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TOPICAL REVIEW

Data-Driven Approaches for Estimation of EV Battery SoC and SoH: A Review

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ABSTRACT Electric vehicle (EV) technologies have marked a staunch foundation in the transportation industry. The precise assessment of State of Charge (SoC) as well as State of Health (SoH) is essential for problems like range anxiety and unanticipated breakdown in EVs. In that regard, we have examined various methodologies, including traditional methods like Coulomb Counting (CC) and Open Circuit Voltage (OCV), advanced filter-based approaches, and contemporary data-driven methods. An extensive evaluation of different methods, along with the identification of strengths and weaknesses, is discussed. Data-driven estimation using Machine learning algorithms demonstrates superior accuracy and adaptability in sophisticated battery management systems. External battery parameters such as voltage, current, time, and temperature (V.C.T.T) and internal battery parameters such as impedance and ultrasonic data are the principal constituents of the Data-driven approaches. In this study, machine learning algorithms exhibited substantial enhancements in predicting and maintaining the lifespan of electric vehicle batteries. Nevertheless, there remains a requirement for ongoing advancement in battery systems to up-hold environmentally friendly transportation and incorporate pioneering estimation techniques to improve the reliability and lifespan of batteries.

INDEX TERMS SoC, SoH, machine learning, batteries, EVs, electrochemical impedance spectroscopy, data-driven models.

I. INTRODUCTION

Modernization and globalization of the transportation industry have led to a humongous transformation in the automobile industry, and electric vehicles (EVs) hold a major contribution in this transformation. Globally, greener and more sustainable mobility solutions are prioritized, making EVs at the forefront of this revolution [1]. Performance and longevity are crucial for any modern vehicle to satisfy demands from a spectrum of customer expectations. State of Charge (SoC) and State of Health (SoH) estimation has garnered significant interest from both industry and academia worldwide. These critical parameters determine the efficiency, driving range, and overall viability of EV batteries, making their accurate assessment essential [2]. Keen observation of SoC and SoH not only impacts the day-to-day operation of EVs but also influences long-term decisions such as battery replacement and maintenance. Moreover, these metrics are fundamental to optimizing battery usage, enhancing vehicle performance, and ensuring the economic and environmental sustainability of electric mobility.

Understanding SoC and SoH is essential due to the evolving nature of electric vehicles and their battery technologies. On the one hand, SoC indicates the current charge level

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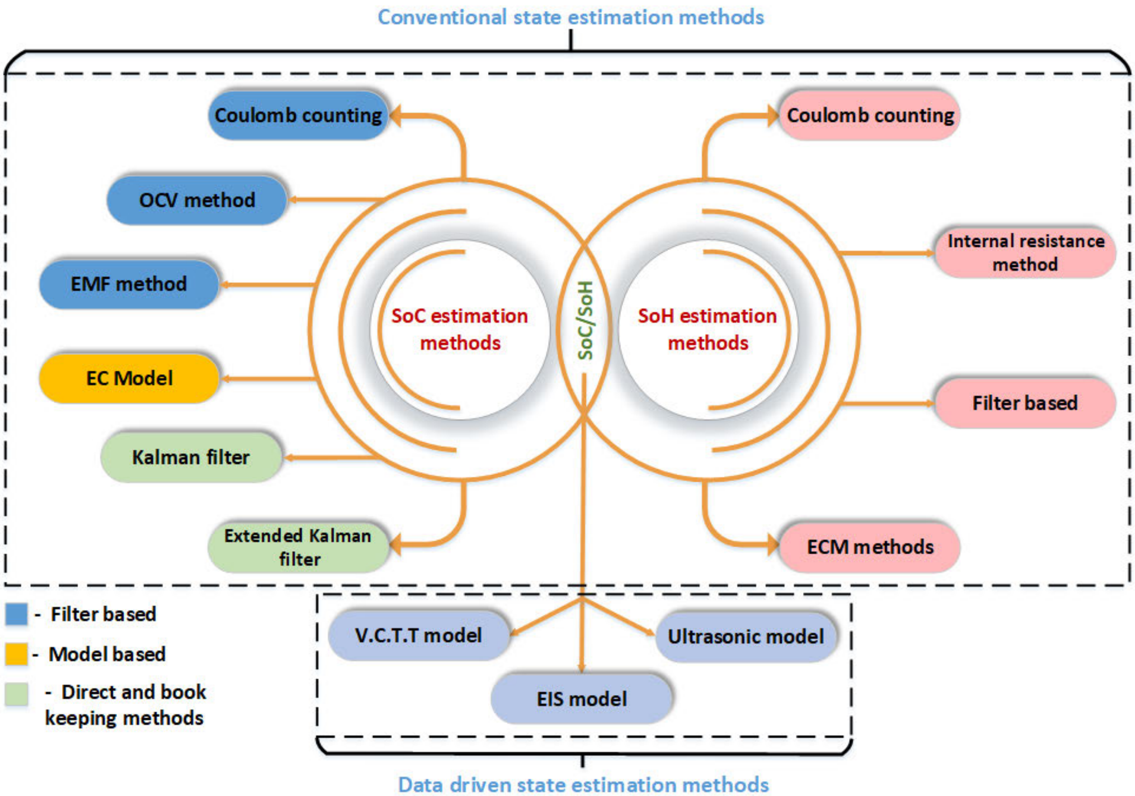

