Innovative Approaches for Improving State of Health Estimation Accuracy in Lithium-ION Batteries

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Abstract: Urgent environmental action is required due to the increasing effects of resource depletion, greenhouse gas emissions, and climate change, especially in the transportation sector. Battery technology has advanced significantly as a result of the change to hybrid and electrified vehicle powertrains, especially with Lithium Ion Batteries (LIBs). Due to their high specific energy (150–280 Wh•g^−1) and specific power (200–300 W•kg^−1), LIBs are used in electric vehicles (EVs) and hybrid electric vehicles (HEVs) as essential components of electrified powertrains.The important topic of battery health monitoring is examined in this study, with a particular emphasis on battery management systems (BMS) and State of Health (SOH) estimation. SOH, a gauge of battery deterioration over time, is essential in establishing the dependability and longevity of batteries. A variety of methodologies for estimating SOH are examined, with a focus on the application of model-based strategies like Kalman filtering and hybrid algorithms that combine machine learning methods like Recurrent Neural Networks (RNNs).An important factor to take into account is how battery aging and performance deterioration are affected by working conditions, such as temperature and charging rates. Simulation results show that the suggested hybrid approach, when compared to conventional techniques such as the Unscented Kalman Filter (UKF), effectively improves the accuracy of SOH estimate. The battery management techniques needed for sustainable energy solutions in contemporary transportation systems are advanced by this research.

Keywords: *Battery Management System, Lithium Ion Battery, State of Health (SOH), Kalman Filter, Hybrid Algorithm, Electric Vehicles (EVs), Renewable Energy.,*

I. INTRODUCTION

The planet's environmental state is clearly in a critical state due to factors including resource depletion, greenhouse gas emissions, and climate change. A massive transformation in the transportation sector is required to address some of the challenges that the world is currently facing. In actuality, there has been a significant increase in the hybridization and electrification of car powertrains recently. The battery is a crucial part of this electric drivetrain. As a result, advancements in battery technologies have been made, particularly with regard to Lithium Ion Batteries (LIB). [1]. The lithium-ion battery (LIB) has been around since the early 1990s and is currently the most promising and rapidly developing battery technology for both high- and low-power applications. This technology is the most appealing for electrified powertrains because of its high specific energy (150–280 Wh•g −1) [2] and high specific power (200–300 W•kg −1). Considerable-performing LIB, but especially long-lasting ones, are in considerable demand due to the expanding market for electric and hybrid vehicles. Batteries have nonlinear characteristics and are intricate electrochemical components [3].

A. State Of Health And Management Of Power Battery

These days, a lot of electric equipment uses lithium ion batteries. The indicator of health status is the primary focus of the study on the life of lithium ion batteries. It is the proportion of the battery's real capacity to its rated capacity in a given charging and discharging scenario or storage environment. The battery is deemed invalid and is disposed of in order to extend its service life when its performance, or SOH, does not fulfill the service standards. Performance metrics like capacity, power, and internal resistance vary across a battery's life cycle [4]. Typical techniques for calculating SOH include defining the maximum capacity, internal resistance, available capacity, battery starter power, and so forth. The simplest way to define SOH is to just count the number of cycles [5]:

SOH = 100 × (1 - Cycle Number/Nominal Total Number of Cycles)

Time can also be taken into consideration while evaluating SOH:

SOH = 100 × (1 - Age/Rated Calendar Life)

When comparing actual capacity to SOH, the following happens:

SOH = 100 × (1 - Actual Capacity/Nominal Capacity)

When the relative real resistance is used to evaluate SOH:

SOH = 100 × (1 - Nominal Resistance/Actual Resistance)

Modules make up the power battery pack (single battery in series and parallel). Many variables that affect how batteries are charged and discharged might cause single cells to behave inconsistently, individual batteries to overcharge or undercharge, or even the battery system as a whole to malfunction [6].

B. Battery Management System

State-of-charge (SOC) estimation and state-of-health (SOH) analysis are two of the many crucial activities performed by BMS. The assessment of state of charge (SOC) functions as a fuel gauge for batteries. SOC is typically defined as "the percentage of the maximum possible charge which is present inside a rechargeable battery." Conversely, SOH is defined as "a'measure' that reflects the general state of a battery and its potential to deliver the specified performance in compared to a fresh battery." Depending on the particular application, the internal resistance or battery capacity is typically used to determine the quantitative definition of SOH. The construction of a basic yet precise battery model is essential for a reliable and efficient battery management system (BMS) since it is necessary to estimate both SOC and SOH online while the system is operating.[7]

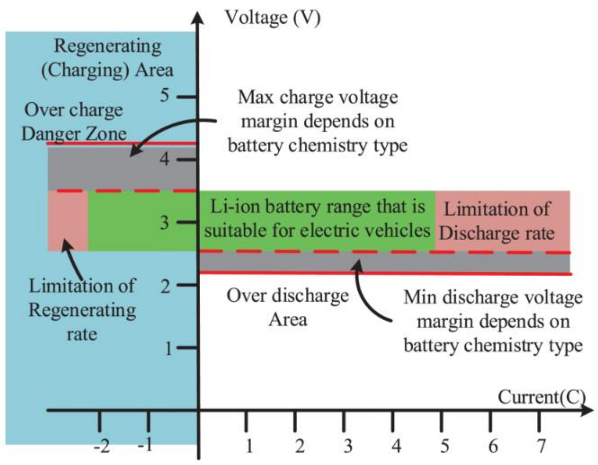

Figure 1. Li-ion battery lifecycle vs. temperature diagram. [10]

There is no set specification for SOH estimate; instead, battery manufacturers define their own standards. SOH can be calculated using a variety of battery characteristics, like as capacity and internal resistance. But it's an assessment

and judgment rather than an exact measurement. Electrolyte breakdown state, electrode dynamic performance, phase shift of the electrode material, and SEI film formation are some of the elements that affect how well Li-ion batteries function over time[8]. Irreversible modifications to the electrolyte composition, anode and cathode characteristics, and structural changes to the battery are features of battery aging. Because of the times when batteries are used and the calendar aging that occurs when batteries are stored, aging can be classified as cycle aging. The assessment of SOH is intimately related to changes in capacity, internal resistance, and power fading, all of which are signs of aging [9]. The selection of the most appropriate parameter for State of Health (SOH) estimation is contingent upon the particular conditions and alterations noted in the battery's external behaviors, such as a decrease in rated capacity or an elevation in temperature resulting from internal modifications like corrosion. The relationship among cycle life and cell temperature of operation emphasizes the ideal range of 15°C to 45°C. Operating at temperatures below 15°C or over 45°C causes cycle life to progressively diminish; further temperature rises cause a dramatic fall because of thermal runaway, as demonstrated in. Li-ion batteries normally operate within a specific current and voltage range, as shown in Fig. 1. The x-axis displays the current (C-rate) and the y-axis displays the voltage (V) based on the battery's nominal capacity. Negative current levels relate to charging or regenerating processes, whilst positive current values show the discharge process [10].

