient methods for energy management, facilitating a greater degree of resilience and efficiency in energy storage systems worldwide.

2 Literature review

Hannan et al. (2017) conducted a thorough analysis of methodologies applied for the estimation of the SoC in LIBs. It made a good case for including them in developing a BMS for improved performance, prolonged lifespan, and the safety of the batteries. They further classified the techniques of SoC estimation into traditional and advanced methods. While the conventional approaches included the Coulomb counting method, which calculated SoC by integrating battery current for a time, being simple and feasible for online, it made itself liable to cumulative errors owing to drift OCV method predicted the SoC through correlation of voltages of the battery at predetermined SoC levels but was limited in accuracy because of the hysteresis effect, temperature changes, and periods during which relatively stable voltages were obtained.

Wang et al. (2021) investigated advanced model-based estimation techniques, such as KF, SMOs, and adaptive filtering techniques. These techniques improved SoC estimation accuracy by embedding the battery ECMs or electrochemical models to accommodate real-time adjustments to battery conditions. Their drawback is that they are parameter-precise and computationally intensive, thus restricting the scope of real-time embedded system applications. The study also highlights the growing role of AI and ML in SoC estimation. Neural networks, SVMs, and deep learning models were found to deliver good predictions through the nonlinear mapping of battery voltage, current, and temperature. These data-oriented approaches are robust to nonlinearities and battery aging effects, but are highly dependent on the size of the training datasets and computational resources.

Shrivastava et al. (2019) opened up new avenues for making batteries more efficient, long-lived, and safe in their operations by properly setting up a BMS. The study involved both traditional and new approaches to SoC estimation, emphasising the benefits and limitations as well as the suitability of different SoC estimation methods towards applications' requirements. The Coulomb counting technique is one of the non-modern techniques. The generalisation that this method makes on SoC is by integrating the battery current over time. The method, although simple and easy to implement in real-time, suffers from accumulation errors due to current sensor drift, inaccuracies in the initial SoC values, and the effects of temperature variation, as proposed by Shrivastava et al. The same analysis goes for the OCV method, which estimates the SoC by correlating the voltage of the battery to predefined SoC levels. It was found to be affected by voltage hysteresis and temperature variation; long periods of rest are also required to obtain accurate battery readings, making it unsuitable for applications that require dynamic SoC tracking. As they studied new methods to improve conventional SoC estimation techniques, Shrivastava et al. also explored advanced estimation techniques, including model-based and AI-driven approaches. Model-based methods, including KF, SMO, and PF, are excellent approaches for dynamically estimating SoC, given that battery characteristics vary. However, these methods require accurate parameters for a battery model and intensive computations, which may not be suitable for real-time applications in embedded systems.

Chandran et al. (2021) considered KF techniques applicable to SoC estimation in LIB because they claim that such methods demonstrate great accuracy, adaptability, and robustness in the face of uncertainties. According to the authors, the reason KF is currently extensively employed in BMSs is due to a recursive estimation approach, which allows real-time state estimation based on a set of measured values. They explained how states of charge were projected in the Kalman filter as it fused the sensor measurements of voltage, current, and temperature with a dynamic model of battery behaviour in a state-space form. Fast and accurate estimations were realised in this configuration, which was ideal for the immediate use in EVs and renewable energy storage applications. Other important capabilities demonstrated by the Kalman filter were its ability to handle measurement noise and uncertainties in the system, such as variations in temperature, changes in loads, and aging effects on batteries, all of which would have contributed to errors in estimating the SoC. The Kalman filter reduced disturbances and corrected state estimates in real-time, improving the accuracy and stability of the SoC determination.

Cui et al. (2022a) have also examined various KF models, such as EKF and unscented UKF, to investigate the nonlinear properties of LIBs. From the results, EKF performs rather effectively but is highly erroneous in cases of stiff nonlinearity. It linearises the system dynamics using a first-order Taylor series expansion. For instance, UKF applies a sigma-point transformation to provide an efficient estimation without explicit linearisation, making it more applicable to highly nonlinear battery systems. They concluded that for SoC estimation, KF and its variants indeed made quite an improvement; however, they performed better with well-identified model parameters for the batteries. Therefore, they also suggested that future work should be directed towards adaptive KF methods, machine learning-assisted parameter estimation, and hybrid approaches of model-based and data-driven methods to increase estimation accuracy, computational efficiency, and adaptable performances with different battery chemistries and aging profiles in the future.

Xu et al. (2022) emphasised the importance of the mathematical model in enhancing the performance of the BMS. In that study, SoC estimation methods were grouped into three major head approaches: electrochemical models, ECMs, and empirical models. The techniques were analysed in terms of their respective strengths, limitations, and applicability in real energy storage systems. It should also be noted that electrochemical models – the Doyle Fuller Newman (DFN) model – provide highly/accurate predictions for the SoC value because it takes into account very detailed physicochemical processes involved, such as the ion transport, kinetics of reactions, and dynamics of diffusion. However, when it comes to very detailed experimentation inside laboratories, such as depth studies in batteries, this modelling must be solved through partial differential equations, making them computationally intensive and rendering them unapplicable for real-time purposes. The intensive need for an extended parameter identification and thorough knowledge of battery chemistry also imposes a constraint on the use of these models in embedded systems.

Feng et al. (2019) discussed several ECM specifications, including the Thevenin model, the Randles model, and the dual-polarisation model, which consists of a combination of resistors, capacitors, and voltage sources that supposedly describe battery dynamics. ECM-based estimated SoC was dependent on parameter optimisation methods and was mostly enhanced through KF, SMOs, or adaptive filtering algorithms. Because they were well established in battery management, particularly in computation, they noted, however, that accuracy related to parameter identification might vary due to age effects, temperature changes, and operating conditions. Other empirical models, including the new ML and AI approaches, will serve as possible alternatives for SoC estimation. These methods include neural networks, SVMs, and deep learning methods such as CNNs and RNNs, which are utilised to enhance model performance on large datasets. The AI-driven models could tolerate the maximum extent of nonlinearity and battery degradation effects; however, Zhang noted that their very applicability relied on top-quality training data, computing resources, and generalisation across a wide range of battery chemistries and conditions.

He et al. (2020) concluded that although model-based approaches were highly required for accurate SoC estimation, due to their limitations, these model-based techniques needed to be integrated with hybrid methodologies comprising both data-driven and model-driven techniques. Their study also suggested that future research might focus on adaptive filtering techniques, improving machine-learning generalisation, and incorporating physics-informed AI models to effectively and efficiently enhance SoC prediction in future generations. These improvements would undoubtedly help develop more trustworthy and cost-effective BMSs for EVs, renewable energy storage, and other applications that require precise battery state estimation.

This paper provides an important start point for future development and innovation of SoC estimation methods by showing that nonlinear battery models with an expanded UIE which estimates the SoC and sensor faults can make all of these aspects more accurate and fault tolerant and the potential for improvement through use of more advanced modelling, adaptive algorithms and live fault detection. Experimental delivery validates the robustness of the estimates and the variations an intelligent management method could take with good results; certainly a good base point to build on and a foundation for newer, more advanced intelligent BMSs. Discussed in depth in the results section, this provides a continuous research base that could lead to improved energy management strategies, ensuring better battery lifetimes and safe operations, while continuing to innovate in SoC technologies.

The manuscript addresses a common limitation of conventional SoC estimation methods – the inability to model and account for sensor faults and external physical disturbances – by incorporating these factors directly into the estimation process as additional state variables through an augmented UIE. In the standard visualisations in the manuscript, traditional SoC estimation methods are often depicted as relying solely on sensor measurements, which are subject to inaccuracies, can be compromised, or are contingent upon faults or disturbances in the external physical environment when performing SoC estimation based on sensor measurements. Therefore, if direct measurements are less than trustworthy, the resulting SoC estimation will be inaccurate. Conversely, the improved approach extends the traditional SoC estimation framework by employing a dynamic model for the detection and estimation of sensor faults and physical disturbances in real-time while maintaining the SoC estimation process. Therefore, the SoC value can be considered a more trustworthy value, despite faults and disturbances, making the estimation more robust and ensuring the battery management is stable and precise, even in poorly distinguished contexts and abnormal adversarial conditions.