FIGURE 1. Conventional and recent battery state estimation methods.

of an EV battery, affecting driving range and charging behavior, which are crucial for consumers and manufacturers. Conversely, SoH determines the battery's long-term health, influencing the economic sustainability and lifespan of EVs. Ensuring dependability and competitiveness in the market requires an accurate estimate of these parameters [3]. The improvement of SoC and SoH estimate techniques is consistent with the advent of electric vehicles (EVs). Conventional procedures reliant on voltage measurements have progressed into sophisticated approaches utilizing data-driven technologies, as demonstrated in Fig. 1. However, this evolution faces challenges due to the unique demands of electric mobility, such as dynamic driving conditions, fast-charging stress, and temperature fluctuations, which require specialized approaches to battery management [4].

SoC is a key indicator of the available battery capacity for EV users, analogous to a fuel gauge in traditional automobiles. It is crucial for making informed decisions about recharging schedules and assessing travel ranges. Precise State of Charge assessment is vital for increasing battery utilization, averting premature depletion and overcharging, hence prolonging battery lifespan. Real-time SoC information allows EV drivers to plan journeys more efficiently, promoting organized energy use and reducing the risk of unexpected power loss. Monitoring SoC is thus vital for enhancing the reliability and user experience of electric vehicles [5]. SoH measures the overall status and residual capacity of an electric vehicle's battery pack, serving as an essential indicator of the battery as it deteriorates. Regular SoH monitoring tracks battery degradation, aging, and performance, providing essential data for predicting lifespan and making informed decisions about maintenance, repairs, or replacement. Effective management of SoH is crucial for the sustainability of electric vehicles, ensuring long-term reliability and minimizing environmental impact [6]. Fig. 3 illustrates the SoC and SoH concept: if 30% of battery health is degraded, only 70% remains useful even if we fully charge it. On the other hand, with 80% of the battery charged, the SoC is 80% [7].

A. MOTIVATION AND CONTRIBUTION

This paper embarks on a comprehensive review journey, exploring the multifaceted landscape of SoC and SoH estimations within the context of electric vehicles. We can briefly summarise the aim of this study in the following points:

- Comparison of recent data-driven studies aiming to predict SoC and SoH of batteries.
- Efficient range prediction of EVs.
- Safe and continuously monitored operation of batteries.
- Fault detection by analyzing data using machine learning techniques.
- Battery service alert by estimating the EoL of a battery.

- Extended battery health using accurate methods for predicting SoH.
- Comparative analysis of all the promising methods of state estimation.
- Exploratory data analysis of battery data for better accuracy in predicting EoL.

B. ORGANIZATION OF THE PAPER

This survey is further structured as shown in the Fig. 2. After a brief introduction in Section I, Section II discusses methods for estimating the SoC, which includes direct measurement, equivalent circuit models, and filter methods. In Section III, the paper outlines various methods for estimating the state of SoH of EV batteries, such as Coulomb counting, internal resistance, and filtering techniques. Then, Section IV examines data-driven estimation approaches that incorporate advanced machine learning techniques and the integration of IoT in battery systems. Section V addresses challenges in the implementation of these estimation methods in the real world.

