Hybrid Adaptive Filtering Approaches for Lithium-Ion Battery State of Charge and Health Estimation

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***Abstract*:** Approach to a hybrid algorithm that would combine Recurrent Neural Networks, Kalman Filters, and estimates the State of Charge and Health of lithium-ion batteries. Normally, the established methods fail while dealing with their non-linear characteristics and dynamic operation, thus sometimes giving erroneous predictions. The proposed Hybrid Kalman Filter (HKF) combines strengths of RNNs and Kalman filters. RNNs are used as they can well model complex temporal dependencies and non-linear relationships in the battery data that improve the Kalman filter prediction capabilities. This algorithm works under two main stages: training the RNN on historical data with the goal to learn the battery dynamics and exploit these insights in real-time estimation of SOC and SOH. The experimental validation also proved that the HKF performs superiorly than other conventional methods such as UKF, especially concerning the lower values of RMSE achieved under changing conditions of C-rate (slow and fast charge/discharge rates). This is what ensures the efficient management of a battery in better performance, safety, and durability. It does have great promise for use in electric vehicles, renewable energy systems, and portable electronics where accurate battery monitoring is important to ensure reliable and efficient operation.

Keywords: Hybrid Kalman Filter (HKF), Kalman filters, State of Charge (SoC) and State of Health (SoH)

I. INTRODUCTION

Lithium-ion batteries have emerged as the dominant energy storage technology, providing the backbone for electric vehicles, consumer electronics, and renewable energy systems with their high energy density, long cycle lives, and low rates of self-discharge. Notably, they let EVs travel further, make electronics more portable, and balance energy supplies by providing backup power when needed from intermittent sources of solar and wind. However, widespread application of LIBs poses problems in monitoring and managing their safety, efficiency, and longevity [1]. State of Charge (SoC) and State of Health (SoH) must be accurately estimated to optimize performance and prevent issues such as overcharging and thermal runaway. Advanced BMS systems based on machine learning, Kalman filters, and real-time data analysis have been developed with a view toward the prediction of SoC and SoH; the overall focus has been extended to enhance lifetime, ensure safety, and innovate continuous advancements within these technologies toward sustainable and reliable applications across the board [2].

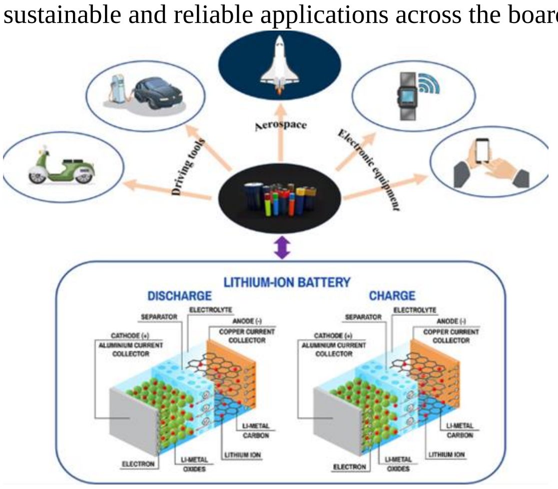

Figure 1 Application scenario and working principle of LIBs [3]

This figure 1 shows the vast applications and working mechanism of LIBs. The top part of the figure shows the application of LIBs in electric vehicles, aerospace, and electronic devices due to their efficiency and reliability. The bottom part of the figure shows the charge and discharge mechanism in a LIB: during discharge, lithium ions move from the anode (graphite) to the cathode (lithium metal oxides) through the electrolyte, generating electricity. During charging, this process is reversed, with ions returning to the anode. The separator prevents short circuits, ensuring safe operation. This visual emphasizes LIBs' versatility and functional principles.

A. State of Charge (SOC)

SOC is a vital parameter that states the remaining energy in a battery as a percentage of its total capacity, like a fuel gauge in cars. It allows efficient energy management and prevents overcharging and deep discharging, keeping the battery within safe limits to maximize durability and performance. SOC is very important for battery management systems because it optimizes energy flow, prevents thermal runaway and capacity degradation, and supports load and thermal management [4]. The optimal SOC range, for instance, is 20%-80%, which minimizes stress on the battery and ensures longer lifespan and safety across applications such as electric vehicles and renewable energy systems.

SOC is the most important variable for improving usability and feedback in battery-powered systems. It enables users to predict range in electric vehicles, plan usage in portable devices, and avoid unanticipated downtime through alerts. SOC is also an important variable in the broader energy system, balancing supply and demand in grid-connected batteries and optimizing regenerative braking in EVs [5]. In renewable energy systems, SOC ensures efficient use of stored energy during peak and low production times, supporting grid stability. Advanced SOC estimation techniques, like Kalman filtering, address battery nonlinearity for precise measurements, enabling smart charging strategies and balancing SOC across networked energy storage systems to enhance performance and battery lifespan.

B. State of Health (SOH)

A parameter in BMS, SOH is the ratio of the total condition of the battery to the original state at the time when it was first new. Given as a percentage, SOH represents the remaining capacity, the internal resistance of the battery, and its energy delivery capability. A 100% SOH means that it is a fresh battery, whereas lower percentages reveal aging or degradation due to cycle fatigue, chemical breakdown, or mechanical wear. Unlike SOC, which reports the available energy at any moment, SOH estimates the performance and life cycle of a battery over its useful life. Hence, it plays an important role in determining battery lifespan, planning maintenance activities, and maintaining the overall safety and efficiency of its operations. SoH allows early detection of degrading or overheating batteries and even short circuits through patterns in degradation, especially where the cell shows high internal resistance or has been experiencing decreasing capacity [6]. SOH, in terms of performance optimization, enables BMS to adapt charging and discharging protocols based on a battery's reduced capacity to maximize its usable life and maintain optimal performance.