3 Proposed method

The research work aims to improve the accuracy and robustness of the LIB, as well as SoC estimation, by introducing an augmented UIE. Often, traditional methods of estimating the SoC fail due to sensor faults, measurement noise, and external disturbances that prevent the field application of these methods. Such problems have called for a great deal of detail in the electric machine model created for the battery. It includes essential features such as an internal resistance in the form of a resistor, two RC loops for transient events, a dependent voltage source corresponding to the SoC/OCV curve, and self-discharge models with some resistors and capacitors to account for the case of a completely charged battery. Hence, this model also provides a realistic representation of a battery's behaviour under varied operational conditions, and this estimation approach will be proven robust in real-time applications. Using Kirchhoff's laws, the dynamic state-space representation of the battery was derived, allowing for the incorporation of voltage variations, transient effects, and resistance effects into the estimation. Furthermore, the model was refined to address input faults and external disturbances, thereby enhancing the performance and reliability of the estimation in various working environments. To achieve accurate and adaptive SoC estimation, the study presented an augmented UIE approach as an alternative and improved estimator compared to traditional ones, which address sensor faults, noise, and dynamic operational conditions.

The system states were thereby defined in the state space, the system inputs were modelled, and an unknown fault was introduced to ensure a real-time, adaptable estimation process. A Lipschitz-based assumption was employed to restrict the system dynamics, allowing for the development of an observer-based estimator that effectively extracts system states and filters out unknown disturbances. In addition, a Lyapunov function was constructed to control the dynamics of the estimation error, ensuring its asymptotic convergence during the estimation process and enabling highly reactive batteries to respond to sudden changes in conditions. The approach was sufficient to make the device applicable to scenarios where precision and reliability are crucial. To assess the efficiency of the presented method, several experiments were conducted using two different battery discharge profiles: regular pulse discharge, where the terminal current followed a periodic pulse routine, and complex pulse discharge, where the battery was subjected to variable frequency dynamic charge-discharge cycles. The proposed estimator was then compared to the EKF, which is often considered the benchmark technique employed in industrial applications for SoC estimation. The results demonstrated that this approach has an edge over the EKF, reducing the SoC estimation error from approximately 5% to 1%, thereby achieving a significant improvement in estimation accuracy. Furthermore, the proposed method offers improved terminal voltage estimation accuracy, a desirable feature for optimising battery performance in real-time applications.

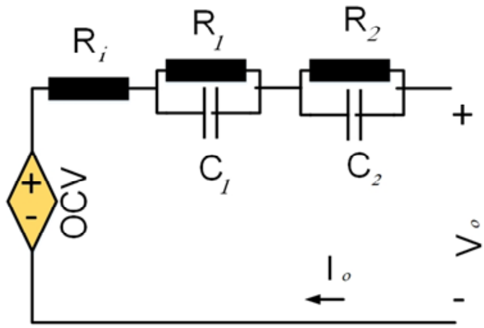
A primary asset of this estimator is its ability to detect and isolate faults in sensors. This characteristic was not present in the EKF, thus significantly strengthening its practical applicability in a fault-tolerant battery management context. Apart from its primary role in improving the accuracy of SoC estimation, the proposed augmented unknown input estimator has several other merits applicable in BMS. First, the performance against unknown inputs and disturbances makes it viable for many applications, including EVs, renewable energy storage systems, and industrial power management. Its very adaptability from LIB chemistries allowed it to be integrated with an assortment of other energy storage technologies without tedious recalibration. The robustness of the estimator against measurement noise and external disturbances has made it even more convenient to be deployed in harsh, unpredictable operating environments with extreme temperature variations and fluctuating power demands in EVs.

This study provided an excellent foundation for future research and improvement in SoC estimation methods. Suppose the proposed method proves more beneficial and increases estimation accuracy. In that case, future development may consider the possible inclusion of adaptive filtering techniques, machine learning-based prediction models, and deep learning-based anomaly detection algorithms that could further refine the estimators. On the other hand, the inclusion of real-time efficiency in battery-powered systems can be achieved by exploring haptic feedback control and energy management strategies based on artificial intelligence algorithms. Maximisation of real-world applicability may lie in future work through the real-time implementation in embedded hardware, which would enable this estimator to be integrated into commercial BMS platforms for real-time deployment in large-scale energy storage systems.

3.1 Battery modelling

Several methods have been proposed for simulating LIBs, including models that explain chemical reactions, physical characteristics, electrical attributes, temperature effects, and experimental investigations. Electrical models are highly popular among engineers and designers because they strike a balance between accuracy and simplicity in design.

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



In this paper, an electrical pattern is employed to represent the battery, as depicted in Figure 1. The setup incorporates a resistor to represent the battery's internal resistance, two loops consisting of resistors and capacitors to mimic the battery's transient characteristics over different time scales, a source of dependent voltage to simulate the battery's SoC/OCV curve, a resistor to demonstrate self-discharge, as well as a capacitor to symbolise the battery's full capacity. By applying Kirchhoff's laws, the terminal voltage can be computed:

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

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

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

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

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

In which V_1 and V_2 denote the voltages across (R_1C_1) and (R_2C_2), respectively. There is typically a nonlinear link between V_{oc} and SoC. Therefore:

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

Taking into account $dI_o/dt = 0$ and utilising equations (2), (5) and (1), the dynamic equation for V_o is:

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

The state vector is denoted as $x = [SoC, V_1, V_2, V_o]^T$. I_o displays the input, and V_o Displays the output of the battery model. By employing equations (2), (3), (4), and (6), the state-space framework of the battery is expressed below:

$$\dot{x} = F(x, v) + \zeta$$
$$o = Cx + \omega \tag{7}$$
$$C = [0 \quad 0 \quad 0 \quad 1]$$

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

$$F(x, v) = \begin{bmatrix} -\dfrac{1}{R_T C_T} SoC - \left(\dfrac{I_o}{C_T}\right) \\ -\dfrac{V_1}{R_1 C_1} + \dfrac{I_o}{C_1} \\ -\dfrac{V_2}{R_2 C_2} + \dfrac{I_o}{C_2} \\ \dot{L}(SoC)\dot{S}oC + \dfrac{V_1}{R_1 C_1} - \dfrac{I_o}{C_1} + \dfrac{V_2}{R_2 C_2} - \dfrac{I_o}{C_2} \end{bmatrix} \tag{8}$$

Following the derivation of the dynamic equations for the battery pattern, the parameters in the battery's state-space representation are identified via experimental procedures. The process for obtaining these parameters is explained in the reference. Once the parameters for the battery pattern are determined and understood, the pattern is simulated numerically using a software platform, resulting in the following correlation.

$$\dot{x} = \begin{bmatrix} -(13.9e-8)SoC - (1.4e-3)I_o \\ -(12e-5)V_1 + 0.045 I_o \\ -0.02 V_2 + (7.6e-3)I_o \\ (-31e-5)SoC^3 + \left((30e-6) - (3.2e-5)I_o\right)SoC^2 \\ +(32e-7)I_o \cdot SoC - \left(I_o + 1\right)(0.02)\exp(-38 SoC) \end{bmatrix} \tag{9}$$
$$o = Cx + \omega$$

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

$$\dot{x} = Mx + q(x) + Nv + Ss(t) + I\zeta(t)$$
$$q(x) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ (-30e-6)SoC^3 + \left((30e-7) - (3e-4)I_o\right)SoC^2 \\ +(31e-7)I_o \cdot SoC - \left(I_o + 1\right)(0.01)\exp(-39 SoC) \end{bmatrix} \tag{10}$$
$$o = Cx + \omega$$

To confirm the precision of the determined pattern, the actual terminal voltage and the simulated terminal voltage are compared and obtained through practical testing. If the variance between the simulated and actual voltages falls below a specific threshold, the battery model identification is considered successful, allowing the iterative estimation design process to continue (2021).

