Accurate Monitoring of Lithium-Ion Battery Performance through Adaptive Unscented Kalman Filters

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Abstract: The sources of modern energy with the best combinations of energy density, cycles, and weight include lithium-ion batteries. It covers a vast area from electric vehicles to the storage of renewable energy. Though there are some significant advantages to LiBs, estimations of the specific values of their performance parameters, State of Charge (SOC), and State of Health (SOH), are inadapted or irrelevant. They emerge from their nonlinear behavior, dynamic operating conditions, and aging effects. This paper surveys advanced estimation techniques, focusing on the Adaptive Unscented Kalman Filter, a method superior to traditional ones, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). Its adaptability allows AUKF to improve accuracy and robustness in SOC and SOH monitoring to address the added complexities in the management of a battery. In addition, hybrid approaches combining physics-based and AI-driven models are discussed to give better estimation and to reduce modelling errors. Practical demonstrations of these approaches have been very effective in improving battery performance and safety. It also discusses the emerging trend of second-life batteries and innovative dispatch strategies that consider degradation models and real-time SOH estimation. This therefore calls for the adoption of more advanced hybrid frameworks to enhance battery efficiency, reliability, and sustainability, thus pushing the frontiers of energy storage technologies.

Keywords: State of Charge (SOC), State of Health (SOH), Adaptive Unscented Kalman Filter (AUKF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Lithium-Ion Battery.

I. INTRODUCTION

Because lithium-ion batteries hold very high energy densities, with the capability for extended cycle lives, as well as a lighter overall design, it's become an unrelenting support in today's technologies. A host of devices including smartphones, laptops, large EVs, and even some systems to complement renewable energy. They have proven indispensable in the quest for energy sustainability and in clean energy initiatives, due to their ability to store energy efficiently and deliver it back into the grid [1]. It is challenging to monitor the SOC and SOH because lithium-ion battery behavior is somewhat complex and variative. The factors which make this a complicated case of SOC estimation include the fact that the behavior is non-linear and depends not only on voltage but also on the amount of charge transferred, age of the cell, temperature conditions, and many others. Similarly, SOH, representing the capacity of a battery to store and deliver its energy, remains sensitive to degradative phenomena like electrode wear, electrolyte decomposition, and cycle aging mechanisms, which can neither be computed quantitatively in real-time [2]. SOC and SOH cannot be measured directly. They must indirectly be determined via estimation by way of modeling and computational techniques. Besides, an inbuilt inaccurateness in the battery model along with sensor noise and environmental variation makes precise monitoring difficult, and therefore, a strong and adaptive estimation approach is required in order to ensure reliable battery management. Advanced filtering techniques play an important role in modern battery management systems so as to obtain more precise estimations of key parameters like SOC and SOH for achieving optimized performance and safety features.

Conventional estimation techniques are not able to detect the non-linear dynamics and uncertainties embedded in lithium-ion batteries. This leads to errors being involved in efficiency and longevity. Advanced filters like EKF and UKF provide robust solutions by combining mathematical models with real-time data for estimation of these parameters to a higher degree of accuracy [3]. These filters handle the complexity of battery behavior through temperature variations, effects of aging, and load conditions. They make these filters really indispensable in battery management systems. AUKF, or the Adaptive Unscented Kalman Filter, further extends this capability since it changes parameters in relation to system uncertainties and changes of the characteristics of the batteries due to time.

Unlike the UKF, where fixed assumptions on noise and system behavior are applied, the AUKF adapts to the changing conditions of the real world and therefore is very applicable in situations involving diverse operating environments for batteries [4]. This adaptability enhances the SOC and SOH estimation accuracy, reduces the number of computational errors, and makes the battery management system more reliable. The significance of AUKF lies in its ability to provide more consistent and reliable monitoring, extend battery life, and ensure safe operation for systems from electric vehicles to renewable energy storage.

II. FUNDAMENTALS OF LITHIUM-ION BATTERY PERFORMANCE

Their main characteristics are identified by key performance indicators, mainly the State of Charge (SOC), State of Health (SOH), and capacity, thus indicating their power storage and deliverance efficiency [5]. The SOC is referred to as how much charge is in the battery when compared to the full capacity or in other words a fuel gauge, while the SOH denotes the overall battery condition and degeneration over the long run. These parameters dictate the influence of internal chemical reactions, temperature fluctuation, discharge rates, and ageing effects on the energy density, efficiency, and life of the battery. It is necessary to gain deep knowledge about these basics in optimizing battery performance, safety, and effective design of battery management systems to ensure dependable operation across a set of applications.