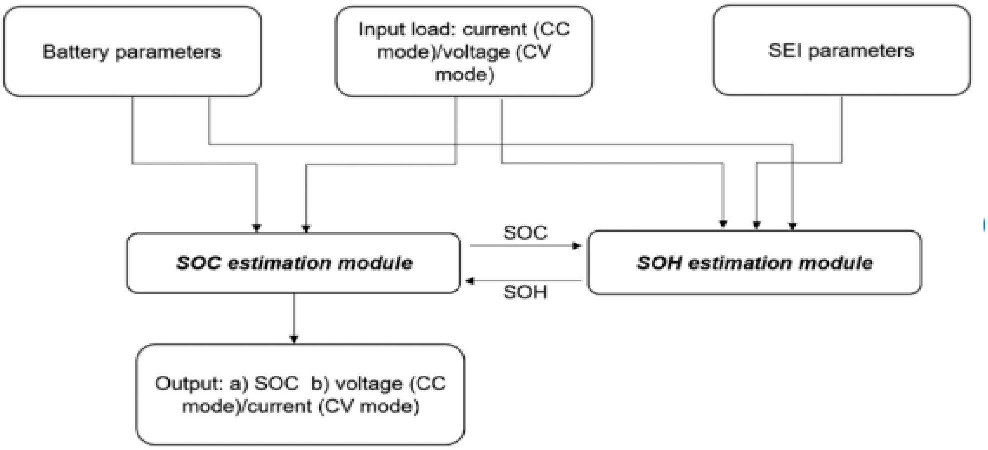

Figure 2 Framework for coupled prediction of state of charge (SoC) and state of health (SoH) of lithium ion battery [8]

This figure 2 depicts the relationship and workflow between SOC estimation module(s) and SOH estimation module(s) in the framework of a BMS. The SOC estimation module computes the current SOC based on battery parameters and input load data, such as current in CC mode or voltage in CV mode. The SOH estimation module further estimates the total battery health considering SOC, battery parameters, and Solid Electrolyte Interphase (SEI) parameters [8]. Outputs are SOC, voltage in CC mode, and current in CV mode, giving necessary data for real-time management of the battery. These interconnected modules ensure the accurate monitoring and efficient control of the battery system. Another key application of SOH is in predictive maintenance, lifecycle management, and cost reduction. With the development of advanced techniques like machine learning models (e.g., FNN, CNN, and LSTM), accurate SOH estimation helps to replace aging batteries on time, reduce downtime, and improve reliability in applications like electric vehicles, renewable energy storage systems, and medical devices. SOH also supports sustainability through warranty management, recycling, and repurposing of batteries for secondary applications in less demanding environments. Additionally, SOH is crucial for intelligent energy distribution in modern energy systems, which ensures that healthier batteries are prioritized for use in networks such as grid storage and EV fleets. By integrating SOH data into advanced analytics and machine learning models, BMS can predict future health trends and make informed decisions to enhance battery performance, reliability, and sustainability [7]. As battery technologies evolve, SOH will remain fundamental in advancing energy systems and enabling safe, efficient, and adaptable applications across industries.

C. Applications of SOC and SOH Estimation

SOC and SOH are two critical metrics in the assessment of battery systems, impacting the extent to which their efficiency, reliability, and safety could be achieved across diverse applications. In particular, in electric vehicles, these metrics assume a very fundamental position in optimizing EV performance while satisfying user needs. Estimation of SOC allows for accurate range prediction, thus eliminating "range anxiety" by letting drivers know how many miles they can drive before needing to recharge. In return, SOH ensures safety as it tracks degradation over time and warns users about aging batteries and prevents sudden failure or thermal runaway. SOC and SOH collectively support intelligent charging strategies that avoid overcharging or over-discharging, which may damage the battery [9]. SOH data also allows the charging system to adjust the rates and intensities according to the current condition of the battery, ensuring safe and effective energy usage. These are the metrics of extending battery lifespan and enhancing safety and reliability with EVs, thus making them indispensable for modern electric mobility solutions.

In renewable energy systems and grid storage, accurate SOC and SOH estimations are equally critical. SOC estimation ensures that the batteries store the excess energy produced during peak periods and release it efficiently during high-demand or low-generation periods, optimizing energy utilization and maintaining grid stability. SOH monitors the long-term health of the batteries, which, in these systems, are often subjected to repeated charge-discharge cycles [10]. Detection of degradations thus gives operators enough headway on scheduled maintenance and replacement, decreasing the likelihood of unwanted failures that disrupt energy provision. Moreover, with SOH optimization, only healthy batteries would perform critical operations and therefore give high system performance besides increasing lifespan in battery lifetime. The use of SOC and SOH will also provide much greater efficiency through optimal management to meet reliability for reliable renewable and efficient grid integration power systems.

II. LITERATURE REVIEW

Ren, Z., & Du, C. (2023) [11] described vehicle electrification is the most effective measure to lower carbon dioxide emission and overcome energy crises. The reason why Lithium-ion batteries (LiBs) are still regarded as the major medium for the energy storage in EVs is their high energy density and longer lifetime. The state of the battery must be monitored to maintain a safe, efficient, and stable operating condition for the battery system. The state-of-charge (SOC) and state-of-health (SOH) are particularly crucial. Data-driven machine learning (ML) techniques, with the emergence of big data, cloud computing, and other advanced techniques, have attracted attention due to their huge potential in state estimation for LiBs. In light of this, this paper reviews the four most studied types of ML algorithms for SOC and SOH estimation: shallow NN, DL, SVM, and GPR methods. The basic principles and uniform flowcharts of different ML algorithms are introduced. Then, the applications of each ML algorithm for state estimation within recent years are systematically reviewed and compared in terms of used datasets, input features, hyperparameter selection, performance metrics, advantages, and disadvantages. In view of this investigation, the current challenges and prospects from four aspects are discussed to provide some inspiration for developing advanced ML state estimation algorithms.

Hallmann, M et al. (2022) [12] said that lithium-ion battery energy storage has witnessed a strong growth during the last year for both mobile as well as stationary applications. For mobile applications, BES units are in the range of 10–120 kWh. Power grid applications of BES are characterized by much higher capacities (range of MWh) and this area particularly has great potential regarding the expected energy system transition in the next years. The optimal operation of BES by an energy storage management system is usually predictive and based strongly on the knowledge about the state of charge (SOC) of the battery. Many factors such as material, electrical, and thermal states of the battery influence the SOC so that an accurate estimation of the battery SOC is a complex issue. The intermediate SOC prediction methods depend on the models of the battery. Three types of modelling for BES have been reported in the literature: fundamental based on material issues, electrical equivalent circuit based on electrical modelling, and balancing based on a reservoir model. Each of these models requires parameterization based on measurements of input/output parameters. These models are used for SOC model-based calculation and in battery system simulation for optimal battery sizing and planning. Empirical SOC assessment methods currently remain the most popular because they allow practical application, but the accuracy of the assessment, which is the key factor for optimal operation, must also be strongly considered. This scientific contribution is divided into two papers. Paper part I presents a holistic overview of the main methods of SOC assessment. Physical measurement methods, battery modelling and the methodology of using the model as a digital twin of a battery are addressed and discussed. Furthermore, adaptive methods and methods of artificial intelligence, which are important for the SOC calculation, are presented.