3.2 Proposed estimator

Take into account the adaptive pattern of the system, which comprises the subsequent equations:

$$\begin{aligned} \dot{x}(t) &= Mx(t) + Nv(t) + q\left(x(t)\right) + Ss(t) + I\zeta(t) \\ o(t) &= Cx(t) \end{aligned} \tag{11}$$

where $x(t) \in R^{n_x}$, $v(t) \in R^{n_v}$, $s(t) \in R^{n_s}$, and $o(t) \in R^{n_o}$ represent the states, inputs, faults, and outputs, respectively. $\zeta(t) \in R^{n_\zeta}$ displays a bounded disturbance, treated as an unknown input. The state-space matrices are denoted as *M*, *N*, *C*, *S*, and *I*, and the nonlinear term is considered as $q(x(t))$. It is typical to suppose that $s(t)$ remains constant to simplify the fault estimation process. However, the system fault can be time-variant, as this work assumes that the second derivative of $s(t)$ the concerning time is zero. To determine the fault, the system's state variables are supplemented below:

$$V(t) = \begin{pmatrix} x(t) \\ \dot{s}(t) \\ s(t) \end{pmatrix} \in R^{n_x + 2n_s} \tag{12}$$

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

$$\begin{aligned} V(t) &= \bar{M}V(t) + \bar{N}v(t) + \bar{q}\left(V(t)\right) + \bar{I}\zeta(t) \\ o(t) &= \bar{C}V(t) \end{aligned} \tag{13}$$

where

$$\bar{M} = \begin{pmatrix} M & 0 & S \\ 0 & 0 & 0 \\ 0 & I & 0 \end{pmatrix}, \bar{N} = \begin{pmatrix} \bar{N} \\ 0 \\ 0 \end{pmatrix}, \bar{q}\left(V(t)\right) = \begin{pmatrix} q\left(x(t)\right) \\ 0 \\ 0 \end{pmatrix}, \bar{I} = \begin{pmatrix} I \\ 0 \\ 0 \end{pmatrix}, \bar{C} = (C \quad 0 \quad 0) \tag{14}$$

Assumption 1: By assuming that the function $\bar{q}(V(l))$ satisfies the Lipschitz property, there is:

$$\left\|\bar{q}\left(V(t)\right) - \bar{q}\left(\hat{V}(t)\right)\right\| \le \bar{\tau}\left\|\bar{\Theta}\left(V(t) - \hat{V}(t)\right)\right\| \tag{15}$$

Here, $\bar{\tau}$ we $\bar{\Theta}$ display the Lipschitz coefficients.

To extend the proposed observer, the following initial steps are necessary:

Lemma 1: The link between matrices *V* and *L* and scalar $\delta > 0$ is stated below:

$$V^T L + L^T V \le \delta V^T V + \delta^{-1} L^T L \tag{16}$$

Here, an unknown input estimator (UIE) is presented. Due to the battery's state-space model in equation (13) and its state-space matrices, including $\bar{M}, \bar{N}, \bar{I}$ and $\bar{C}$. The proposed estimator is given as follows:

$$\begin{aligned} \dot{v}(t) &= \Gamma v(t) + \Pi \bar{q}\left(\hat{V}(t)\right) + \Delta o(t) \\ \hat{V}(t) &= v(t) + \Psi o(t) \end{aligned} \tag{17}$$

where $\hat{V}(t) \in R^{t_V}$ displays the estimation of $V(t)$. Additionally, $\Gamma \in R^{n_V \times n_V}$, $\Delta \in R^{n_V \times n_o}$, $\Psi \in R^{n_V \times n_o}$, and $\prod \in R^{n_V \times n_V}$ are the observer gains. Due to equation (17), the input and output of the battery model are considered as inputs to the estimator. In equation (17), parameters Γ, Δ, Ψ, and Π are unknown and must be determined such that the estimation error dynamics are asymptotically stable. Therefore, the dynamics of the estimation error are first derived. Then, based on these estimation error dynamics, the stability condition is transformed into a linear matrix inequality (LMI) problem. Finally, by solving this LMI problem, the unknown parameters are obtained.

The estimation error dynamic $e(t) = V(t) - \hat{V}(t)$ can be computed as follows, with $\Delta = \Delta_1 + \Delta_2$:

$$e(t) = V(t) - \hat{V}(t) = V(t) - v(t) - \Psi o(t) = \left(I_n - \Psi \bar{C}\right) V(t) - v(t) \tag{18}$$

$$\begin{aligned} \dot{e}(t) = {} & \left(\bar{M} - \Psi \bar{C} \bar{M} - \Delta_1 \bar{C}\right) \dot{e}(t) + \left(\bar{M} - \Psi \bar{C} \bar{M} - \Delta_1 \bar{C} - \Gamma\right) v(t) \\ & + \left[\left(\bar{M} - \Psi \bar{C} \bar{M} - \Delta_1 \bar{C}\right) \Psi - \Delta_2\right] o(t) + \left[\left(I_n - \Psi \bar{C}\right) \bar{N} - \Pi \bar{N}\right] v(t) \\ & + \left(I_n - \Psi \bar{C}\right) \bar{q}\left(V(t)\right) - \Pi \bar{q}\left(\hat{V}(t)\right) + \left(I_n - \Psi C\right) \bar{I} \zeta(t) \end{aligned} \tag{19}$$

If the subsequent equations are applicable:

$$\left(I_t - \Psi \bar{C}\right) \bar{I} = 0, \Gamma = \bar{M} - \Psi \bar{C} \bar{M} - \Delta_1 \bar{C}, \Pi = I_t - \Psi \bar{C}, \Delta_2 = \Gamma \Psi \tag{20}$$

Then equation (19) is simplified in the following manner:

$$\dot{e}(t) = \Gamma e(t) + \left(I_n - \Psi \bar{C}\right)\left(\bar{q}\left(V(t)\right) - \bar{q}\left(\hat{V}(t)\right)\right) = \Gamma e(t) + \left(I_n - \Psi \bar{C}\right) \tilde{q} \tag{21}$$

Equation (21) confirms that the impacts of disturbances are completely disentangled. The suggested technique aims to design the matrix Γ in a manner that ensures the asymptotic stability of equation (21).

Theorem 1: Assuming the estimation error dynamics in equation (21) under Assumption 1, with given $\lambda_s < 0$ and $\delta > 0$. If there exist matrices $R > 0$, Z, L, r, and t that satisfy the feasibility problem outlined below:

$$\begin{pmatrix} \begin{array}{c} \bar{M}^T R + R \bar{M} - Rr \bar{C} M - Lt \bar{C} M - Z \bar{C} - \bar{C}^T Z^T \\ -\bar{M}^T \bar{C}^T r^T R - \bar{M}^T \bar{C}^T t^T L^T + \delta \bar{\tau}^2 \bar{\Theta}^T \bar{\Theta} - \lambda_s R \end{array} & R - Rr\bar{C} - Lt\bar{C} \\ * & -\delta I \end{pmatrix} \leq 0 \tag{22}$$

where $Z = R\Delta_1$, $L = R\Psi_0$, $r = \bar{I}(\bar{C}I)^{\dagger}$, $t = I - (\overline{CI})(\overline{CI})^{\dagger}$, $\Psi = r + \Psi_0 t$, then for a UIO in equation (17), the estimation error dynamic in equation (14) exhibits asymptotic stability.