C. Basics of Soh and Its Classification

The state-of-health (SoH) of a battery takes cell aging into account and explains how the battery under study differs from a new battery. Its definition is the proportion of the battery's rated capacity to its maximum charge. As may be seen below, it is given as a percentage.

SOH (in %) = $\frac{Qmax}{Cr}$

Where Qmax is the maximum Charge available of the battery

Cr is the rated capacity.

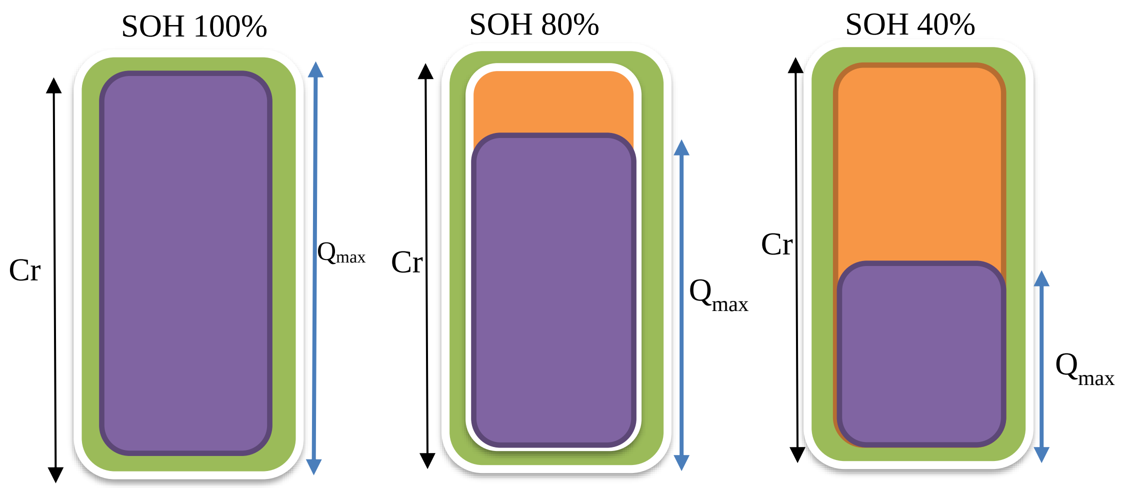

Figure2. Evolution of the SoH of a battery during aging

A secondary battery's health has an impact on its discharge profile. As seen in Fig. 2, the battery discharges more quickly the lower the SoH. Over time, a battery's performance or "health" tends to steadily decline due to irreversible physical and chemical changes that occur with usage and aging, until the battery eventually dies or is no longer functional. The SOH is a gauge of the battery's status in relation to a new battery and indicates the point in its life cycle that it has reached. The SOH is not specified by battery manufacturers because they only provide new batteries. The SOH only comes into effect for batteries that have entered service or have begun to age on the shelf.

D. Model Based method:

The SOH is a figure of merit that shows how much the battery has degraded. However, direct measurements cannot be used to calculate it. It must be determined using SOH indicators, which are the battery's capacity, resistance, or impedance (some research lists internal resistance and battery impedance as the same indication, but this work has listed them separately because the methods employed for estimating them are different). Model-based approaches to estimate these indications and assess the battery state of health have recently attracted a lot of attention in automotive research due to their real-time feasibility. Utilizing SOH indicator-aware battery behavior models, these techniques characterize battery behavior. These indicators are identified in order to estimate the battery states and their performances. The literature offers a number of techniques for identifying these signs. This section reviews the primary model-based techniques for SOH estimations [11].

- KALMAN FILTER
- ADAPTIVE FILTERING
- ADAPTIVE UNSCENTED KALMAN FILTER
- LINEAR KALMAN FILTER
- ELECTROCHEMICAL MODEL

II. LITERATURE REVIEW

Yang et al. (2024) [12] highlighted the impact of aging degrees and heat variations on the internal properties of lithium-ion battery (LIB) energy storage devices during operation. Their study developed an electrical simulation model for LIB packs, integrating thermal effects and employing the dual extended Kalman filter (DEKF) algorithm for state of charge (SOC) and state of health (SOH) estimation. The model, based on a second-order resistor-capacitor equivalent circuit, demonstrated precise predictions with mean absolute errors (MAE) of less than 1.50% for SOC and 3.37% for SOH. Additionally, the thermal module accurately estimated battery pack temperature with a margin of error (MOE) under 6.60%.

Fahmy et al. (2024) [13] investigated efficient methods for assessing LIB SoH, proposing a hybrid approach combining dual adaptive unscented Kalman filter (DAUKF) with Coulomb counting (CCA). Their study utilized Gazelle optimization to enhance parameter identification, achieving over 8% improvement in model accuracy compared to other techniques across various scenarios. Validation against commercial Panasonic LiBs showed DAUKF-CCA's capability to estimate SoC and SoH with errors of less than 1%, demonstrating its effectiveness in LIB management systems.

Wang et al. (2024) [14] emphasized the importance of accurately estimating SOC and SOH for lithium-ion batteries used in electric vehicles (EVs). They proposed an improved firefly algorithm (IFA) to optimize Gaussian process regression (GPR) models, enhancing predictive accuracy by 6.75% and 91.64% for SOC and SOH, respectively, compared to existing methods. Their research underscored the significance of machine learning techniques in advancing battery diagnostics, offering greater precision and flexibility in monitoring battery health.