Jiang, S., & Song, Z. (2022) [13] spoke about batteries are crucial parts in the life of modern humans. Of various battery types, lead acid dominates over 70% market shares of sales from rechargeable markets and used everywhere in our life. With regard to accidents or other adverse issues and ensuing loss, a more important value needs to calculate SOH estimation for lead acid. This work reviews various SOH estimation methods for lead-acid batteries. In the first section, we briefly introduce the concept of SOH and the mechanism of battery aging. Then, different SOH estimation methods are categorized into four classes: direct measurement-based, model-based, data-driven, and other methods. Finally, we provide a detailed analysis of the characteristics of each method and discuss the corresponding advantages and limitations in practical applications. Based on these characteristics, we then systematically evaluate and compare different types of methods. We indicate the recommended method for different scenarios, and also the reasons for choosing such a method. We also make marks of unsolved problems of each method, which inspires the further studies.

Bokstaller, J., Schneider, J., & vom Brocke, J. (2023) [14] presented that the number of IoT devices with batteries is growing quite rapidly. The prediction of battery health is crucial to support maintenance action as well as proactive replacement to avoid a failure due to outages. This study provides an overview of the current literature on the use of the IoT functionality for monitoring and predicting battery health. We explain the battery health concepts commonly discussed in the literature, namely, State of Charge (SoC), State of Health (SoH), and remaining useful life (RuL). We present definitions, use cases, and examples synthesized from a final selection of 23. We identify and assess important components of how best to combine such components to build a state-of-the-art battery health tracking platform. The acquisition sensors send information about the battery to the IoT-connected controller that, in turn sends for pre-processing. Then, the aggregated data is sent using wireless networking to a cloud-based monitoring platform where it is kept in a database system, which can be visualized to the customer via a visualization interface.

Liu, Y et al, (2023) [15] highlighted that the State of health (SOH) estimation is important for a lithium-ion battery (LIB) health state management system, and the accuracy of SOH estimation is dependent on the level of degradation of the LIB. However, due to the complicated electrochemical reactions within Li electrons and many factors outside affecting internal reactions, it is difficult to make an accurate estimate of SOH according to the characteristics of the surface state of the battery, including current, voltage, and temperature. In this study, therefore, the knowledge graph method has been used in the analysis of keyword co-occurrences and citations in the literature of LIB degradation and SOH estimation to determine the research hotspots. Reorganization and rearrangement according to research trends on internal and external mechanisms and factors for (LIBs) degradations are reported in addition to chemical and physical degradation processes which involve formation and fracture of a SEI layer, Li plating, and dendrite, with consideration and inclusion from modelling aspects. An analysis of the interrelationship between these degradation factors and their effects on capacity and power decay as well as their correlation with SOH estimation is presented. In addition, a comparative analysis of existing SOH estimation methods is presented and the applicable scenarios and technical problems of each method are summarized. The key issues such as model simplification, estimation methods based on random data, and second-life SOH are analysed and discussed. The results indicate that the estimation results of methods mixing multiple models tend to be more accurate. Finally, the development trend of SOH estimation methods under complex degradation conditions and usage scenarios is analytically discussed.

Table 1 Comparative Analysis of Literature on SOC and SOH Estimation

References	Topic	Key Contributions	Methods	Applications	Challenges
Ren & Du (2023) [11]	Vehicle Electrification and ML	Focuses on SOC and SOH estimation for LiBs in EVs using machine learning (ML) techniques. Reviews ML algorithms like shallow NN, DL, SVM, and GPR for SOC and SOH estimation.	Data-driven ML techniques: shallow NN, DL, SVM, GPR. Analyzed datasets, input features, and hyperparameters.	SOC and SOH estimation in EVs.	Challenges include handling large datasets, achieving high accuracy, and improving algorithm performance.

Hallmann et al. (2022) [12]	Lithium-Ion Battery Energy Storage	Examines SOC assessment methods in battery energy storage (BES) systems. Discusses physical measurement, electrical equivalent circuit, and reservoir models.	Empirical SOC assessment, physical measurement methods, digital twin modeling, AI methods.	Mobile and stationary applications, BES in grid power systems.	Accuracy in SOC assessment remains a challenge; methods like digital twins and adaptive algorithms are promising but complex.
Jiang & Song (2022) [13]	SOH Estimation for Lead-Acid Batteries	Reviews SOH estimation methods for lead-acid batteries. Categorizes methods into direct measurement-based, model-based, data-driven, and others. Provides recommendations based on application scenarios.	Direct measurement, model-based methods, data-driven approaches.	Focused on SOH for lead-acid batteries in everyday applications.	SOH estimation is limited by unsolved issues like parameter variability and incomplete models; practical applicability is emphasized.
Bokstaller et al. (2023) [14]	IoT and Battery Health Monitoring	Explores IoT functionality in monitoring SOC, SOH, and remaining useful life (RuL). Describes a cloud-based monitoring platform integrating IoT sensors and visualization interfaces.	IoT-connected controllers, cloud platforms, data visualization, predictive maintenance.	SOC, SOH, and RuL tracking for IoT-connected devices and platforms.	Building a state-of-the-art IoT-based battery tracking system requires addressing networking, sensor accuracy, and real-time analysis challenges.
Liu et al. (2023) [15]	SOH Estimation in LIBs	Analyzes LIB degradation and SOH estimation using a knowledge graph method. Discusses degradation mechanisms like SEI layer formation and Li plating. Evaluates SOH estimation methods and scenarios.	Knowledge graph analysis, comparative analysis of SOH estimation methods, mixed-model approaches.	SOH estimation under complex degradation and usage scenarios.	Mixed models provide more accurate SOH estimation; challenges include model simplification and addressing random data-based estimation issues.

III. OBJECTIVES

The work is being focused on achieving the following key objectives from the work:

- To use MATLAB/SIMULINK to create a battery model and investigate its charging and discharging properties.
- To investigate how the battery responds to cycles of charging and discharging at varying rates in terms of its state of health (SOH) and state of charge (SOC).
- Design a model based on Kalman filters to accurately estimate battery SOC and forecast battery SOH.
- Reduce the RMSE and increase the Kalman filter's prediction power by developing a hybrid algorithm that uses a learning-based approach.