A. Explanation of key battery parameters

SOC is one of the important parameters that show how much charge a battery holds with respect to its full capacity. It is always expressed as a percentage value; 100% indicates that a battery is fully charged, while 0% indicates a fully discharged one. SOC can be considered an instant indicator of available energy just like a fuel gauge for a conventional engine [6]. The estimation of SOC is very challenging because the relationship between voltage and capacity is nonlinear, which varies with temperature, load conditions, and battery aging. The precise estimation of SOC is crucial for efficient energy usage and avoiding overcharging or deep discharging, which can drastically degrade battery life and performance.

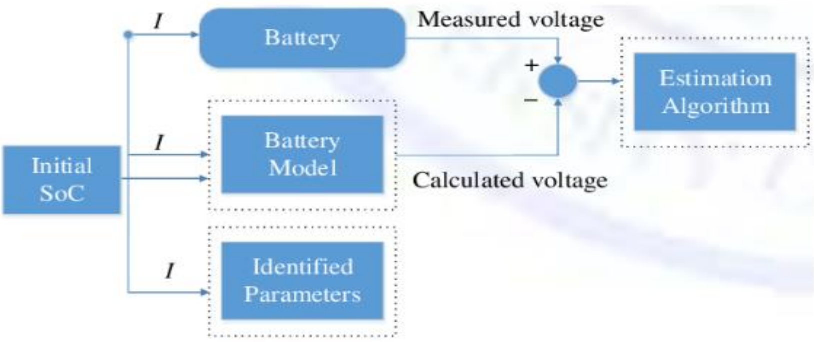

Figure 1. Framework of the Model Base state of charge (SoC) estimation [7]

This figure 1 describes a state of charge estimation scheme for a battery. The battery's measured voltage is compared with a calculated value obtained from the battery model, identified parameters using the current, I, and initial SoC as inputs. The difference between the measured and calculated voltages is fed to an estimation algorithm that refines the SoC estimation. State of Health (SOH) is the measure of the general condition and lifespan of a battery, which indicates its capacity to store and supply energy compared to its original state when new. It is often expressed as a percentage, where 100% is a new, fully functional battery. SOH declines with time due to aging, material degradation, and repeated charge-discharge cycles [8]. Some of the key indicators of SOH are capacity fade, internal resistance, and self-discharge rates. Understanding SOH is crucial for predicting battery lifespan, planning maintenance, and ensuring the safe and reliable operation of systems that depend on lithium-ion batteries.

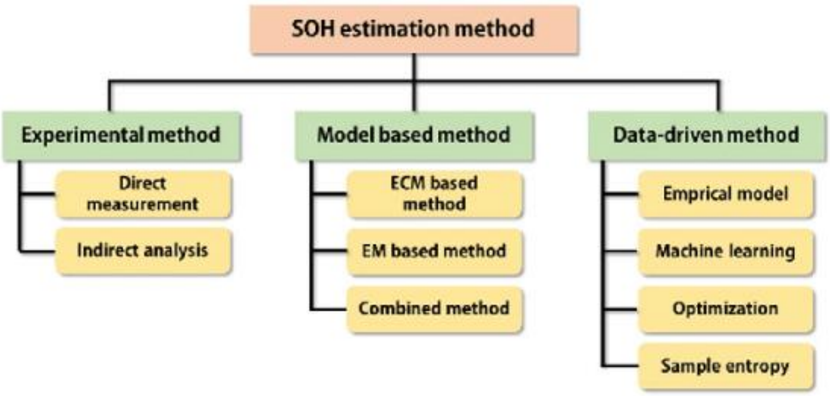

Figure 2 Classification of SOH estimation methods [9]

This figure 2 shows the different techniques used to estimate the State of Health (SOH) of a battery. These can be classified into three types: Experimental methods, including direct measurement and indirect analysis; Model-based methods, including Equivalent Circuit Models (ECM), Electrochemical Models (EM), or any combination; and Data-driven methods, using empirical models, machine learning, optimization, and sample entropy analysis [9]. Each of the methods gives a different perspective of assessing battery health, based on the respective techniques and tools. Other performance metrics include internal resistance, capacity, energy efficiency, and thermal stability. These determine the overall performance of the battery. The higher the internal resistance, the lesser the battery's ability to provide high current loads. The battery will have increased power losses and heat generation with high resistance. The total amount of energy a battery can hold is its capacity, and energy efficiency refers to the amount of energy that a battery delivers over the amount consumed during charge/discharge cycles. Thermal stability is important in ensuring safety since thermal runaway, due to high heat, can be a failure path. All these measurements together help better understand a battery's performance and guide the design of a more robust battery management system.