Li et al. (2021) [15] explored the critical parameters influencing the health of traction batteries, including charging/discharging methods, temperature, and state of charge (SoC). Their findings highlighted that deep discharges significantly reduce battery lifespan, while high and low temperatures affect battery morphology and performance. The study underscored the importance of comprehensive battery health management strategies tailored to specific operational conditions to prolong battery life and optimize performance.

De Castro et al. (2024) [16] provided an overview of the IEEE Vehicle Power and Propulsion Conference (VPPC22), emphasizing its role in advancing electric mobility technologies. The conference, held at the University of California, Merced, addressed the growing importance of zero-emission vehicles (ZEVs) in reducing greenhouse gas emissions and improving air quality, highlighting California's commitment to phasing out traditional vehicles by 2035.

Camboim et al. (2024) [17] discussed the reuse potential of lithium-ion batteries (LiBs) from electric vehicles (EVs) in applications requiring lower power demands. Their study proposed a subspace system identification (SSI) approach for estimating the state of health (SoH) of LiBs, demonstrating accurate SoH estimation with root mean square error (RMSE) values as low as 1.32 mV. The SSI method allowed for online estimation during LiBs' initial lifespan in EVs, avoiding the need for extensive testing and specialized equipment, thus facilitating efficient battery reuse strategies.

III. OBJECTIVE

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

- To design a battery model and study it's charging and discharging characteristics in MATLAB/SIMULINK.
- To study the battery state of charge (SOC) and state of health (SOH) when the battery is subjected to charging and discharging cycles at different rates.
- Design Kalman filter based model for correct battery SOC estimation and there by predict the battery SOH.
- Improve the prediction capability of Kalman filter by making a hybrid algorithm with learning-based method and reduce the RMSE.

IV. METHODOLOGY

A. Setup of Equivalent Circuit Model for the Lithium Battery

The external features and internal electrochemical reaction characteristics can be efficiently described by an accurate battery model, which is crucial during the SOC and SOH evaluation of electric batteries. The ratio of nominal battery capacity to remaining battery capacity given the same environmental circumstances and designated discharge rate is known as the state of charge (SOC):It is possible to feed the load with either solar or wind energy depending on availability by modeling the Dual Voltage Source Inverter system, which increases system reliability.

$$SOC = \frac{Q_{res}}{Q_N} \times 100\%$$

where QN is the nominal battery capacity and Qres is the battery capacity left after the partial electric amount has been discharged. The researchers discovered that the ohmic resistance and real maximum battery capacity are more significantly affected by variations in SOH through a comparative investigation of the variation between old and new batteries [23]. SOH is described as follows from the standpoint of ohmic resistance:

$$SOH_R = \frac{R_O(end) - R_O(t)}{R_O(end) - R_O(0)} 100\%$$

The battery SOH is represented by SOHR, which is determined by the ohmic resistance R0; the ohmic resistance at t is represented by R0(t); the ohmic resistance at t is defined by R0(end); and the ohmic resistance at battery delivery from the factory is represented by R0(0).

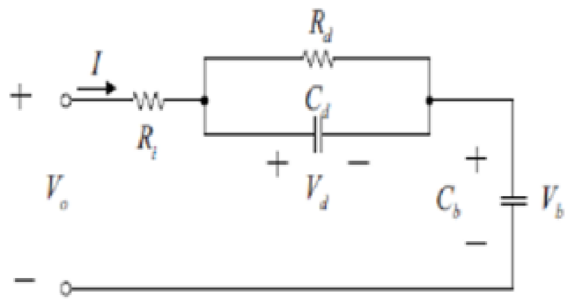

Figure 3.Equivalent Circuit for battery

Fig. 3 illustrates an analogous circuit model [5] using them to roughly depict a chemical reaction inside a lithium-ion battery pack. Cell electrochemical polarization and concentration polarization, which reflect the battery's instantaneous response to charge or discharge, are described by the bulk capacitance (Cb), which reflects the battery pack storage capacity, and the surface capacitance (Cd), which indicates the battery diffusion effects. The polarization resistance and the internal resistance are represented by the resistances Ri and Rd, respectively. The symbols Vb and Vd stand for the voltages across the bulk capacitor and surface capacitor, respectively. Vo and I stand for the batteries pack terminal voltage and current, respectively.

Table 1: 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 Kalman filter and lossless transformation constitute the foundation of UKF. It can successfully address the issues of low EKF estimation accuracy and stability. Nonlinear distribution statistics have great computation accuracy since the high-order term need not be disregarded. Since the state space model of the battery is nonlinear, it must be linearized before using EKF to estimate the battery's condition. During the linearization process, the Jacobian matrix must be constructed, adding complexity to the computation and decreasing estimation accuracy. The UKF increases the accuracy of the estimation by directly utilizing the sigma point for nonlinear transformation rather than linearizing the battery model.

Step1. The mean and variance of the state variables are calculated using certain guidelines to determine the sigma points.

Step2. To obtain the new sigma point set, the state-space model will act on sigma points.

Step3. By weighing the fresh collection of points, the state variable's great estimate is obtained.

Step4. Repeat the previous operation process to iterate as show in figure 4.