IV. METHODOLOGY

Batteries play a vital role in solar energy, electric vehicles (EVs), hybrid electric vehicles (HEVs), and smart grid systems, with rechargeable lithium-ion (Li-ion) batteries being widely preferred due to their high energy and power ratios. Therefore, it is essential to understand the charging and discharging behavior of Li-ion batteries to design efficient circuits and optimize performance. One important factor that impacts the behavior of a battery is the State of Charge (SOC), which denotes the ratio of current capacity to nominal capacity. For HEV applications, this SOC estimation would be very vital in ensuring the proper charge/discharge management to enhance overall efficiency.

A. Setup of Equivalent Circuit Model for the Lithium Battery

Accurate modelling of the battery is the basis of State of Charge (SOC) and State of Health (SOH) evaluation for power batteries. A battery model can effectively describe both external features and the internal electrochemical reactions that happen inside a battery. SOC measures the ratio of residual to nominal capacity of the battery, or the remaining energy under specific environmental and operational conditions. While it reflects battery health and age, SOH informs users concerning the actual working capacity. Analysing a brand new versus older battery shows scientists that SOH varies inversely with the degree of both the ohmic resistance and the max capacity of such a cell or battery. Sometimes, one even determines battery-soh with resistance from ohms, but aging will have made that different compared to fresh.

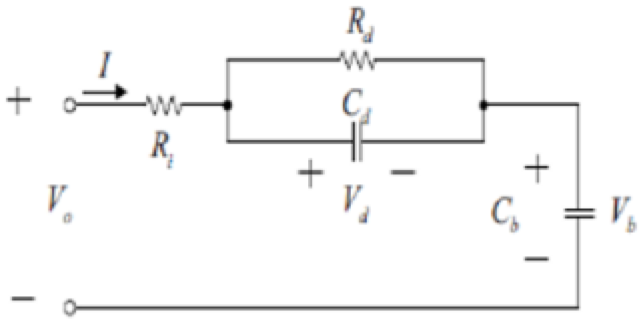

Figure 3 Equivalent Circuit for battery

This circuit provides an equivalent model of a lithium-ion battery, demonstrating its dynamic behavior in charging and discharging. The bulk capacitance C_b, represents the battery's storage capacity for energy, and surface capacitance C_d, captures the diffusion effects. The internal resistance R_i, reflects the inherent energy loss in the battery, whereas the polarization resistance R_d, accounts for electrochemical and concentration polarizations. The terminal voltage (V_o) is the sum of the voltages across these components, capturing the dynamic response of the battery to current flow (I). This model helps understand and predict the performance of a battery under various conditions.

Battery models are designed to connect internal state variables like SOC, internal resistance, and electromotive force with the measurable external parameters such as voltage, current, and temperature. Among the models proposed, an analogous circuit model is widely adopted to simulate dynamic properties of a lithium-ion battery. These models depict the processes that occur internally within the battery by using different components like bulk capacitance, surface capacitance, polarization resistance, and internal resistance. The bulk capacitance captures the storage capacity of the battery, while the surface capacitance models the diffusion effects. The internal resistance and polarization resistance reflect the electrochemical and concentration polarization of the battery, respectively. This kind of model can characterize the transient responses of the battery during charging and discharging. In addition, the SOC-OCV relationship is nonlinear and depends on environmental factors such as temperature. Such dependencies incorporated into battery models provide accurate predictions of performance, thus aiding in the development of efficient energy systems for applications ranging from electric vehicles to renewable energy storage.

Table 2 Battery Parameters used for modelling

Parameters	**Values**
Thermal Mass	100 J/K
Initial SOC	30%
Temperature	293K
Cell capacity	27Ah
Heat transfer coefficient	5 W/(K*m^2)

B. Unscented Kalman Filtering Algorithm

The Unscented Kalman Filter (UKF) improves the accuracy of state estimation for nonlinear systems, such as battery models, by not requiring linearization, which is necessary for the Extended Kalman Filter (EKF). UKF uses sigma points for direct nonlinear transformation, avoiding Jacobian matrices and thus simplifying calculations and enhancing precision. The iterated UKF calculates the state variable mean, variance, uses the state space transformation to transform it into sigma, and then produces weighing of new sigma points to find a better approximate state. Adding noise to all state and measurements, the output optimizes in each step what the state really is, mainly using input signals, observed and prior states' variables. This enables more accurate calculation and stability over complex systems related to SOC or SOH.

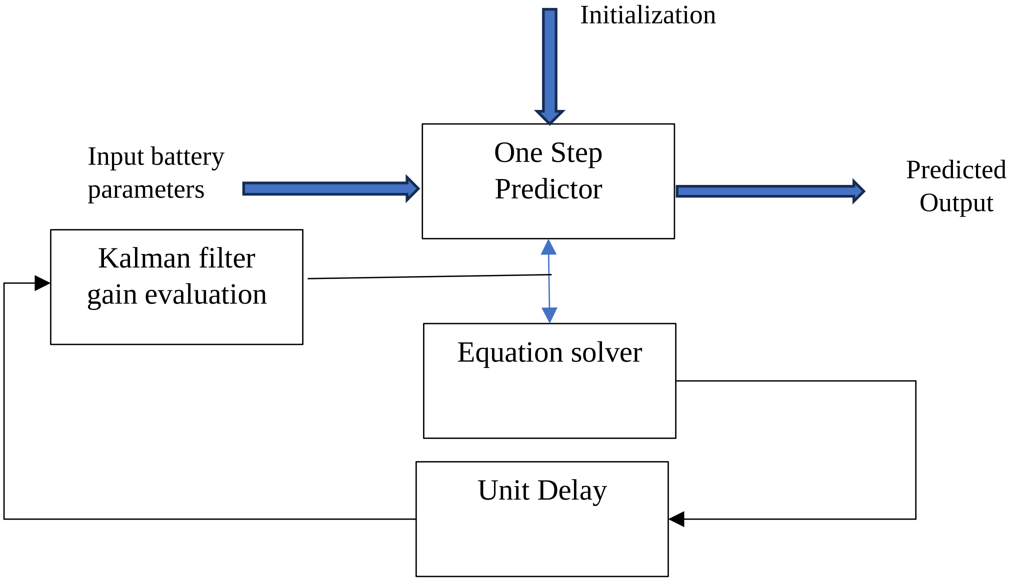

Figure 4 Unscented Kalman filter Block SOH diagram for SOC and estimation

This figure 4 shows a block diagram of a prediction model, possibly for a battery system, with Kalman filtering and iterative computation. The process starts with input battery parameters and an initialization step feeding into the One Step Predictor, which produces a predicted output. The Kalman filter gain evaluation block calculates the correction factors required in the prediction process. It receives inputs from both the predictor and the Kalman filter to refine iteratively, feeding its output into a Unit Delay block, where past computations are retained as feeds to further iterations. This feedback loop allows for continuous refinement of predictions based on updated parameters and past performances.