SOC and SOH of a battery can only be estimated to be correct to optimize the lifetime of a battery, to maintain safety, and to attain peak efficiency. Among the batteries most widely used today, the ones employed in high reliability applications like electric vehicles, renewable energy storage, and portable electronics are primarily Lithium-ion. This means that overcharging or deep discharging of batteries degrades battery life significantly, as SOC estimation is incorrect [10]. Internal overheating resulting from overcharging can lead to chemical instability, which may create safety hazards, such as thermal runaway or fire. Likewise, deep discharging can degrade electrode materials and reduce capacity, thus affecting overall battery performance. Accurate SOC estimation ensures optimum charge and discharge cycles, hence prolonging the life of a battery and consistent performance over an extended period. The third critical parameter depends on precise estimation of parameters. Safety: Chemical and thermal dynamics of a lithium-ion battery make it an area of criticality in operation, as significant deviations from the limits established lead to severe damage, thereby indicating the significance of monitoring SOC and SOH in a battery management system to actuate the relevant safety mechanism in overvoltage or undervoltage situations or cases of excessive internal resistance. Moreover, energy consumption efficiency is closely related to the accuracy of parameter estimations [11]. It prevents energy wastage and optimizes power delivery. It enables accurate monitoring of SOH, thus making it possible for predictive maintenance. This would eliminate the chances of sudden failures, thereby ensuring that the system works as desired. In electric vehicles and renewable energy systems, which depend on battery performance for both cost and user experience, estimation will play a major role in safe, efficient, and durable energy solutions.

B. Challenges in measuring SOC and SOH directly.

The direct measurement of SOC and SOH is problematic since lithium-ion batteries have non-linear and dynamic behavior. The various parameters including temperature, current, voltage, and the impacts of aging do not easily lend towards the development of a clear and direct correlation with measurable parameters, such as SOC or SOH [12].

The value of SOC or SOH can never be obtained directly as SOC or SOH is a non-physical characteristic. Hence it is computed, rather than sensed like the cases with temperature and voltage by direct measurement via appropriate sensors, respectively. The performance of lithium-ion batteries varies significantly depending on different conditions such as high loads, extreme temperatures, and various discharge rates [13]. These variations have complicated the correct measurement of SOC and SOH because the actual behavior of a battery does not follow standard models. Aging a battery adds further complexity because degradation mechanisms such as capacity fade and increased internal resistance change the characteristics of the battery with time [14]. Changes are often nonlinear and difficult to model precisely, which makes it even harder to measure SOC and SOH.

III. KALMAN FILTERING TECHNIQUES

It is also referred to as Linear Quadratic Estimation and is regarded as one of the most effective algorithms for the estimation of the state of a dynamic system through the incorporation of both past states and current observations. There are two basic steps: prediction and update. For prediction, it uses a model of the mathematical process to predict what the system currently is given past estimated states. This is a prediction based purely on historical data and assumes no new observations are available [15]. It ensures continuity in state estimation, especially during intervals where real-time measurements are not present. In this manner, it keeps a baseline understanding of the behavior of the system. This refinement in the prior estimate is achieved in the update step by introducing new observations, thereby smoothing out prior knowledge with the newest data to make a better estimation of the present and future state of the system. The filter adjusts its prediction of the state using the observations available to reduce uncertainties and inherent errors in the system model. If no observations are received for a specific period, the filter starts making successive predictions to fill up the gap. On the other hand, when several observations are received within the same interval, the filter makes multiple updates in its estimations, using various observation models corresponding to different H_k matrices [16]. This iterative and adaptive approach allows Kalman Filtering to remain robust and effective in the management of dynamic systems across many domains.

The Kalman Filter (KF) is an algorithm that is often used to estimate the state of dynamic systems when the system of interest is affected by uncertainties or noise. Being a linear quadratic estimator, it makes a prediction for the future state of the system by learning from the previously calculated states, which then improves on that estimate through the usage of the available measurements. KF presumes linearity in both system dynamics and the measurement model. In addition, the noises added in both process and measurement follow the Gaussian distribution [17]. The operation is divided into two major steps: the prediction step, which is a forecast of the current state based on past data, and the update step, which incorporates new observations to correct and refine the estimate. This therefore enables the KF to have a pretty accurate state estimation over time, which makes it very effective in applications such as navigation, signal processing, and control systems.