Proof: Take into account the candidate Lyapunov's function and the stability situation as presented below:

$$G\left(e(t)\right) = e(t)^T \,\mathrm{Re}(t), R > 0 \tag{23}$$

$$\dot{G}(e(t)) \leq \xi_s G(e(t)) \tag{24}$$

The derivative of the candidate Lyapunov function along the trajectory of the estimation error dynamic is expanded as:

$$\begin{aligned} &\dot{G}(e) = \dot{e}^T \operatorname{Re} + e^T R\dot{e} \\ &\Rightarrow \dot{G}(e) = e^T \left(\bar{M}^T R + R\bar{M} - R\Psi\bar{C}\bar{M} - R_i\Delta_1\bar{C} - \bar{C}^T \left(R_i\Delta_1\right)^T - \bar{M}^T\bar{C}^T\Psi^T R\right)e \\ &+e^T R_i \left(I_n - \Psi\bar{C}\right)\left(\bar{q}_i(x) - \bar{q}(\hat{x})\right) + \left(\bar{q}(x) - \bar{q}(\hat{x})\right)^T \left(I_n - \Psi\bar{C}\right)^T \operatorname{Re} \end{aligned} \tag{25}$$

Based on equation (15) and Lemma 1:

$$\begin{aligned} &e^T S\left(I_t - R\bar{C}\right)\left(s(x) - s(\hat{x})\right) + \left(s(x) - s(\hat{x})\right)^T \left(I_n - \Psi\bar{C}\right)^T \operatorname{Re} \\ &\leq \frac{1}{\delta} e^T R\left(I_n - \Psi\bar{C}\right)\left(I_n - \Psi\bar{C}\right)^T R^T e + \delta\left\|\bar{q}(x) - \bar{q}(\hat{x})\right\|^2 \\ &\leq \frac{1}{\delta} e^T R\left(I_n - \Psi\bar{C}\right)\left(I_n - \Psi\bar{C}\right)^T R^T e + \delta\bar{\tau}^2 e^T \bar{\Theta}^T \bar{\Theta}^e \end{aligned} \tag{26}$$

By substituting equation (26) into equation (25), there is:

$$\begin{aligned} &\dot{G}(e) \leq e^T \left(\bar{M}^T R + R\bar{M} - R\Psi\bar{C}\bar{M} - R\Delta_1\bar{C} - \bar{C}^T \left(R\Delta_1\right)^T - \bar{M}^T\bar{C}^T\Psi^T R\right. \\ &\left.+\frac{1}{\delta} R\left(I_n - \Psi\bar{C}\right)\left(I_n - \Psi\bar{C}\right)^T R^T + \delta\bar{\tau}^2\bar{\Theta}^T\bar{\Theta}\right)e \end{aligned} \tag{27}$$

Based on equations (24) and (27), if the following inequality is satisfied, then the stability condition along the trajectory of the estimation error dynamics is upheld:

$$\begin{aligned} &\bar{M}^T R + R\bar{M} - R\Psi\bar{C}\bar{M} - R\Delta_1\bar{C} - \bar{C}^T \left(R\Delta_1\right)^T - \bar{M}^T\bar{C}^T\Psi^T R \\ &+\frac{1}{\delta} R\left(I_n - \Psi\bar{C}\right)\left(I_n - \Psi\bar{C}\right)^T R^T + \delta\bar{\tau}^2\bar{\Theta}^T\bar{\Theta} - \lambda_s R \leq 0 \end{aligned} \tag{28}$$

Assuming $\Psi = r + \Psi_0 t$, $r = \bar{I}(C\bar{I})^\dagger$, $t = I - (\bar{C}\bar{I})(\bar{C}\bar{I})^\dagger$, $Z = R\Delta_1$ and $L = R\Psi_0$, equation (18) can be simplified in the following manner:

$$\begin{aligned} &\bar{M}^T R + R\bar{M} - Rr\bar{C}\bar{M} - LtC\bar{M} - Z\bar{C} - \bar{C}^T Z^T - \bar{M}^T\bar{C}^T r^T R - \bar{M}^T\bar{C}^T t^T L^T \\ &+\frac{1}{\delta} R\left(I_n - \Psi\bar{C}\right)\left(I_n - \Psi\bar{C}\right)^T R^T + \delta\bar{\tau}^2\bar{\Theta}^T\bar{\Theta} - \lambda_s R \leq 0 \end{aligned} \tag{29}$$

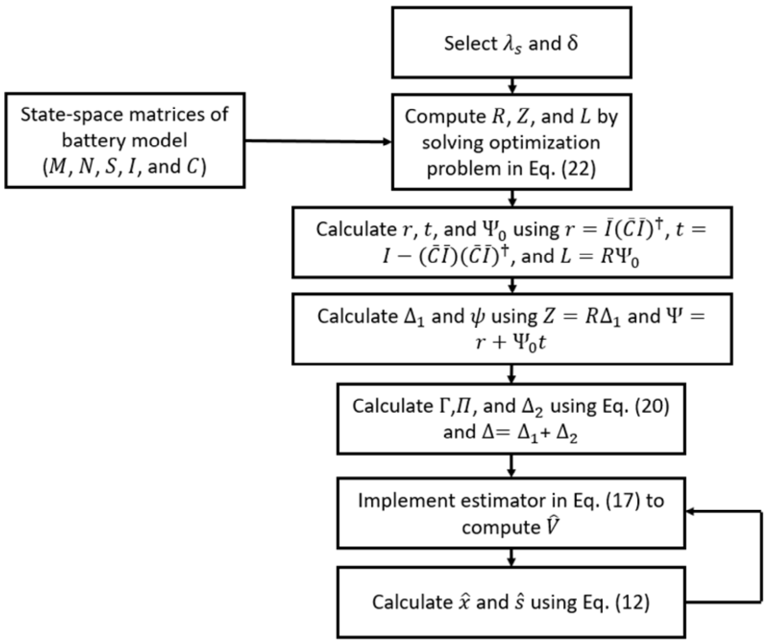
By employing the Schur complement lemma, the following results are obtained:

$$\begin{pmatrix} \bar{M}^T R + R\bar{M} - Rr\bar{C}\bar{M} - Lt\bar{C}\bar{M} - Z\bar{C} - \bar{C}^T Z^T & \\ -\bar{M}^T\bar{C}^T r^T R - \bar{M}^T\bar{C}^T t^T L^T + \delta\bar{\tau}^2\bar{\Theta}^T\bar{\Theta} - \lambda_s R & R - Rr\bar{C} - Lt\bar{C} \\ * & -\delta I \end{pmatrix} \leq 0 \tag{30}$$

Hence, equation (22) has been verified, and thus, the proof is concluded.

Remark 1: The proposed estimator has low computational complexity and is easy to implement. Therefore, it is suitable for practical and real-time applications. Additionally, sensor errors, including bias and scale factor, are considered a form of sensor fault. As a result, the proposed estimator performs well even when the sensor is not calibrated. However, the estimator is not resistant to variations in the battery model caused by temperature changes, and the estimation error may increase. Therefore, developing an estimator that considers the effects of temperature is suggested as future work. The implementation algorithm of the proposed estimator is shown in Figure 2.

Figure 2 The implementation algorithm of the proposed estimator



4 Outcomes and discussion

The findings from this research demonstrated how the proposed augmented UIE improved the accuracy and reliability of SoC estimation in LIBs. The proposed method addressed a major constraint in traditional estimation-based methods, namely, sensor faults and external physical disturbances. Experimental results validated that the estimation procedure based on UIE had an SoC estimation error of about 1%, while the EKF estimated an error of nearly 5%. The terminal voltage estimation error of UIE proved to be almost zero, whereas that with EKF was between 0.02 and 0.03 V. This demonstrates that the proposed method is robust across all operating conditions, particularly in dynamic ones. The study further validated that UIE could detect and isolate sensor faults, a feature lacking in conventional SoC estimation methods. The technique proves particularly useful in practical situations, such as the use of EVs and the application of renewable energy storage schemes, where sensor faults may severely compromise the performance and even the safety of a battery. Experimental results showed that under different discharge test programs and both standard pulse versus more complicated pulse conditions, the estimator maintained accuracy.

The proposed algorithm outperformed the EKF even in the most complex test, thereby demonstrating its applicability across a wide range of operating conditions. The most traditional techniques for SoC estimation, including Coulomb counting, OCV methods, and model-based approaches, were found to be deficient in terms of parameter sensitivity, computational complexity, and environmental variation when their findings were compared with those of previous studies. This limitation was removed in the UIE through the inclusion of an advanced fault-tolerant mechanism and an adaptive estimation framework, which improved both the accuracy and the reliability of the estimation. The results of prior studies indicated that AI and ML-based SoC estimation models can provide high accuracy. However, it should be noted that in most instances, they require extensive amounts of data for training and demand significant computational power to execute. The UIE, however, provides an alternative that is computationally efficient and does not require extensive training data, making it highly suitable for real-time embedded applications. Such implications of this study go beyond an improved understanding of SoC estimation. The diagnosis and rehabilitation of sensor faults also enhance the fault tolerance of the BMS against mismatched state estimates, thereby preventing inaccurate degradation performance or hazardous situations. Such applications include EVs, spacecraft, and large-scale energy storage systems, where battery reliability is crucial. It further suggests hybrid SoC estimation models that combine the predictive capabilities of physics with the advanced capabilities of AI models for estimating SoC.