The estimation of the state of charge of a battery is very important for optimizing battery systems in applications such as electric vehicles, renewable energy storage, and portable electronics. Proper SOC estimation ensures efficient utilization of the battery, prolongs its lifespan, maintains system reliability, and allows for accurate State of Health (SOH) assessments. While it continues to work well with linear and well-defined conditions for the system to be under, those conventional algorithms often fail under the intrinsic nonlinearities and nonstationary of real-world battery systems. To address this limitation, the present research introduces the hybrid algorithm that combines the advantages offered by RNNs in particular LSTM networks with Kalman filters to improve SOC estimation accuracy. RNNs are excellent in capturing complex temporal dependencies and non-linear relationships in sequential data, making them an ideal choice for modelling the dynamic behavior of batteries. The predictive capability of RNNs allows the Kalman filter to work with more accurate state predictions, thereby improving its overall performance. The hybrid framework works in two major phases: a training phase and a real-time estimation phase. During training, the RNN is trained on historical battery data that includes voltage, current, temperature, and SOC to predict future SOC values from observed measurements. The trained model is then combined with the real-time estimation phase, where the real-time data is processed through the RNN to predict the SOC, which is then refined by the Kalman filter to give a more accurate estimate. The process involves the following key steps: data collection and pre-processing for clean and correctly formatted input data, RNN training to develop a strong predictive model, initialization of the Kalman filter with appropriate parameters, real-time SOC estimation combining RNN predictions and refinement by the Kalman filter, and continuous operation for ongoing updates and predictions. This hybrid approach offers a number of significant benefits in SOC and SOH estimation, particularly its ability to model non-linear relationships and adapt to changes over time. It captures the non-linear dynamics of electrochemical processes and thus gives an accurate prediction of SOC, even in transient states like rapid charging or discharging. This capability of learning the aging patterns of batteries, including capacity fade and changes in internal resistance, helps the model to adapt over time. In conjunction with the robust estimation of the Kalman filter, it makes sure that SOC and SOH are evaluated precisely even under changing usage conditions or battery aging. This will yield a dependable monitoring tool for the battery health, estimation of the remaining useful life, and performance optimization in different applications.

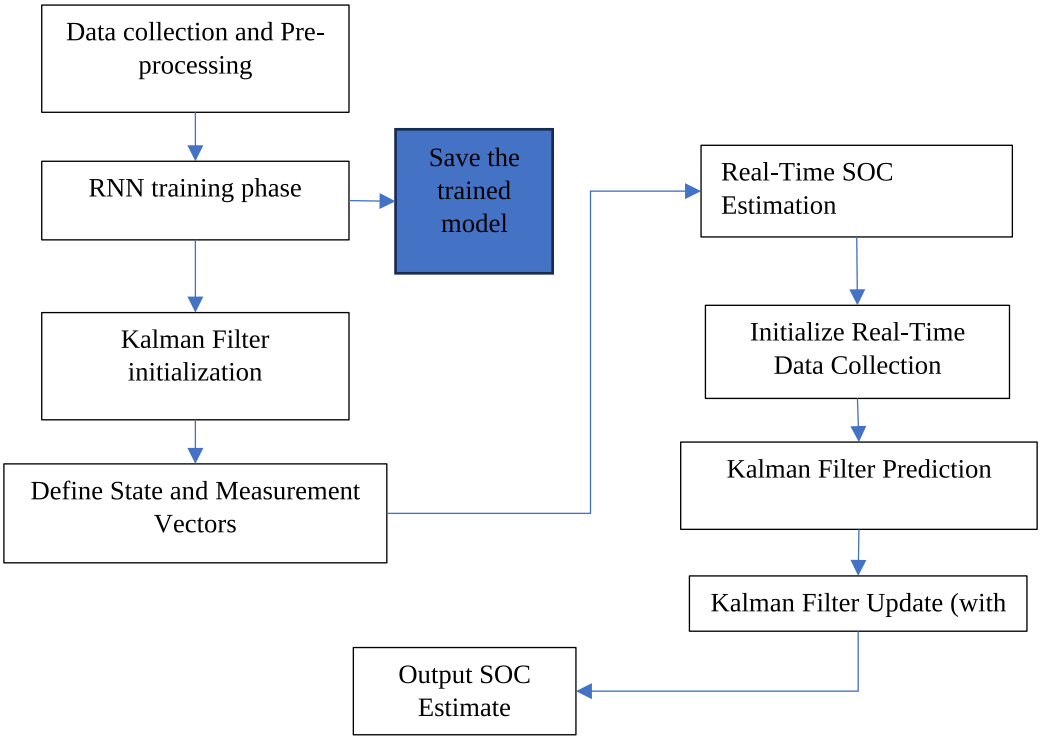

Figure 5 Proposed Hybrid method algorithm for battery SOC estimation

This flowchart combines a Recurrent Neural Network model with a Kalman filter toward the hybrid implementation of State of Charge estimation on batteries. There is data capture and pre-processing by ensuring that voltages, current, and states of charge collected are clean for input and correct in format before use in a training phase as part of recurrent neural network learning through historical battery records to predict its state of charge. The model after being trained, saves and puts into use during runtime. Step definition in the initialization process by a Kalman filter requires determination of appropriate state and measurement vectors that may be estimated for prediction in SOC. The SOC can thus be determined real time since SOC prediction relies on RNN's capability and can make this feed for inputting it in a Kalman filter which undergoes the predict and updates this prediction in light of actual measured SOC. This gives a very accurate SOC estimate refined and built up based on the capability of non-linear modelling through RNNs, together with the strength of robustness in dealing with measurement noise and uncertainties. Hence, precise adaptation to different states of battery operation can be established.