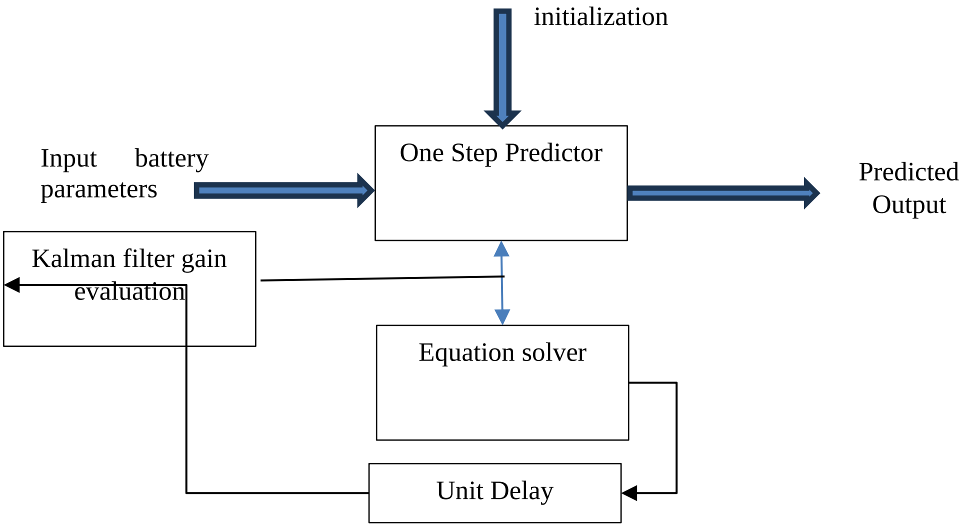

Figure 4.Unscented Kalman filter Block diagram for SOC and SOH estimation

C. Hybrid algorithm with Kalman Filter improved by Recurrent Neural Network

Battery State of Charge (SOC) estimation is a critical component in the management and optimization of battery systems, particularly in applications such as electric vehicles, renewable energy storage, and portable electronics. Accurate SOC estimation ensures efficient battery usage, extends battery lifespan, and maintains system reliability and also impacts accurate battery state of health (SOH) estimation. Traditional methods of SOC estimation, such as the Kalman filter, work very well under linear assumptions and with well-defined system dynamics. Most of these techniques never consider nonlinear and non-stationary characteristics inherent in real-world battery system.

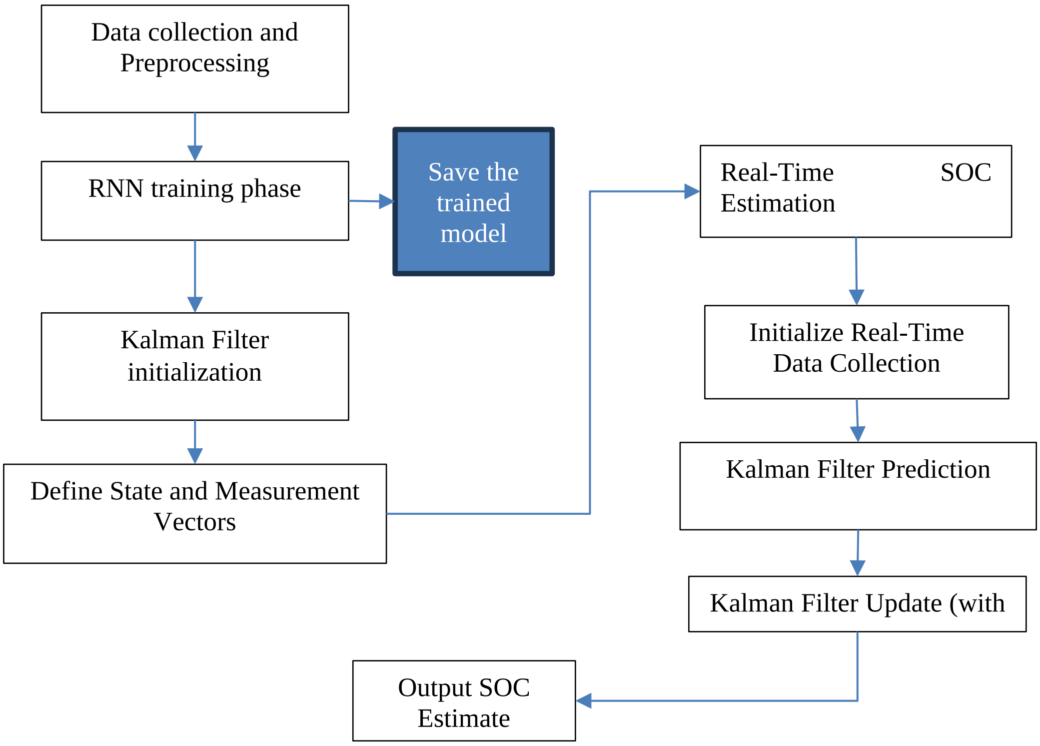

Figure 5. Proposed Hybrid method algorithm for battery SOC estimation

Fig. 5 illustrates the algorithm of Hybrid method for battery SOC estimation step by step. To this end, and to address these challenges, a hybrid algorithm is proposed in this thesis. This strategy combines the strengths of Recurrent Neural Networks and Kalman filters to improve the accuracy of SOC estimation. Especially through the variant, the Long Short-Term Memory network, RNNs can deal effectively with complex temporal dependencies and nonlinear relations in sequential data; therefore, they are suitable for modeling dynamic behavior in battery systems. The predictive power of RNNs will be used to supply their output to a Kalman filter with more accurate state predictions to improve its performance.

V. SIMULATION AND RESULT ANALYSIS

Traditional methods often fall short in accurately predicting SOC and SOH due to the non-linear and dynamic nature of battery systems. By integrating RNNs with Kalman filters, this work addresses these limitations, offering more precise and reliable estimates. Accurate SOC estimation prevents overcharging and deep discharging, which damage the battery; on the other hand, precise SOH estimation helps in understanding the degradation patterns and the remaining useful life of the battery. This work is thus divided into the following two cases:

a) Condition 1: Analysis of the SOH prediction at slow C-rate

b) Condition 2: Analysis of the SOH prediction at fast C-rate

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

Slow C-rate conditions typically represent scenarios where the battery is subjected to gentle and prolonged charge/discharge cycles. This analysis helps in understanding the battery's performance and degradation behavior under such conditions, which are common in applications like standby power supplies and certain electric vehicle charging cycles.

Insights gained from analyzing slow C-rate conditions can be used to optimize battery usage strategies for applications that prioritize longevity over high performance. This helps in extending the battery life and improving the overall cost-effectiveness of battery-operated systems.

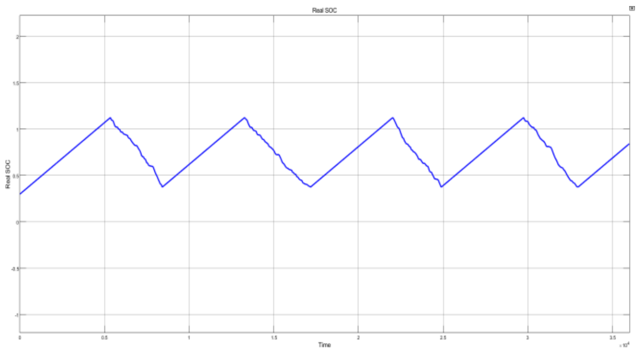

Figure 6.Real Battery SOC with slow C-rate

The figure 6. Shows, depicts the real state of charge conditions of the battery under test. The battery is made to get charged and discharged at long time intervals. The c-rate affects the battery SOH over the course of time.