There are, however, several limitations despite the promising results: the present study primarily focused on one aspect of battery chemistry and did not sufficiently evaluate the performance of the estimator across other lithium-ion chemistries, including lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC). Future work should assess the extent to which the UIE methodology can generalise across different battery chemistries to ensure wider applicability. While the UIE algorithm adequately addressed the sensor faults, additional studies are needed to investigate the long-term stability of the method in real field conditions, particularly during extreme temperature variations and aging effects. The proposed augmented UIE would improve the precision and accuracy of SoC estimation in LIBs, while also simultaneously estimating the system pi fault or fault disturbance. Imagine an array of smart sensors that not only measure but also react to sensor errors, providing simultaneous dual estimates of both the battery's SoC and the sensor disturbance. So that if the sensors fail or deliver a faulty measurement, we can identify the error, correct it, and then make a new estimation of the SoC. As a direct consequence, we should be able to make more accurate battery SoC estimates and do so in a more reliable manner, allowing the BMS to operate reliably, which in turn will enhance real safety and increase battery lifetimes.

In this section of the article, the analysis of the empirical trial outcomes is presented. To examine the productivity of the recommended technique in determining the battery charge level, a series of practical tests was conducted using the setup shown in Figure 3. 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. During these tests, a programmable resistance reservoir was used to create different battery discharge scenarios. Additionally, the effectiveness of the suggested technique was compared with the EKF, which is the most extensively utilised approach for determining battery charge levels in industrial applications. These experiments were conducted in two separate situations. In the first case, the battery was discharged by a resistive load, causing the battery terminal current to form a regular pulse. In the second scenario, a resistor was adjusted so that the battery terminal current exhibited a complex pulse shape with a non-constant frequency.

Figure 3 Test setup (see online version for colours)

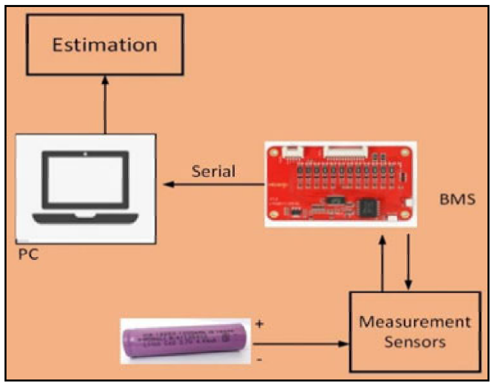
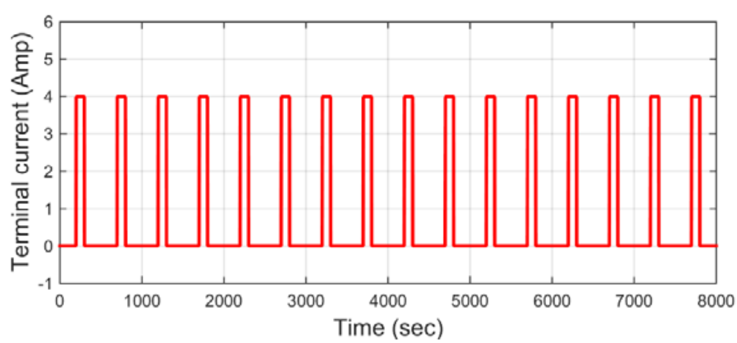


Figure 4 Battery current (first scenario) (see online version for colours)



As mentioned, in the first scenario, a resistor is set so that the battery terminal current has a regular pulse shape with a constant frequency. In this scenario, the battery terminal current diagram, as displayed in Figures 4 and 5, compares the productivity of the suggested technique in determining the battery charge level with the EKF method. As shown in this figure, the proposed approach accurately determines the battery charge level with high precision compared to the EKF. Specifically, the suggested technique achieves an error of approximately 1%, while the EKF method has an error of around 5% in determining the battery charge level. To further validate the effectiveness of the technique in this scenario, Figure 6 compares the productivity of the technique in determining the terminal voltage with that of the EKF method. This figure does not confirm all the statements made above; rather, it displays the evaluation of the suggested method. In other words, despite the jumps occurring at the edges of the current pulse, the terminal voltage estimation by the presented technique has an error close to zero. In contrast, the Kalman method has an estimated error of approximately 0.02 volts in estimating the terminal voltage.

Figure 5 SOC determination (first case) (see online version for colours)

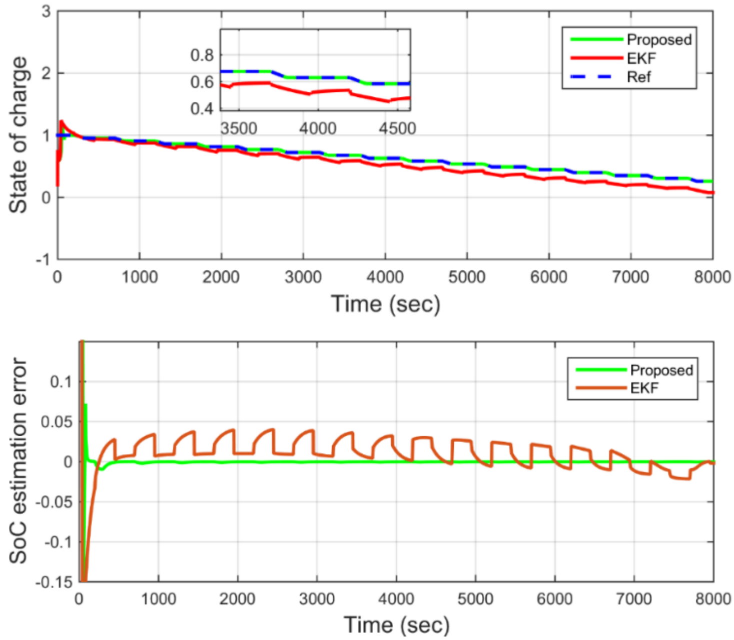


Figure 6 Voltage estimation (first case) (see online version for colours)

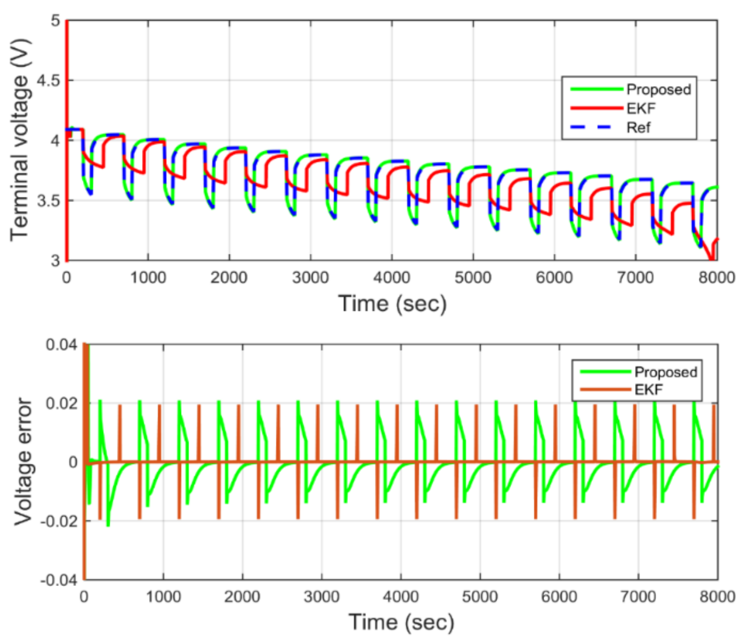


Figure 7 Battery current (second case) (see online version for colours)