V. RESULTS

The non-linear and dynamic nature of battery systems is challenging traditional methods, resulting in inaccurate predictions of SOC and SOH. This work addresses the challenge by integrating RNNs with Kalman filters, thus providing accurate SOC estimation to avoid damage from batteries and reliable SOH predictions for monitoring degradation and remaining useful life. The study focuses on two cases, namely slow C-rate conditions in which gradual degradation is captured for long-term reliability and fast C-rate conditions in which rapid degradation because of stress and temperature is modelled for high-demand applications. This is to ensure the accurate and adaptive battery health assessment for different conditions.

A. Condition 1: Analysis of the SOH prediction at slow C-rate

Slow C-rate conditions describe gentle, extended charge/discharge cycles, typically found in standby power supplies and certain electric vehicle charging applications. The analysis of these conditions allows for the development of optimization strategies that focus on longevity, which extends the battery life and maximizes the cost-effectiveness of battery-operated systems.

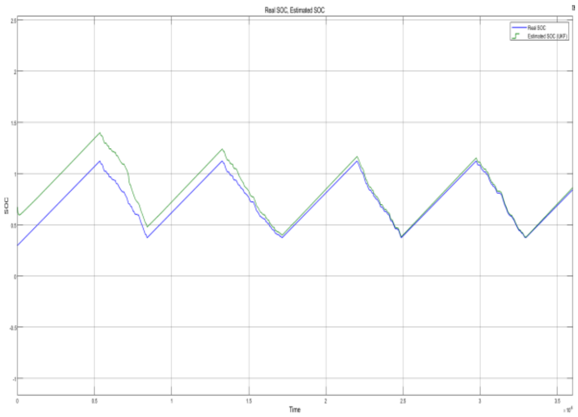

Figure 6 Comparative Analysis of real SOC and estimated SOH with time using UKF when the C-rate is slow

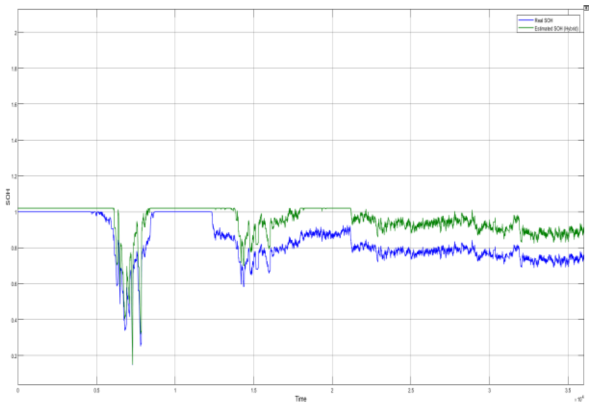

Figure 7Comparative Analysis of real SOH and estimated SOH with time using UKF when the C-rate is slow

The figure 6 represents the estimated State of health (SOH) is plotted in green colour and real SOC is plotted in blue colour. There is a different in the value of SOC in the real state of battery and that estimated by UKF. The root means square error found is 0.5805. The figure 7 represents the estimated State of health (SOH) is plotted in green colour and real SOH is plotted in blue colour. There is a different in the value of SOH in the real state of battery and that estimated by UKF. The root means square error found is 0.1281.

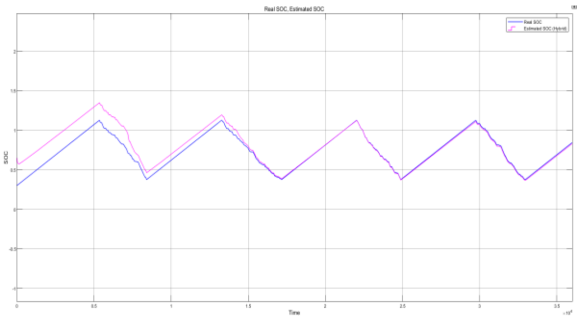

Figure 8 Comparative Analysis of real SOC and estimated SOC using hybrid algorithm when the C-rate is slow

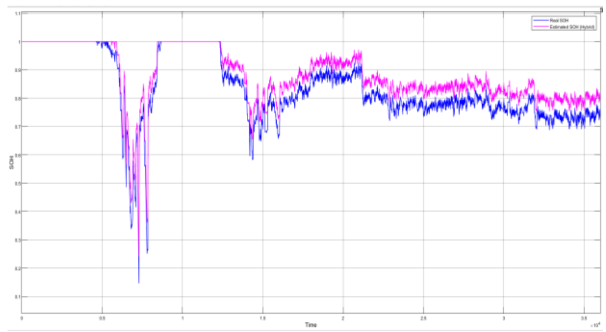

Figure 9 Comparative Analysis of real SOH and estimated SOH using hybrid algorithm when the C-rate is slow

The figure 8 represents the estimated State of Charge (SOC) is plotted in pink colour and real SOC is plotted in blue colour. There is a different in the value of SOC in the real state of battery and that estimated by proposed hybrid algorithm. The root means square error found is 0.5471. The figure 9 represents the estimated State of health (SOH) is plotted in pink colour and real SOH is plotted in blue colour. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root means square error found is 0.0635.

	Estimated SOC	**Estimated SOH**
RMSE in prediction by UKF	0.5805	0.1281
RMSE in prediction by HKF	0.5471	0.0635

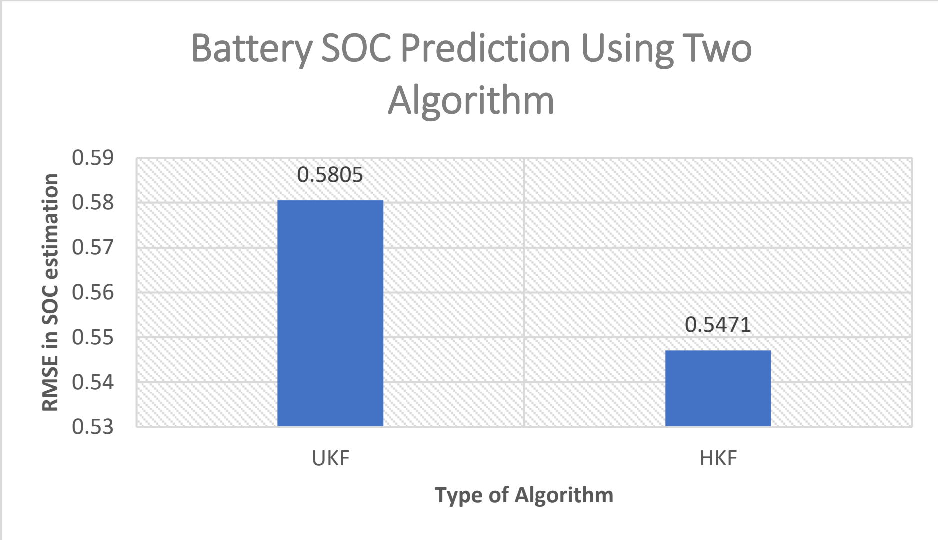

Figure 10 Comparison of RMSE in prediction of SOC by two algorithms with slow c rate