The EKF extends the functionality of the KF to extend it to handle systems with nonlinear dynamics, very common in practice. The basic KF operates on linear models. The EKF linearizes the nonlinear system equations around the current state estimate by a first-order Taylor expansion [18]. This would enable the filter to approximate how the system will behave and the estimation of states accordingly, despite the presence of non-linearity. Although the EKF retains the general form of prediction and update steps, it uses Jacobian matrices in its computations, adding a level of complexity. Still, the EKF has emerged as a central component in fields like robotics, aerospace, and battery management where nonlinear systems abound. The EKF is an extension of the Kalman Filter to more complicated estimation problems due to its applicability to nonlinear problems.

The Unscented Kalman Filter is an advanced version of the Kalman Filter that is developed to solve the problems of non-linear systems. Unlike the EKF, which linearizes non-linear systems using a first-order Taylor expansion, the UKF applies a deterministic sampling technique called the Unscented Transform. This method produces a set of careful sample points selected to capture both the mean and covariance of the system state [19]. These then propagate through the non-linear model of the system, thereby generating a more accurate representation of underlying dynamics without an explicit need for linearization. Because the UKF can handle nonlinearities directly, it is highly efficient for many applications such as robotics, navigation, and battery state estimation. While the UKF has the topmost advantage of handling nonlinear systems with great accuracy and robustness, since a UKF avoids the approximations introduced by linearization, it thus gives more precise state estimates over systems that manifest strong nonlinearity. Notably, with the UKF, there is much lesser instability along with errors when poor linearization's are involved due to the associated limitations of the EKF. Its importance is even further underlined in applications that have significantly high levels of non-linearity in both their system dynamics and measurement models, such as autonomous vehicles, aerospace systems, and lithium-ion battery management [20]. UKF results in improvement of the estimation accuracy and reliability, which will ensure safer operation, improved system performance, and a longer life for critical components. Therefore, it is an essential tool in modern control and estimation tasks.

IV. ADAPTIVE UNSCENTED KALMAN FILTER (AUKF)

The Adaptive Unscented Kalman Filter, abbreviated as AUKF, is an extension of the Unscented Kalman Filter. It introduces some adaptive mechanism to deal with uncertainties and dynamic changes in the behavior of systems under consideration. The two-step procedure for prediction and update steps remains the same in the AUKF, such that sigma points are propagated through the non-linear system model in the prediction procedure and updated by the new observations to refine the estimation. What differs AUKF is that it has time-varying covariance matrices of measurement and process noises, which have been tuned up according to real-time observations as well as system performance [21]. Thus, in the case of events like variations in parameters and environmental changes or aging effects, the filter becomes accurate. The AUKF thus continuously adjusts its noise assumptions to minimize estimation errors and improve robustness against any unmatched modelling inaccuracies or unexpected disturbances. This makes the AUKF very effective for applications such as lithium-ion battery management, where operating conditions and system parameters can vary widely [22]. Its adaptive nature ensures accurate state estimation, enhances system reliability, and provides a basis for predictive maintenance and efficient operation in complex and dynamic environments.

A. Benefits of AUKF

Adaptive Unscented Kalman Filter is efficient to deal with the uncertainty in the dynamic systems, because it constantly updates its online process and measurement noise covariance matrices. In comparison with the traditional fixed-noise-based filtering algorithms, the AUKF is responsive to a dynamic environment as well as its adaptive response towards changing system behavior [23]. This adaptability proves particularly useful in applications, such as in the management of a lithium-ion battery: it would comprise uncertainty due to temperature fluctuations and varying loads or aging effects. However, the assumptions of the AUKF calibrated based on actual data keep their robustness because estimation errors may be reduced significantly, and also state-prediction reliability becomes better.

One of the key advantages of the AUKF is that it can be used to counteract modelling errors in the system. Most real-world systems, whether they are non-linear or time-varying, cannot be modelled exactly using mathematical models. Traditional filters such as the EKF or even the standard UKF may not perform well under these conditions and will degrade [24]. The AUKF, on the other hand, removes such hindrances by adaptively adjusting its parameters against the actual measured data. Therefore, it can reduce the gap between the model and the true system and give much more accurate and reliable estimation of the state. In this regard, the AUKF finds a first choice for the application in complex systems where accurate modelling is difficult or even infeasible.