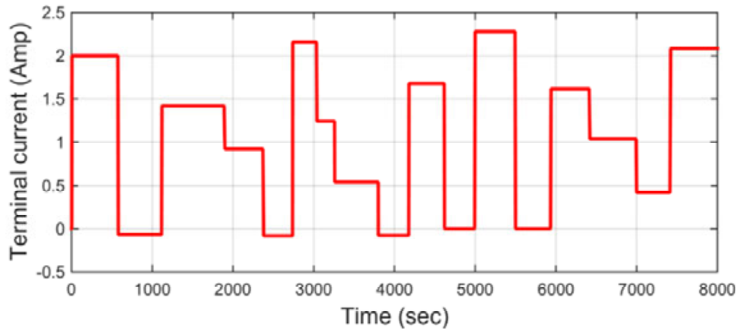
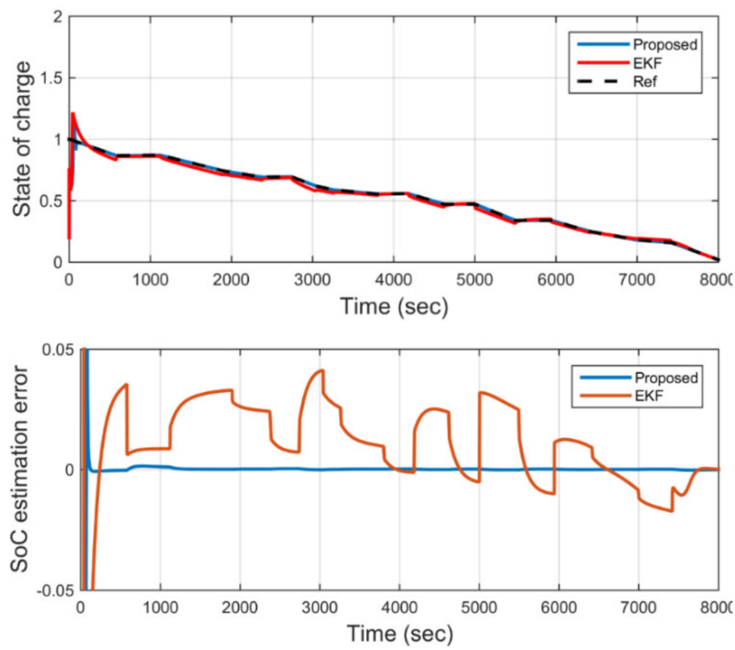
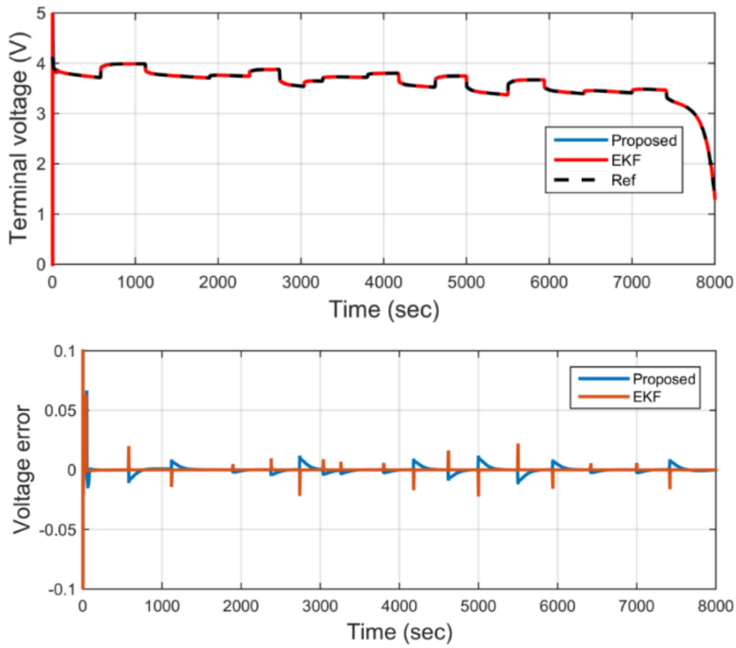


Figure 8 SOC determination (second case) (see online version for colours)



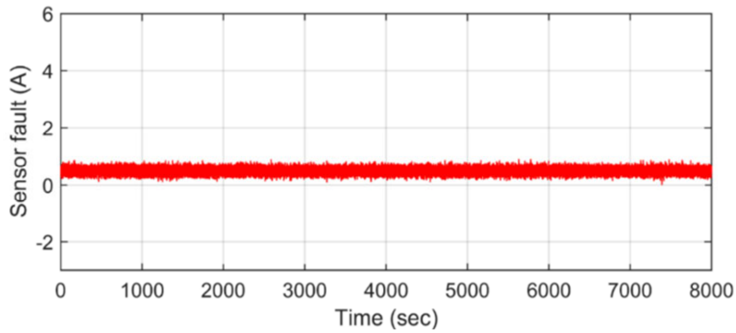
In the second scenario, the test becomes more challenging. In this scenario, the resistive load is set so that the battery terminal current behaves as displayed in Figure 7. In other words, at certain times, the battery is in a discharge state. In contrast, at other times, it is in a charge state, and the frequency of changes in the battery current is not constant. Figures 8 and 9 compare the productivity of the preferred technique with the EKF method in determining the charge level and the terminal voltage. As shown in Figure 8, the proposed technique can determine the battery charge level with high precision, even in this more challenging scenario. Specifically, as in the previous scenario, the EKF method exhibits an error that is 4% greater than that of the proposed technique in determining the battery SoC. To further investigate the effectiveness of the techniques, Figure 9 displays the determination of the terminal voltage. According to this figure, the suggested technique determines the terminal voltage with zero error, while the EKF method has an estimated error of approximately 0.03 volts. Figure 10 displays the estimation of a sensor fault using the proposed estimator. The EKF method, however, was unable to detect this fault, and the estimation of other state variables was adversely affected by it.

Figure 9 Voltage estimation (second case) (see online version for colours)



With the introduction of a UIE, both accuracy and reliability in the estimation process for LIBs and SoC are greatly boosted. In most conventional methodologies, model error, disturbances, and sensor faults can compromise the intended reliability of the estimate in real-world applications by causing significant deviations in the estimates. Fortunately, the augmented UIE can consider unknown inputs, i.e., sensor faults and disturbances, as part of its estimation framework by treating these as additional states. In this way, the estimator can simultaneously estimate the internal states of the battery and the sensor's conditions. The result is that the estimator can detect when sensor faults occur and offset their effect on the SoC estimate. The actual accuracy of the estimate is significantly improved, even if it is known that a fault exists or a disturbance is present. Furthermore, with sensors capable of detecting and correcting faults in real-time, the estimator becomes inherently more resilient to operating with uncertainty, potential aged conditions, and external variations. Thus, we can achieve stable performance and reliable results when those three factors above are no longer controlled, contributing to more stable and readily available battery management activities. In conclusion, the augmented UIE presents an exciting avenue for achieving more accurate, reliable, and fault-resilient SoC estimation in the battery domain, thereby directly supporting safer and more meaningful battery management in stored energy applications (Figure 11).

Figure 10 Fault estimation (see online version for colours)



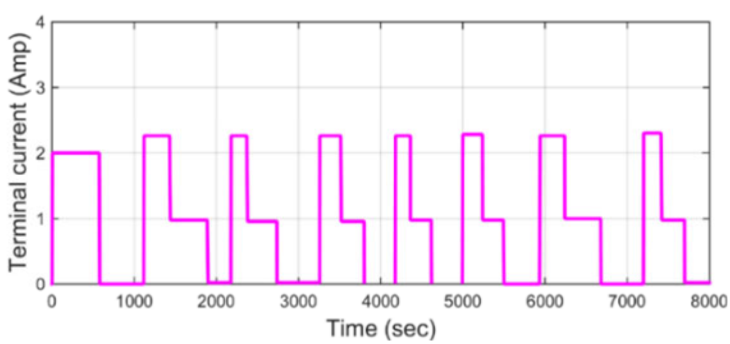
To better examine the performance of the proposed method, a series of practical experiments was conducted in the laboratory under more complex conditions, specifically at lower temperatures. The results obtained were then compared with those of a new advanced method. These tests were performed at 0 °C, and as shown, the battery was discharged according to the profile depicted in part A of Figure 10. The estimation results under these test conditions are presented in parts b and c of this figure. As is clear from these figures, the proposed method outperforms the ASMO method, estimating the charge level and terminal voltage with greater accuracy and faster convergence speed.

Table 1 compares the results of the experiments obtained numerically and presents the RMS error for estimating the charge level.