The figure 10 compares the SOC estimation accuracy using the Unscented Kalman Filter (UKF) and the Hybrid Kalman Filter (HKF) under slow C-rate conditions. The HKF had a lower RMSE of 0.5471 compared to the UKF's 0.5805, which indicates that the HKF is more accurate in capturing the dynamics of the battery and reducing the estimation errors. This makes the HKF a more effective and reliable choice for precise battery management and monitoring applications.

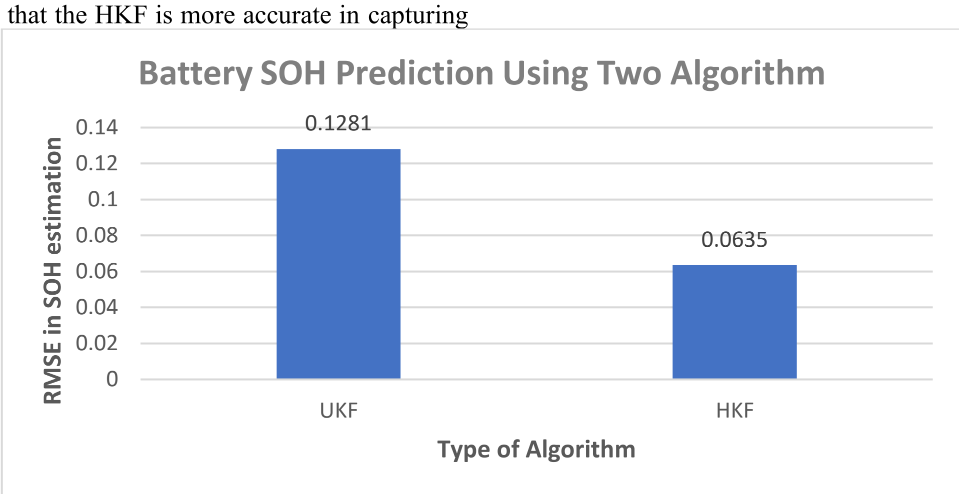

Figure 11 Comparison of RMSE in prediction of SOH by two algorithms with slow c rate

For comparison of the predictions of SOH under slow C-rate conditions, HKF is clearly a much better fit than UKF in terms of accuracy. For instance, its RMSE stands at 0.0635, which is much less compared to the 0.1281 for the UKF. This translates into much reduced prediction errors and high accuracy in estimating the SOH.

B. Condition 2: Analysis of the SOH prediction with charging and discharging conditions with high C-rate

Fast C-rate conditions refer to fast charge/discharge cycles, typical in high-performance applications such as electric vehicles when accelerating or regenerative braking and fast charging portable electronics. In these conditions, precise SOH prediction is essential to ensure the battery's safety and performance under stress. Through quick degradation patterns analysis, failures can be prevented and optimized battery performance achieved.

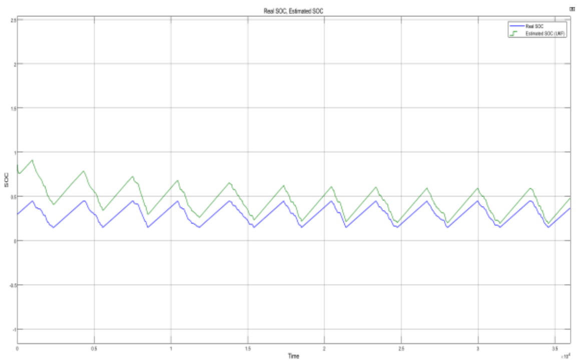

Figure 12 Comparative graph of real SOC and estimated SOC with high c rate

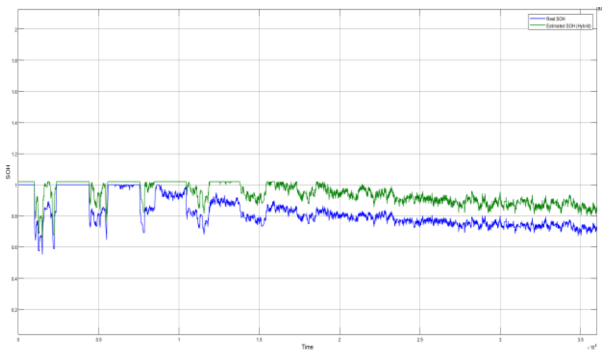

Figure 13 Comparative graph of real SOH and estimated SOH with high c rate

The figure 12 represents the estimated State of Charge (SOC) by UKF which is plotted in green colour and real SOC is plotted in blue colour when the battery charging and discharging rate is high. There is a different in the value of SOC in the real state of battery and that estimated by UKF. The root means square error found is 0.2200. The figure 13 represents the estimated State of health (SOH) by UKF which is plotted in green colour and real SOH is plotted in blue colour when the battery charging and discharging rate is high. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root means square error found is 0.1299.