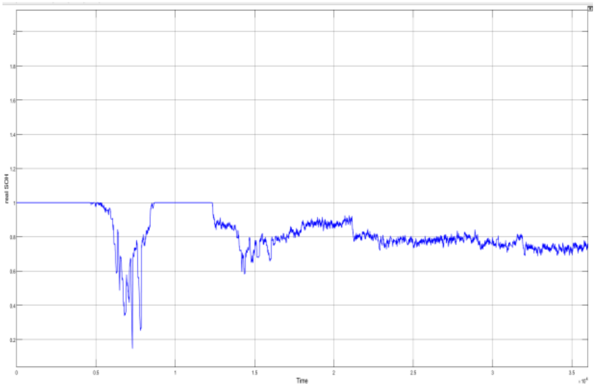

Figure 7.Real Battery SOH with slow C-rate

The figure7. Shows, depicts the real state of health conditions of the battery under test. The battery is made to get charged and discharged at long time intervals. The c-rate affects the battery SOH over the course of time which degrading slowing as inferred from the graph.

a) Unscented Kalman Filter Prediction

A permanent magnet synchronous generator (PMSG), which transforms mechanical torque to three phases of electrical power, has been used to model wind energy systems. The wind speed fluctuates between 0 and 12 m/s, which causes changes in the production. With the use of a rectifier, the three phase output voltage is transformed into DC. Figure 12 displays the DC output by the wind energy system.

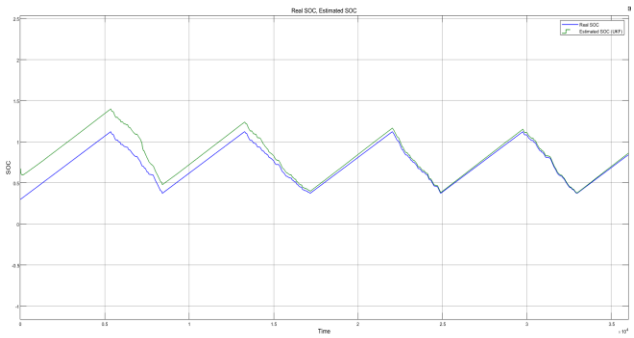

Figure 8.Comparative Analysis of real SOC and estimated SOH with time using UKF when the C-rate is slow

The graph represents the estimated State of health (SOH) is plotted in green colour and real SOC is plotted in blue colour shows in fig 8. There is a different in the value of SOC in the real state of battery and that estimated by UKF. The root mean square error found is 0.5805.

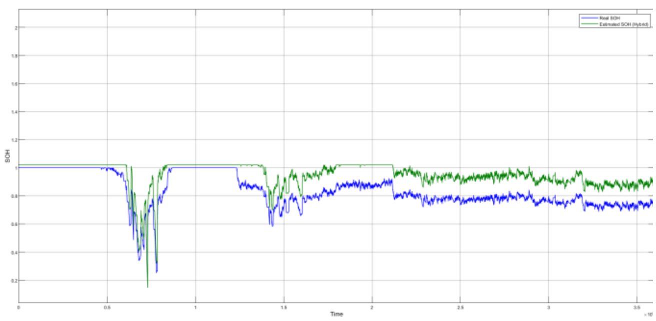

Figure 9.Comparative Analysis of real SOH and estimated SOH with time using UKF when the C-rate is slow

The graph represents the estimated State of health (SOH) is plotted in green colour and real SOH is plotted in blue colour shows in fig 9. There is a different in the value of SOH in the real state of battery and that estimated by UKF. The root mean square error found is 0.1281.

b) Proposed Hybridized Kalman filter with Recurrent Neural Network

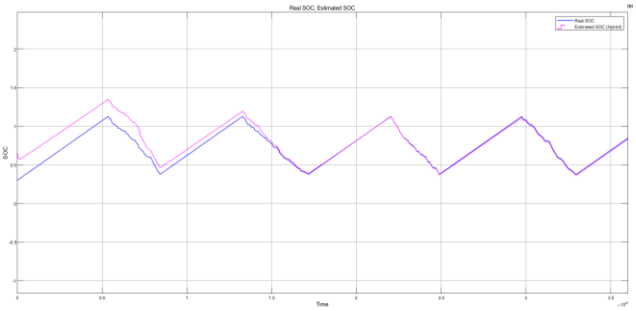

Figure10. Comparative Analysis of real SOC and estimated SOC using hybrid algorithm when the C-rate is slow

The graph represents the estimated State of Charge (SOC) is plotted in pink colour and real SOC is plotted in blue colour shows in fig 10. There is a different in the value of SOC in the real state of battery and that estimated by proposed hybrid algorithm. The root mean square error found is 0.5471.

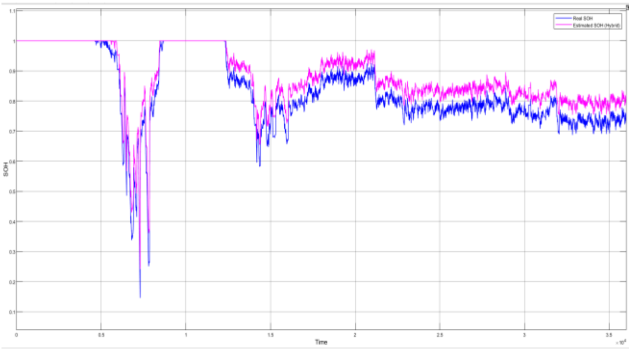

Figure 11. Comparative Analysis of real SOH and estimated SOH using hybrid algorithm when the C-rate is slow

The graph represents the estimated State of health (SOH) is plotted in pink colour and real SOH is plotted in blue colour shows in fig 11. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root mean square error found is 0.0635.