Table 1 RMS comparison for all methods

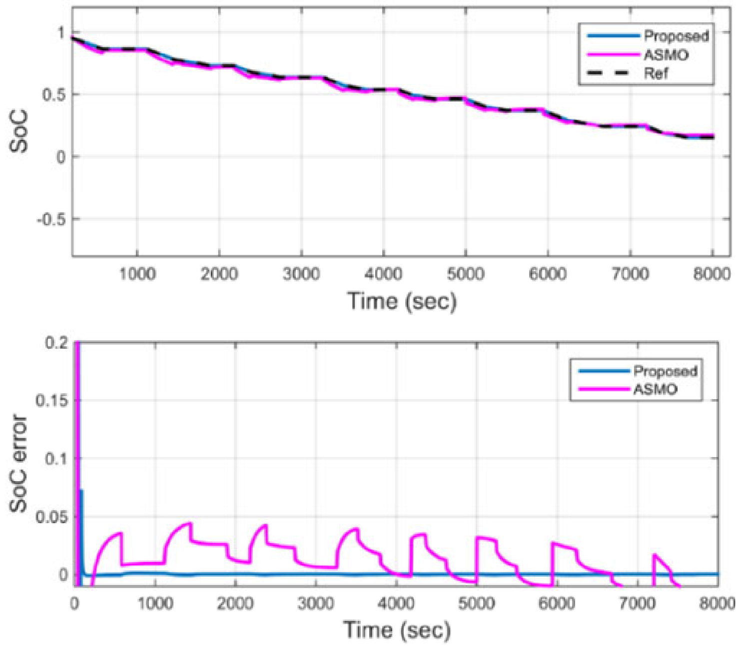
	SoC estimation error in profile 1	*SoC estimation error in profile 2*	*SoC estimation error in profile 3*
Proposed	0.009	0.0082	0.008
EKF	0.048	0.043	-
ASMO	-	-	0.045

Figure 11 Experimental tests for comparison to ASMO (see online version for colours)

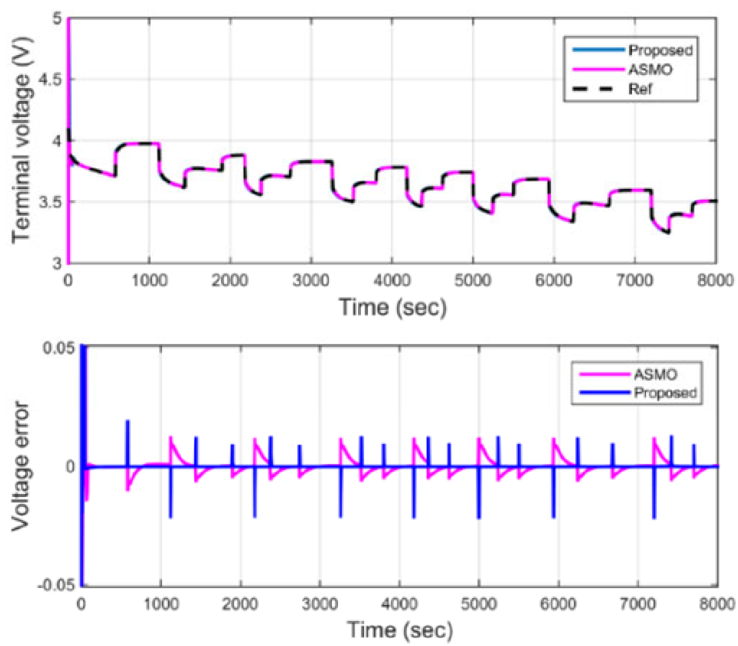


(a)

Figure 11 Experimental tests for comparison to ASMO (continued) (see online version for colours)



(b)



(c)

5 Conclusions

In summary, this study presents a new approach that enhances the accuracy of estimating SoC in LIB packs by utilising nonlinear battery models in conjunction with an estimator for unmeasured inputs. The key part of the development was to include sensing faults in the model as additional variables, so correction of the sensing fault error is achieved in parallel with an estimate of SoC. The fault-tolerant design here is useful when estimating SoC, as it helps prevent estimation errors and increase the reliability of BMSs, which is essential to ensure safety, performance, and longevity for EVs and renewable energy sources. The experimental validation confirmed the robustness of the method, with results showing an improvement in the accuracy of the estimation and the real-time fault detection, providing additional confidence in its applicability. The system's ability to detect and correct sensor faults dynamically in real-time demonstrates its usefulness for more complex real-world implementations, where sensor dependability will vary widely. The importance of incorporating integrated fault-tolerant mechanisms within improved energy storage systems was made clear, as they can improve operational stability and safety under a diverse range of conditions. Overall, the proposed methodology represents a significant advancement in battery management technology by creating a more reliable, efficient, and safe framework for energy storage systems to support diverse energy systems. Future work should focus on developing more sophisticated algorithms that can potentially increase estimation accuracy and reduce the time required to identify faults. Additionally, the development of holistic methods that optimise energy management protocols, prioritising safety, efficiency, and resilient systems for evolving applications, is also warranted.

Declarations

No funding was received to assist with the preparation of this manuscript.

The author has no competing interests to declare that are relevant to the content of this article.

References

Anand, P.P., Jayanth, G., Rao, K.S., Deepika, P., Faisal, M. and Mokdad, M. (2024) 'Utilising hybrid machine learning to identify anomalous multivariate time-series in geotechnical engineering', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 1, pp.32–41.

Babu, K.A., Arulvendhan, K., Srinivasan, P., Ahmad, M.A., Prabha, A., Thariq, M.M., Ali, M.M.S. and Angelin, C.C. (2024) 'Economical infotainment solution augmented with advanced telematics for collision detection, vehicle localization, and real-time health status monitoring', *AVE Trends in Intelligent Health Letters*, Vol. 1, No. 4, pp.206–216.

Chandran, V., Patil, C.K., Karthick, A., Ganeshaperumal, D., Rahim, R. and Ghosh, A. (2021) 'State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms', *World Electric Vehicle Journal*, Vol. 12, No. 1, p.38.

Cui, Z., Dai, J., Sun, J., Li, D., Wang, L. and Wang, K. (2022a) 'Hybrid methods using neural network and Kalman filter for the state of charge estimation of lithium-ion battery', *Mathematical Problems in Engineering*, Vol. 2022, No. 1, p.9616124.

Cui, Z., Wang, L., Li, Q. and Wang, K. (2022b) 'A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network', *International Journal of Energy Research*, Vol. 46, No. 5, pp.5423–5440.

Du, J., Liu, Z., Wang, Y. and Wen, C. (2016) 'An adaptive sliding mode observer for lithium-ion battery state of charge and state of health estimation in electric vehicles', *Control Engineering Practice*, Vol. 54, No. 9, pp.81–90.

Feng, Y., Bai, F., Xue, C. and Han, F. (2021) 'State-of-charge and state-of-energy estimation for lithium-ion batteries using sliding-mode observers', in *2021 40th Chinese Control Conference (CCC)*, Shanghai, China, pp.2382–2385.

Feng, Y., Xue, C., Han, Q-L., Han, F. and Du, J. (2019) 'Robust estimation for state-of-charge and state-of-health of lithium-ion batteries using integral-type terminal sliding-mode observers', *IEEE Transactions on Industrial Electronics*, Vol. 67, No. 5, pp.4013–4023.

Guo, S. and Ma, L. (2023) 'A comparative study of different deep learning algorithms for lithium-ion batteries on state-of-charge estimation', *Energy*, Vol. 263, No. 10, p.125872.

Hannan, M.A., Lipu, M.S.H., Hussain, A. and Mohamed, A. (2017) 'A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: challenges and recommendations', *Renewable and Sustainable Energy Reviews*, Vol. 78, No. 9, pp.834–854.

He, Z., Yang, Z., Cui, X. and Li, E. (2020) 'A method of state-of-charge estimation for EV power lithium-ion battery using a novel adaptive extended Kalman filter', *IEEE Transactions on Vehicular Technology*, Vol. 69, No. 12, pp.14618–14630.

Ikwuagwu, C.V., Achebe, C.N. and Ononiwu, N.H. (2024) 'Investigating variability in power capacity through experimental testing of lithium-ion batteries', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 2, No. 1, pp.12–20.