B. Applications of AUKF in Lithium-Ion Battery Management

The Adaptive Unscented Kalman Filter is efficient in handling uncertainty in dynamic systems because it keeps adjusting its process and measurement noise covariance matrices online. In comparison to the conventional fixed-noise-based filtering algorithms, the AUKF adaptively responds to the change in system behavior with the dynamic environment [25]. This adaptability proves particularly helpful in applications like the management of a lithium-ion battery, which would involve uncertainty caused by fluctuations in temperature, varying loads, and aging effects. The AUKF remains highly robust by calibrating its assumptions on the basis of real-time data to decrease estimation errors and improve state-prediction reliability.

A major benefit of the AUKF is that it can be used to counteract modelling errors in the system. Most real-world systems, whether they are non-linear or time-varying, cannot be modelled exactly using mathematical models. Traditional filters such as the EKF or even the standard UKF may not perform well under these conditions and will degrade [26]. The AUKF, in contrast, alleviates such obstacles by dynamically tuning its parameters against actual measured data. Thus, it can minimize the gap between the model and the true system, providing much more accurate and reliable estimation of the state. In this regard, the AUKF finds a first choice for the application in complex systems where accurate modelling is difficult or even infeasible.

V. ADVANTAGES AND LIMITATIONS

The estimation methods, like the AUKF, are deemed more favorable than the traditional ones; other examples are EKF and standard UKF. AUKF can be viewed as a method capable of handling non-linear systems with tremendous accuracy and adapting to conditions to make state estimation very accurate under possible complex scenarios. Its adaptability is another strength; by dynamically adjusting process and measurement noise covariance matrices based on real-time observations, the AUKF accounts for system uncertainties and environmental variations effectively [27]. Moreover, its robustness in handling inaccuracies in system modeling makes it especially suitable for applications where a precise mathematical representation of the system is challenging, such as in lithium-ion battery management.

Although the strengths of the AUKF should be recognized, there are areas of concern related to this algorithm, too. Computationally intense is the chief limitation. With sigma points for generating and propagation alongside dynamic adjustments in covariance matrices for both noises, complexity may arise making it difficult, particularly in limited computational power available in real time. The system also has another weakness; sensitivity to initial conditions [28]. The performance of the AUKF significantly depends on proper state and noise covariance initialization, and improper initialization leads to suboptimal or diverging results. This could be compensated with careful implementation and consideration of hardware constraints. Real-world conditions in implementing AUKF impose various challenges in its implementation. Significantly, unpredictable disturbances, noisy measurements, or changes in parameters of the actual system may create variations that decrease the accuracy of the filter [29]. The AUKF is prepared to adapt these variations, yet improper tuning and inadequate training may decrease its effectiveness. Furthermore, the implementation of AUKF in existing systems, such as battery management systems, typically requires significant computational power, which is not always feasible for all applications, especially low-power or embedded processors.

These challenges can be addressed by investigating hybrid approaches combining the AUKF with other techniques, such as machine learning or reduced-order models, in order to improve performance while reducing computational requirements. Efficient implementation strategies, such as optimizing the selection of sigma points and leveraging parallel computing, can reduce computational overhead [30]. Additional techniques of robust initialization and adaptive tuning mechanisms can be used to make the filter robust against poor initial conditions and variability in real world. In doing so, the aforementioned challenges can be addressed by the AUKF for its deployment in many applications with state estimation accuracy and reliability.

VI. RECENT ADVANCES AND INNOVATIONS

Accurate SOC estimation in LiBs is a challenging task due to their nonlinear behavior over their lifetime. It is essential to balance accuracy, robustness, and low implementation complexity. Over the last decade, several studies have been conducted to analyse and compare various SOC estimation methods for commercial LiBs. However, little work has addressed SOC estimation through a physics-aware AI-based point of view concerning LiBs. This paper strives to fill that gap by appraising several approaches for SOC estimation, especially drawing attention to those hybrid approaches incorporating model-based strategies and artificial intelligence-based strategies [31]. Hybrids are therefore divided into the PAAIB and AI-enhanced physical models. The research method integrates a comprehensive review of existing literature discussing the fundamental principles of MB and AIB methods, analyses their strengths, and limitations in capturing the complex dynamics of battery behavior. On this background, a deep exploration into hybrid SOC estimation techniques with elaboration through each category based on various performance metrics follows. The paper presents the main contents as a comprehensive analysis of hybrid SOC estimation techniques, a comparative review of recent studies, and strategic recommendations for future research. This effect demands the implementation of hybrid SOC estimation methods for precise and robust improvement in the estimate of SOC and its application for practical use cases. The last section of this paper will come to a concise conclusion summarizing the major findings highlighted with a deep sense of an imperative to integrate hybrid methods and their significance while enhancing the reliability in the functionality in battery management of electric vehicles systems.