Accurate SOC readings provide valuable data for algorithms that predict SOH. SOH estimation models use details of charge/discharge cycles, among other inputs, to predict how much usable life remains in the battery. Inaccuracies in SOC can lead to incorrect SOH estimations, potentially leading to unexpected failures or suboptimal use of the battery capacity.

Table 2: Comparative analysis of RMSE in prediction of SOC and SOH at slow c-rate

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

Table 2. Below, provides a comparison of State of Charge estimation Root Mean Square Error using Unscented Kalman Filter and Hybrid Kalman Filter with slow C rate. For the two algorithms, Root Mean Square Error was used as a metric to test their accuracy in SOC estimation. For the UKF, this produced an RMSE of 0.5805, while the HKF returned an RMSE of 0.5471.

This difference in RMSE shows that the hybrid Kalman filter gives a considerably more correct estimate of State of Charge than the Unscented Kalman Filter. The lower value of the RMSE for HKF indicates its improved ability in capturing the dynamics of the battery system and thereby reduces the estimation error. Therefore, HKF is a more accurate and stable algorithm to predict the SOC of a battery, which provides the basis for its considerable suitability in applications that require precision in their battery management and monitoring system.

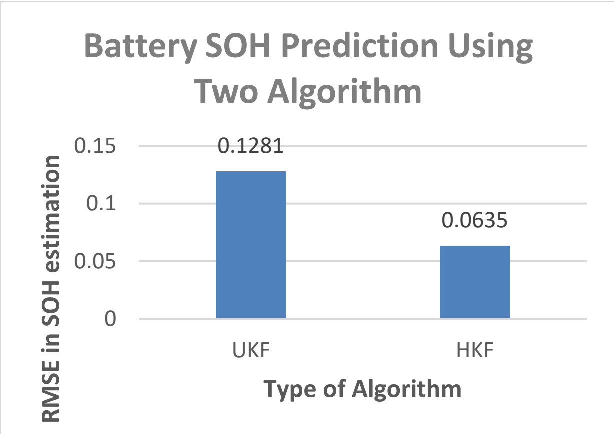

Figure 12.Comparison of RMSE in prediction of SOH by two algorithms with slow c rate

The graph 12. shows a comparison of Unscented Kalman Filter (UKF) vs. Hybrid Kalman Filter (HKF) for State of Health prediction under a test regime with very slow C-rate conditions. This indicates immense potential for an accuracy increase in the latter. Again, the Root Mean Square Error will be the metric for assessing the precision of SOH estimation that each algorithm provides. The results show that the UKF gives 0.1281 for the RMSE rating, indicating a much higher resultant error in its SOH predictions. On the other hand, the HKF gives a much lower RMSE rating of 0.0635, depicting a considerable reduction in prediction error.

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

Fast C-rate conditions simulate scenarios in which the battery is under fast charging/discharging cycles. This is typical in very high-performance applications, such as when an electric vehicle has acceleration or regenerative braking and portable electronics requiring quick charging. Accurate SOH prediction under fast C-rate conditions is critical for ensuring the safety and performance of batteries in high-stress applications. By understanding how the battery degrades quickly, preventive measures can be implemented to avoid failures and optimize performance.

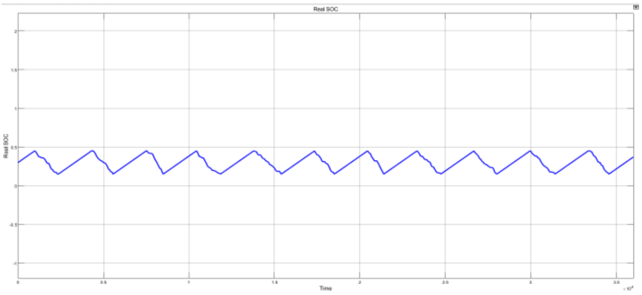

Figure 13. Simulation graph representation of real battery SOC with high C- rate

The graph represents the real State of charge (SOC) is plotted in blue colour in y- axis which ia charged and discharged frequently at a high C-rate shown in figure 13. The charging rate of SOC is increased with respect to time (in sec) when it goes upwards and discharges when the blue colour line goes downwards.

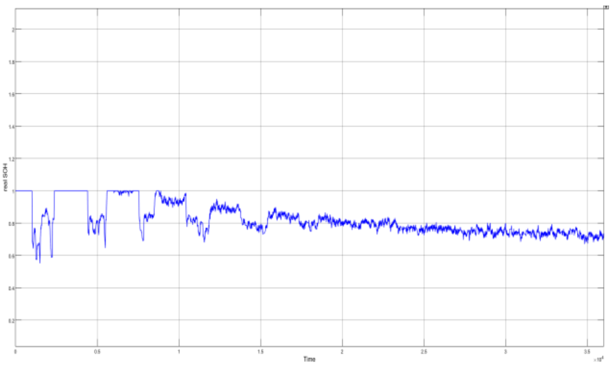

Figure 14.simulation graph representation of real battery SOH with high C- rate

The figure depicts the real state of health conditions of the battery under test. The battery is made to get charged and discharged short time intervals. The c- rate affects the battery SOH over the course of time which degrading slowing as inferred from the graph shown in figure 14.

a) Unscented Kalman Filter Prediction

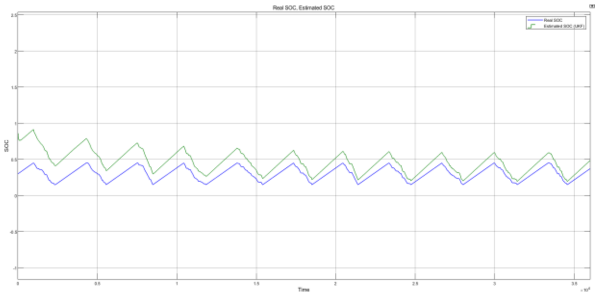

Figure15. Comparative graph of real SOC and estimated SOC with high c rate

The graph 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 shown in figure15. There is a different in the value of SOC in the real state of battery and that estimated by UKF. The root mean square error found is 0.2200.