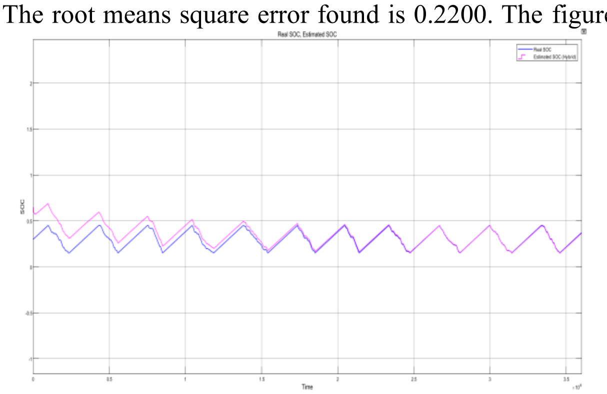

Figure 14 Comparative graph of real SOC and estimated SOC with high c rate

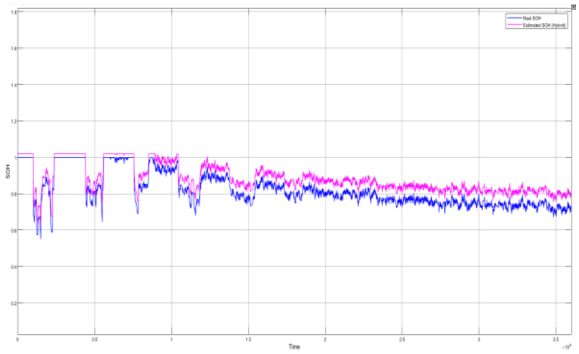

Figure 15 Comparative graph of real SOH and estimated SOH with high c rate

The figure 14 represents the estimated State of Charge (SOC) by HKF which is plotted in pink colour and real SOC is plotted in blue colour when the battery charging and discharging rate is high. There is a different in the value of SOC in the real state of battery and that estimated by HKF. The root means square error found is 0.1223. The figure 15 represents the estimated State of health (SOH) by HKF which is plotted in pink colour and real SOH is plotted in blue colour when the battery charging and discharging rate is high. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root means square error found is 0.0646.

Table 4 Comparative analysis of RMSE in prediction of SOC and SOH at fast c-rate

	Estimated SOC	Estimated SOH
RMSE in prediction by UKF	0.22	0.1299
RMSE in prediction by HKF	0.1223	0.0646

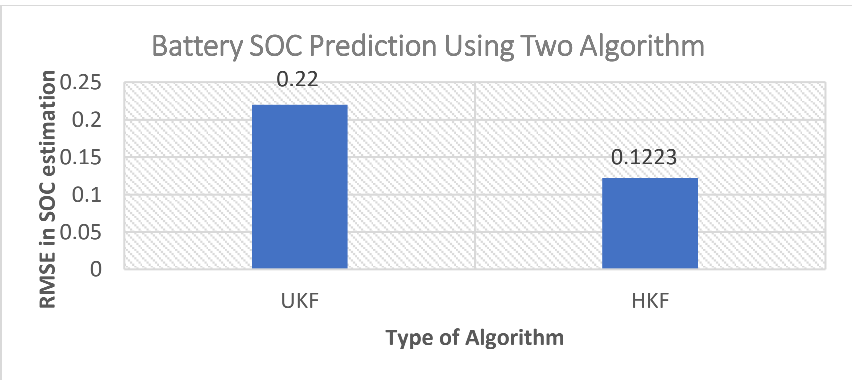

Figure 16 Comparison of RMSE in prediction of SOC by two algorithms with fast c rate

The figure 16 compares the SOC prediction performance of the Unscented Kalman Filter (UKF) and the Hybrid Kalman Filter (HKF) using RMSE as the metric. The UKF has a higher RMSE of 0.22, which means more estimation error, while the HKF has a significantly lower RMSE of 0.1223, which reflects better accuracy. This shows that the HKF outperforms the UKF in SOC prediction, making it a more reliable choice for precise battery management.

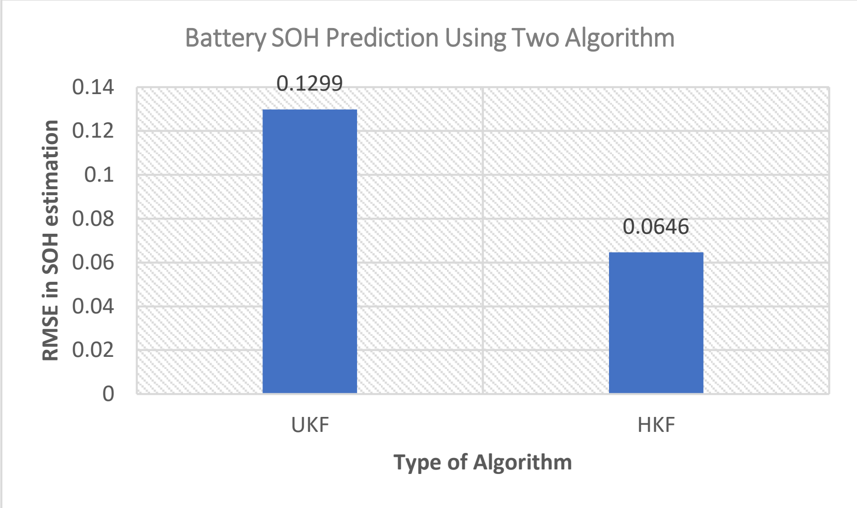

Figure 17 Comparison of RMSE in prediction of SOH by two algorithms with fast c rate

The figure 17 compares the prediction accuracy of SOH under fast C-rate conditions using RMSE as the metric. The UKF has a higher RMSE of 0.1299, which means it has a higher prediction error, whereas the HKF has a significantly lower RMSE of 0.0646, which means it is more accurate. This shows that the HKF is more effective in giving more accurate predictions of SOH than the UKF.

VI. CONCLUSION

The integration of RNNs with Kalman filters provides a new layer for a breakthrough in the field of battery management, especially addressing areas in which traditional methods possess flaws in estimating SOC and SOH. Traditional approaches are under-equipped to address the non-linear nature and dynamics of any real-time battery system, thereby causing inaccuracies in predicting outcomes. The hybrid algorithm combines the predictive strengths of RNNs with the robustness of Kalman filters. This provides greater accuracy as well as flexibility to handle variations in operational conditions. For a variety of C-rate conditions, the hybrid approach is quite robust and thus represents excellent performance in capturing subtle and complex changes in behavior during slow and fast charge/discharge cycles. This adaptability leads to a considerable reduction in the estimation errors, thereby making the predictions of SOC and SOH much more reliable. The algorithm provides precise real-time predictions that significantly enhance battery management through optimized utilization, prevention of overcharging or over-discharging, and support for early detection of potential failures or degradation. Moreover, the hybrid algorithm is contributing toward the total security and longevity of battery systems in critical applications including electric vehicles, renewable energy storage, and portable electronics. The developed solution is more than the currently available answers toward challenging issues of the estimation of the health of a battery, thus leading to solid building blocks for advanced intelligent battery management systems to emerge toward even more secure, efficient, and sustainable storage of energy solutions in the future.

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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