The smart battery management system, or BMS, is significantly important in upgrading the functionality and efficiency of electric vehicles. A precise estimation of the state of health and the remaining useful life in BMS improves the battery's safety, longevity, and reliability. Due to capacity degradation caused by the charging and discharging operations, it is difficult to obtain an accurate estimation of SOH and RUL. The conventional research on estimating the SOH and RUL of lithium-ion battery (LIB) is based on the single model framework [32]. However, the single model for SOH and RUL estimation may not deliver accurate outcomes due to the complex internal LIB mechanism and varying external conditions. Hybrid techniques combining two or more models have attracted huge attention in recent years by the research community as they yield higher accuracy and robustness in performance under diverse environmental conditions. Yet, hybrid techniques for SOH and RUL estimation of BMS in EVs are still at the implementation stage. Therefore, the novelty of this work is to present a comprehensive review of hybrid approaches for SOH and RUL estimation in LIB with an emphasis on methodologies, executions, advantages, disadvantages, accuracy, and contributions. Furthermore, the co-estimation of SOH and RUL using the same model is becoming highly popular among researchers across the globe. Therefore, the review work presented here also explores different techniques that are used to co-estimate the SOH and RUL simultaneously. Further, the critical operation factors associated with SOH and RUL estimation framework are analysed related to the dataset, model execution, battery parameters and their features. The applicability of the reviewed hybrid SOH and RUL estimation techniques are discussed along with current issues and limitations. Thus, selected future proposals are given with the aim that the automobile industries develop a certain and accurate approach using the framework of hybrid co-estimation to estimate LIB's SOH and RUL.

Lithium-ion batteries are an important energy storage device and have been widely used in various fields due to their remarkable advantages. High precision in estimating the battery's state of health greatly enhances the safety and dependability of the application process. Data-driven prediction methods, which are the mainstream, depend on direct data analysis and offer higher accuracy compared to traditional model-based prediction methods that are complex and have limited accuracy [33]. Accordingly, this paper reviews how to predict the SOH of LIBs through the latest data-driven algorithms and proposes a general prediction process that would include obtaining datasets for the charging and discharging process of LIBs, handling of related data and features, and the selection of relevant algorithms. The advantages and limitations of various processing methods and cutting-edge data-driven algorithms are summarized and compared, and methods with potential applications are proposed. Effort was also made to point out their application methods and application scenarios, providing guidance for researchers in this area.

Lithium-ion batteries have revolutionized the portable and stationary energy industry, seeing wide applications in the automotive, consumer electronics, renewable energy, and many more markets. However, their efficiency and longevity are closely tied to measuring their SOC accurately and SOH. The need for precise algorithms to estimate SOC and SOH has increased with the spread of lithium-ion batteries in industrial and automotive applications. Although the advantages of lithium-ion batteries are apparent, challenges concerning their efficient and safe management cannot be ignored. The precise estimation of both SOC and SOH is extremely important for proper battery management, a maximal lifetime of the battery, optimized performance, and in order to avert sudden failures [34]. Therefore, this has been a growing area of scientific and industrial interest, especially development of reliable algorithms for SOC and SOH estimation. Reviewing the current state-of-the-art on SOC and SOH estimation algorithms for lithium-ion batteries is a focus of this article. This will involve an analysis and assessment of the latest promising theoretical and practical techniques applied to address the challenges of accurate SOC and SOH estimation. Further, critical evaluation of different approaches will be highlighted, such as advantages, limitations, and potential areas for improvement. The aim is to give a clear view of the current landscape and to identify possible future directions for research and development in this crucial field for technological innovation.