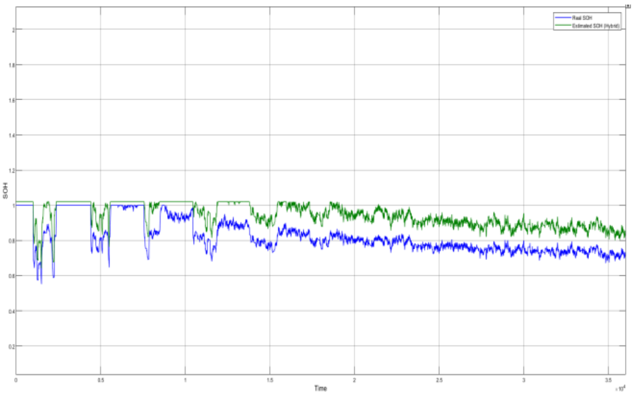

Figure 16. Comparative graph of real SOH and estimated SOH with high c rate

The graph 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 as shown in figure 16. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root mean square error found is 0.1299.

c) Proposed Hybridized Kalman filter with Recurrent Neural Networks (HKF)

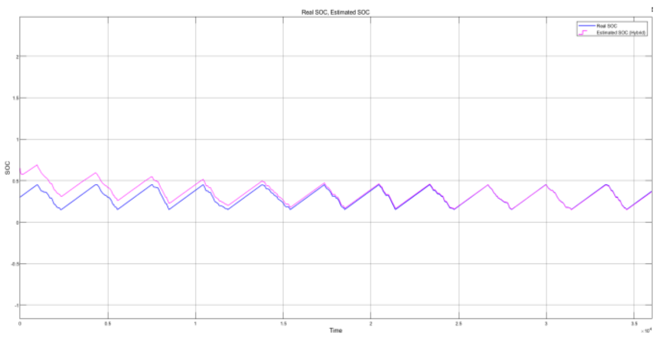

Figure 17.Comparative graph of real SOC and estimated SOC with high c rate

The graph 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 as shown in figure 17. There is a different in the value of SOC in the real state of battery and that estimated by HKF. The root mean square error found is 0.1223.

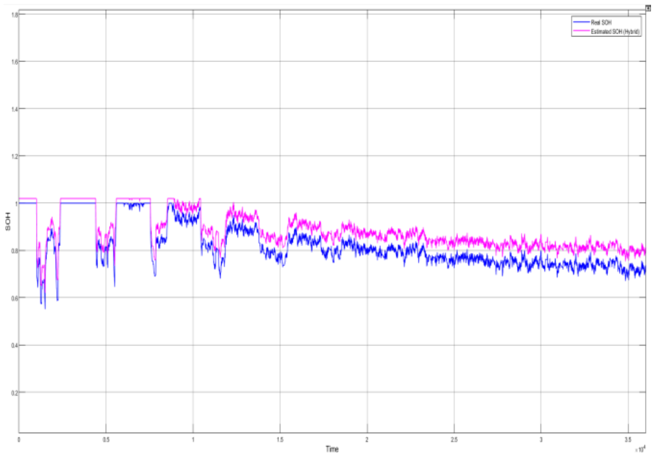

Figure 18.Comparative graph of real SOH and estimated SOH with high c rate

The graph 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 as shown in figure 18. There is a different in the value of SOH in the real state of battery and that estimated by HKF. The root mean square error found is 0.0646.

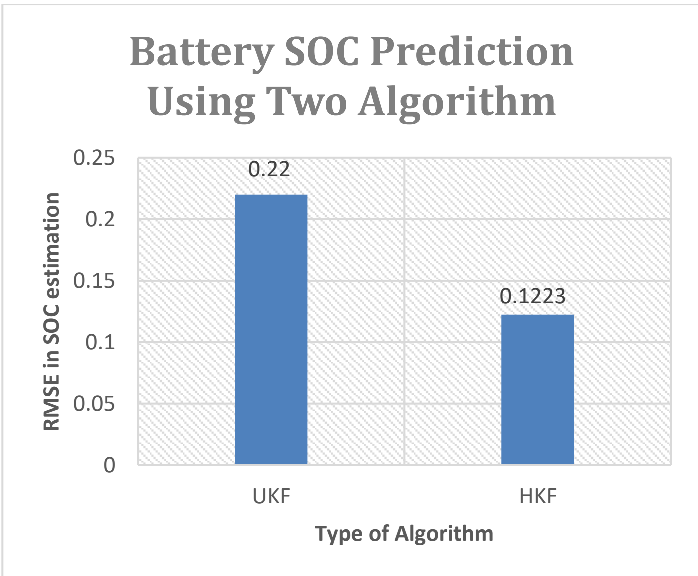

Figure 19.Comparison of RMSE in prediction of SOC by two algorithms with fast c rate

Figure 19 compares the performance of the Unscented Kalman Filter and the Hybrid Kalman Filter in State of Charge prediction, measured using the root mean square error in SOC estimation. In this case, the UKF comes aorta an RMSE of 0.22. It goes without saying that the UKF will predict the state of charge for the said battery with a higher estimation error. The HKF's root mean square error value goes as low as 0.1223 at its bar, which indicates far fewer estimation errors compared to the UKF. This clearly depicts a better performance by the Hybrid Kalman Filter in predicting the SOC than the Unscented Kalman Filter. This comparatively lower value in RMSE indicates that HKF provides a more accurate SOC estimate, and hence this could be very important to apply for effective battery management.

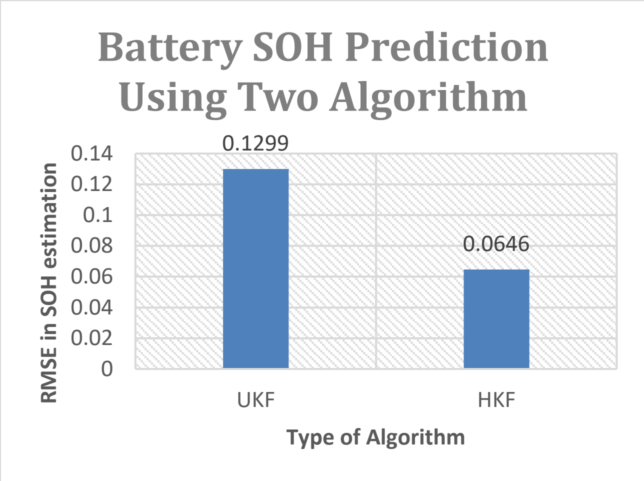

Figure 20.Comparison of RMSE in prediction of SOH by two algorithms with fast c rate

Figure 20 Performance comparison of Unscented Kalman Filter and Hybrid Kalman Filter on predicting the SOH of a battery by means of Root Mean Square Error in fast C rate conditions. The UKF is represented as a blue bar, for which the RMSE is 0.1299. An increased RMSE means that the UKF has a rather bigger error in SOH estimation. The RMSE bar for HKF shows as low as 0.0646. This indicates that the HKF realizes a much smaller prediction error compared to the UKF.