John Joseph, F.J., Chinnusamy, K., Jeganathan, J.J., Obaid, A. and Rajest, S.S. (2025) *Optimizing Patient Outcomes through Multi-Source Data Analysis in Healthcare*, IGI Global, USA, DOI: 10.4018/979-8-3693-9420-5.

Kothuru, S.K. (2023) 'Emerging technologies for health and wellness monitoring at home', *FMDB Transactions on Sustainable Health Science Letters*, Vol. 1, No. 4, pp.208–218.

Krishna Vaddy, R. (2023) 'Data fusion techniques for comprehensive health monitoring', *FMDB Transactions on Sustainable Health Science Letters*, Vol. 1, No. 4, pp.198–207.

Kumar, C.S., Sathya, A., Deb, R. and Rahman, M.M. (2024) 'Managing electronic waste: a comprehensive review of current state and challenges', *FMDB Transactions on Sustainable Environmental Sciences*, Vol. 1, No. 1, pp.10–18.

Liu, Y., He, Y., Bian, H., Guo, W. and Zhang, X. (2022) 'A review of lithium-ion battery state of charge estimation based on deep learning: directions for improvement and future trends', *Journal of Energy Storage*, Vol. 52, No. 8, p.104664.

Ma, L., Hu, C. and Cheng, F. (2021) 'State of charge and state of energy estimation for lithium-ion batteries based on a long short-term memory neural network', *Journal of Energy Storage*, Vol. 37, No. 5, p.102440.

Madhuranthakam, R.S. (2024) 'Scalable data engineering pipelines for real-time analytics in big data environments', *FMDB Transactions on Sustainable Computing Systems*, Vol. 2, No. 3, pp.154–166.

Mehta, G., Bose, S.R. and Selva Naveen, R. (2023) 'Optimizing lithium-ion battery controller design for electric vehicles: a comprehensive study', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 2, pp.60–70.

Mokdad, M. (2024a) 'Dynamics of energy sources: development, challenges, and transitions', *FMDB Transactions on Sustainable Environmental Sciences*, Vol. 1, No. 2, pp.57–68.

Mokdad, M. (2024b) 'Environmental strategic dynamics of global energy management and security', *FMDB Transactions on Sustainable Environmental Sciences*, Vol. 1, No. 2, pp.91–106.

Nath, A., Gupta, R., Mehta, R., Bahga, S.S., Gupta, A. and Bhasin, S. (2020) 'Attractive ellipsoid sliding mode observer design for state of charge estimation of lithium-ion cells', *IEEE Transactions on Vehicular Technology*, Vol. 69, No. 12, pp.14701–14712.

Nomula, V.K., Steffi, R. and Shynu, T. (2023) 'Examining the far-reaching consequences of advancing trends in electrical, electronics, and communications technologies in diverse sectors', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 1, pp.27–37.

Obeid, H., Petrone, R., Chaoui, H. and Gualous, H. (2022) 'Higher order sliding-mode observers for state-of-charge and state-of-health estimation of lithium-ion batteries', *IEEE Transactions on Vehicular Technology*, Vol. 72, No. 4, pp.4482–4492.

Panyaram, S. (2024) 'Enhancing performance and sustainability of electric vehicle technology with advanced energy management', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 2, No. 2, pp.110–119.

Paramasivan, P., Rajest, S.S., Chinnusamy, K., Regin, R. and John Joseph, F.J. (2024) 'Clinical and comparative research on maternal health', *Advances in Medical Technologies and Clinical Practice*, IGI Global, USA, DOI: 10.4018/979-8-3693-5941-9.

Pierre, T.J., Tao, C., Vénant, K. and Erneste, B. (2024) 'Speed management blueprint: conception of an IoT-based electric vehicle speed limiter monitoring system for Kigali city vehicles', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 2, No. 1, pp.33–48.

Ramya, L.N., Bose, S.R., Selva Naveen, R. and Islam Chowdhury, R. (2023) 'Advanced solar charge controller: integrating MPPT technology and online data logging for efficient energy management', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 2, pp.107–120.

Sehrawat, S.K. (2024) 'Emerging trends in healthcare transformation through cutting-edge technologies', *AVE Trends in Intelligent Health Letters*, Vol. 1, No. 3, pp.168–177.

Senapati, B., Regin, R., Rajest, S.S., Paramasivan, P. and Obaid, A.J. (2023) 'Quantum dot solar cells and their role in revolutionizing electrical energy conversion efficiency', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 1, pp.49–59.

Shenbagavalli, T., Lakshmi, K.V.N., Nikhil, M.S. and Mehmood, A. (2024) 'Greenhouse gas control and sustainable economic development: an environmental impacts analysis', *FMDB Transactions on Sustainable Environmental Sciences*, Vol. 1, No. 1, pp.1–9.

Shi, Y., Ahmad, S., Tong, Q., Lim, T.M., Wei, Z., Ji, D., Eze, C.M. and Zhao, J. (2021) 'The optimization of state of charge and state of health estimation for lithium-ion batteries using combined deep learning and Kalman filter methods', *International Journal of Energy Research*, Vol. 45, No. 7, pp.11206–11230.

Shrivastava, P., Soon, T.K., Idris, M.Y.I.B. and Mekhilef, S. (2019) 'Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries', *Renewable and Sustainable Energy Reviews*, Vol. 113, No. 6, p.109233.

Siddique, M., Sarkinbaka, Z.M., Abdul, A.Z., Asif, M. and Elboughdiri, N. (2023) 'Municipal solid waste to energy strategies in Pakistan and its air pollution impacts on the environment, landfill leachates: a review', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 1, pp.38–48.

Srilakshmi, U., Sandhya, I., Manikandan, J., Bindu, A.H., Regin, R. and Rajest, S.S. (2024) 'Design and implementation of energy-efficient protocols for underwater wireless sensor networks', in *Advances in Computer and Electrical Engineering*, pp.417–430, IGI Global, USA.

Sundararajan, V., Steffi, R. and Shynu, T. (2023) 'Data fusion strategies for collaborative multi-sensor systems: achieving enhanced observational accuracy and resilience', *FMDB Transactions on Sustainable Computing Systems*, Vol. 1, No. 3, pp.112–123.

Victor Ikwuagwu, C., Ononiwu, N.H. and Adeyemi, K. (2023) 'Comprehensive energy analysis and performance evaluation of lithium-ion battery integration in photovoltaic systems: a comparative study on reliability and environmental impact', *FMDB Transactions on Sustainable Energy Sequence*, Vol. 1, No. 2, pp.83–93.

Wang, Z., Feng, G., Zhen, D., Gu, F. and Ball, A. (2021) 'A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles', *Energy Reports*, Vol. 7, No. 12, pp.5141–5161.

Wei, M., Ye, M., Li, J.B., Wang, Q. and Xu, X. (2020) 'State of charge estimation of lithium-ion batteries using LSTM and NARX neural networks', *IEEE Access*, Vol. 8, No. 1, pp.189236–189245.

Xu, C., Zhang, E., Yan, S., Jiang, K., Wang, K., Wang, Z. and Cheng, S. (2022) 'State of charge estimation for liquid metal battery based on an improved sliding mode observer', *Journal of Energy Storage*, Vol. 45, No. 1, p.103701.

Zhang, C., Li, X., Chen, W., Yin, G.G. and Jiang, J. (2015) 'Robust and adaptive estimation of state of charge for lithium-ion batteries', *IEEE Transactions on Industrial Electronics*, Vol. 62, No. 8, pp.4948–4957.

Zhang, D., Zhong, C., Xu, P. and Tian, Y. (2022) 'Deep learning in the state of charge estimation for Li-ion batteries of electric vehicles: a review', *Machines*, Vol. 10, No. 10, p.912.

Zhang, S., Guo, X. and Zhang, X. (2020) 'An improved adaptive unscented Kalman filtering for state of charge online estimation of lithium-ion battery', *Journal of Energy Storage*, Vol. 32, No. 12, p.101980.

Zhao, F., Li, Y., Wang, X., Bai, L. and Liu, T. (2020) 'Lithium-ion batteries state of charge prediction of electric vehicles using RNNs-CNNs neural networks', *IEEE Access*, Vol. 8, No. 5, pp.98168–98180.