In light of emerging electric vehicle (EV) battery retirement issues, second-life batteries (SLBs) have recently gained increasing interest for the capability to prolong the life-span of existing batteries and delay the manufacturing of new ones. As SLBs degrade, the process differs from new batteries because it requires more attention as SLBs are highly susceptible to external stress and easily prone to physical collapses. Hence, their dispatching approaches, at least in their degradation aspects are critical tools with which investors or end-users explore their technical or economic viability. In this regard, an optimized dispatch approach using degradation with a real-time on-line state-of-health (SoH) estimate is developed while integrating SoH into the optimisation as one of the evolving parameters that contribute to the decrease in battery's performance. This online SoH estimation model has leveraged the estimation capability of the Kalman filter in order to provide more precise values by combining short-term estimation and long-term prediction results [35]. In addition, the heterogeneous characteristics among these retired batteries due to their diverse first-life usage patterns and working conditions are considered by giving different initial values of SoH and degradation paths. A comparison of the case study performance between the proposed approach-an alternative dispatch approach considering degradation with a state of charge (SoC) based model-and a dispatch approach with no degradation consideration is carried out subsequently. The results show that the proposed approach leads to less battery degradation and saves costs with the batteries operating in a complementary way (not charging/discharging uniformly) to improve energy balancing and energy arbitrage.

Table 1 Comparative Analysis of Recent Advances and Innovations in Lithium-Ion Battery Management

Refe no.	Aspect	Focus Area	Approach	Advantages	Limitations	Future Directions
[31]	SOC Estimation	Accuracy in SOC estimation	Hybrid approaches (physics-aware AI-based, AI-enhanced physical models)	Improved accuracy and robustness; handles non-linear battery behavior	Computational complexity; limited real-world implementation	Adoption of hybrid methods for improved accuracy in practical applications
[32]	SOH and RUL Estimation	Enhancing BMS in electric vehicles	Hybrid techniques combining model-based and AI methods	High accuracy; robustness under diverse environmental conditions	Still in implementation stage; challenges in co-estimation models	Development of hybrid co-estimation frameworks for reliable SOH and RUL estimation
[33]	Data-Driven Methods	SOH prediction through AI	Algorithms analyzing charging/discharging datasets	Higher accuracy; simpler than traditional models	Limited generalization; dependency on quality of datasets	Proposal of a general prediction process and exploration of new data-driven methods
[34]	SOC and SOH in BMS	Precision for battery management	Reliable algorithms for SOC and SOH estimation	Optimized performance; extended battery lifetime; improved reliability	Complex internal mechanisms; environmental and operational challenges	Advancing algorithms to address efficiency and safety concerns in SOC and SOH estimation
[35]	Second-Life Batteries (SLBs)	Lifecycle optimization for retired EV batteries	Real-time SOH estimation integrated with dispatch models leveraging Kalman Filter	Prolonged lifespan; reduced costs; improved energy balancing	Susceptible to external stress; variability in initial conditions due to diverse first-life usage	Development of optimized dispatch methods considering degradation and heterogeneity

VII. CONCLUSION

Lithium-ion batteries have become inevitable parts of modern energy applications because of their high-energy storage density, long cycle life, and lightweight design, although complex problems in the correct estimation of parameters like State of Charge (SOC) and State of Health (SOH) remain because of nonlinear behavior and dynamic operating conditions along with susceptibility to aging effects. Advanced estimation techniques, such as Kalman Filter variants and hybrid approaches that integrate physics-based and AI-driven models, are opening up the way for more robust and precise monitoring of battery states. These innovations address critical challenges such as computational complexity, model inaccuracies, and real-world variability, while simultaneously improving battery performance, safety, and reliability. This Adaptive Unscented Kalman Filter has also displayed tremendous potential to adaptively accommodate varying conditions so that it produces accurate and uniform estimations of battery SOC in electric vehicles or SOH for renewable energy storage systems. Methods, including new hybrid frameworks in the estimation of both SOC and SOH and even data-driven algorithms, are at the forefront in driving innovation to optimize battery lifetime while maintaining higher levels of operation safety. Second-life batteries increase the necessity for designed dispatch and degradation models to extract maximum value from used batteries in second-life applications. This broad review aims at calling for further research into advanced estimation and management techniques, of which hybrid estimations are some examples, to enhance the effectiveness, sustainability, and innovativeness of the lithium-ion battery technologies going forward. These will be the critical methods in the future of energy storage and more broadly in the transition to clean and reliable energy solutions.

Conflict of Interest: The corresponding author, on behalf of all authors, confirms that there are no conflicts of interest to disclose.

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