V. CONCLUSION

Making the switch to sustainable transportation solutions is essential in response to the urgent global issues brought on by resource constraint, climate change, and environmental degradation. Considering the developments in Lithium Ion Battery technology, electrification and hybridization of vehicle powertrains have become some of the important strategies. With their high specific energy and power density, electric vehicles and hybrid electric vehicles are becoming increasingly common only because of LIBs. The long-term viability and efficient operation of LIBs, therefore, depend largely on the accurate monitoring of their State of Health. It is the key identifier of a battery's performance and deterioration, and so SOH will impact operating longevity and dependability. This work has reviewed various SOH estimators, with attention paid to the model-based approaches using Kalman filters and hybrid approaches involving machine learning techniques such as recurrent neural networks. The study can reveal that exogenous factors have an impact on aging and performance decay of batteries, including changes in temperature and charging rates. These simulation results suggest the proposed hybrid approach can provide better SOH estimation accuracy than more traditional methods such as UKF. The hybrid algorithm improves predictive skills and optimizes battery management strategies critical in sustainable transportation systems through advanced modeling and data-driven methodologies. Lastly, the paper adds to the continuing discourse on alternative and sustainable energy by providing insights into practical battery management techniques. It contributes to the long-term goal of building cleaner, more efficient transportation systems that would have fewer negative impacts on the climate and promote global sustainability targets through the development of SOH estimating approaches.

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

REFERENCES

[1] Yang, F., Xu, Y., Su, L., Yang, Z., Feng, Y., Zhang, C., & Shao, T. (2024). State of charge and state of health estimation of lithium-ion battery packs with inconsistent internal parameters using dual extended Kalman filter. Journal of Electrochemical Energy Conversion and Storage, 21(1), 011004.

[2] Fahmy, H. M., Hasanien, H. M., Alsaleh, I., Ji, H., & Alassaf, A. (2024). State of health estimation of lithium-ion battery using dual adaptive unscented Kalman filter and Coulomb counting approach. Journal of Energy Storage, 88, 111557.

[3] Wang, C., Su, Y., Ye, J., Xu, P., Xu, E., & Ouyang, T. (2024). Enhanced state-of-charge and state-of-health estimation of lithium-ion battery incorporating machine learning and swarm intelligence algorithm. Journal of Energy Storage, 83, 110755.

[4] Li, D., Zhimao, M., Mingsheng, C., & Jin, D. (2021). Influence factors and identification of state-of-health for traction battery. In IOP Conference Series: Materials Science and Engineering (Vol. 1043, No. 5, p. 052037). IOP Publishing.

[5] Bhangu B S, Bentley P and Stone D A 2005 IEEE Trans. Veh.Technol. 54 783–94.

[6] Jiayi T 2016 Science and Technology Outlook. 26 267–8.

[7] Weng, C., Sun, J., & Peng, H. (2014). A unified open-circuit-voltage model of lithium-ion batteries for state-of-charge estimation and state-of-health monitoring. Journal of power Sources, 258, 228-237.

[8] N. Xue, "Design and optimization of Li-ion batteries for electric-vehicle applications", 2014.

[9] A. Hamidi, L. Weber and A. Nasiri, "EV charging station integrating renewable energy and second-life battery", Proc. Int. Conf. Renew. Energy Res. Appl. (ICRERA), pp. 1217-1221, Oct. 2013.

[10] R. R. Kumar, C. Bharatiraja, K. Udhayakumar, S. Devakirubakaran, K. S. Sekar and L. Mihet-Popa, "Advances in Batteries, Battery Modeling, Battery Management System, Battery Thermal Management, SOC, SOH, and Charge/Discharge Characteristics in EV Applications," in IEEE Access, vol. 11, pp. 105761-105809, 2023, doi: 10.1109/ACCESS.2023.3318121.

[11] Park, J.; Lee, M.; Kim, G.; Park, S.; Kim, J. Integrated Approach Based on Dual Extended Kalman Filter and Multivariate Autoregressive Model for Predicting Battery Capacity Using Health Indicator and SOC/SOH. Energies 2020, 13, 2138. https://doi.org/10.3390/en13092138

[12] Yang, F., Xu, Y., Su, L., Yang, Z., Feng, Y., Zhang, C., & Shao, T. (2024). State of charge and state of health estimation of lithium-ion battery packs with inconsistent internal parameters using dual extended Kalman filter. Journal of Electrochemical Energy Conversion and Storage, 21(1), 011004.

[13] Fahmy, H. M., Hasanien, H. M., Alsaleh, I., Ji, H., & Alassaf, A. (2024). State of health estimation of lithium-ion battery using dual adaptive unscented Kalman filter and Coulomb counting approach. Journal of Energy Storage, 88, 111557.

[14] Wang, C., Su, Y., Ye, J., Xu, P., Xu, E., & Ouyang, T. (2024). Enhanced state-of-charge and state-of-health estimation of lithium-ion battery incorporating machine learning and swarm intelligence algorithm. Journal of Energy Storage, 83, 110755.

[15] Li, D., Zhimao, M., Mingsheng, C., & Jin, D. (2021). Influence factors and identification of state-of-health for traction battery. In IOP Conference Series: Materials Science and Engineering (Vol. 1043, No. 5, p. 052037). IOP Publishing.

[16] de Castro, R., Moura, S., Esteves, R., & Corzine, K. (2024). Guest Editorial Introduction to the Special Section on Next Generation Zero-Emission Vehicles. IEEE Transactions on Vehicular Technology, 73(4), 4526-4529.

[17] Camboim, M. M., & Giesbrecht, M. (2024). Online state of health estimation of lithium-ion batteries through subspace system identification methods. Journal of Energy Storage, 85, 111091.