Section VI presents a comparative analysis of recent state-of-the-art methods. A novel approach proposed to improve battery estimation techniques is discussed in Section VII. Section VIII explores future research directions and potential developments in the field. Finally, the paper concludes in Section IX, summarizing key points and findings from each section.

II. STATE OF CHARGE (SOC) ESTIMATION

The most significant battery management system parameter is SoC, providing insights into the remaining energy in a battery. A precise SoC calculation is essential in ensuring the efficient and secure operation of EVs since it assists in minimizing deep draining or overcharging, which can significantly shorten battery life and efficiency [4]. Multiple approaches have been devised for SoC estimation, each having its benefits as well as challenges. The techniques involved can be roughly categorized based on data, models, filters, and direct measurement/book-keeping methods summarized in subsections A, B, and C. To estimate SoC, direct measurement methods that integrate the current over time include the Coulomb counting approach [8]. The Equivalent Circuit Model (ECM), which is a model-based method, utilizes an electrical circuit analogous to represent battery behavior [9]. Filter-based methods use the Kalman filter and its derivatives for SoC estimation [10]. Data-driven approaches utilize machine learning and other modern computational techniques for predicting SoC using real-time and historical data. [11]. Combining these methods can lead to more robust and accurate SoC estimation. In one instance, hybrid models that incorporate Coulomb counting, neural networks, and Kalman filters have demonstrated promising results in resolving the limitations of individual methods [12]. This section explores various SoC estimation techniques, highlighting their principle, application, and advancement in the field. SoC in terms of classical estimations can be classified as shown in Fig. 4, and the details of each method are discussed in the following subsections.

A. METHOD OF DIRECT MEASUREMENT AND BOOK-KEEPING

1) COULOMB COUNTING

This technique estimates a battery's SoC by integrating the current flowing in and out over time. It tracks the quantity of charge added while charging and dropped during discharging, starting from a known initial SoC [13]. Accuracy depends on precise current measurements and initial SoC knowledge denoted as

$$SoC(t) = SoC(t_0) + \int_{t_0}^{t} \frac{\eta I(\tau) d\tau}{Q_n}, \tag{1}$$

t is the time at which we want to calculate the SoC, t_o is the time when the initial SoC was noted. Q_n is the nominal battery capacity [4]. For the sake of convenience, we can consider η, the coulombic efficiency, as a unit value. It is described as the ratio of the charge that was delivered during discharge to the charge that was stored during the last recharge. In order to calculate the percentage, $SoC(t)$ is multiplied with 100% to get $SoC_{\%}(t)$ [14]. This approach is relatively simple to use and can be implemented for both offline and online cases, as the current can be easily calculated. However, it faces issues such as the prediction of the initial SoC and noise accumulation over time. Eqn. 1 shows that SoC prediction depends on the initial SoC; therefore, an incorrect initial value can lead to significant errors in the predicted value. Numerous approaches have been put out to deal with these problems. For example, in [12], the Coulomb counting approach's initial SoC estimate problem is improved by a method that predicts SoC errors and regularly resets the SoC during vehicle stopovers, including at traffic lights, to increase accuracy. The basis for modifying the SoC is the OCV versus SoC curve discussed in the next subsection, which helps to improve the accuracy by 2.07%.

In [8], the authors discussed the CC method's noise issue. Any variations in the current or voltage can affect the estimated SoC because it integrates current over time. Thus, the Kalman filter method is a superior strategy, which accounts for noise and is more suitable for real-world EV applications. In [15], authors highlight the use of hybrid models for better results, combining Fuzzy logic [16] with Coulomb counting to compensate for initial value errors and improve accuracy. The system, simulated in Simulink for different initial SoC values, showed improved accuracy. In [17], authors have divided the proposed work into 2 phases: First is the data collection phase at varying load and temperature, and the second is utilizing the Feed-Forward Neural Network (FFNN) in conjunction with CC to estimate the SoC. For the CC method, an estimate was made; however, it was found that the estimated and real values for changes in load and temperature differed significantly. To solve this problem, the FFNN method was used for the estimation, which uses its capability of the hidden layers and thus

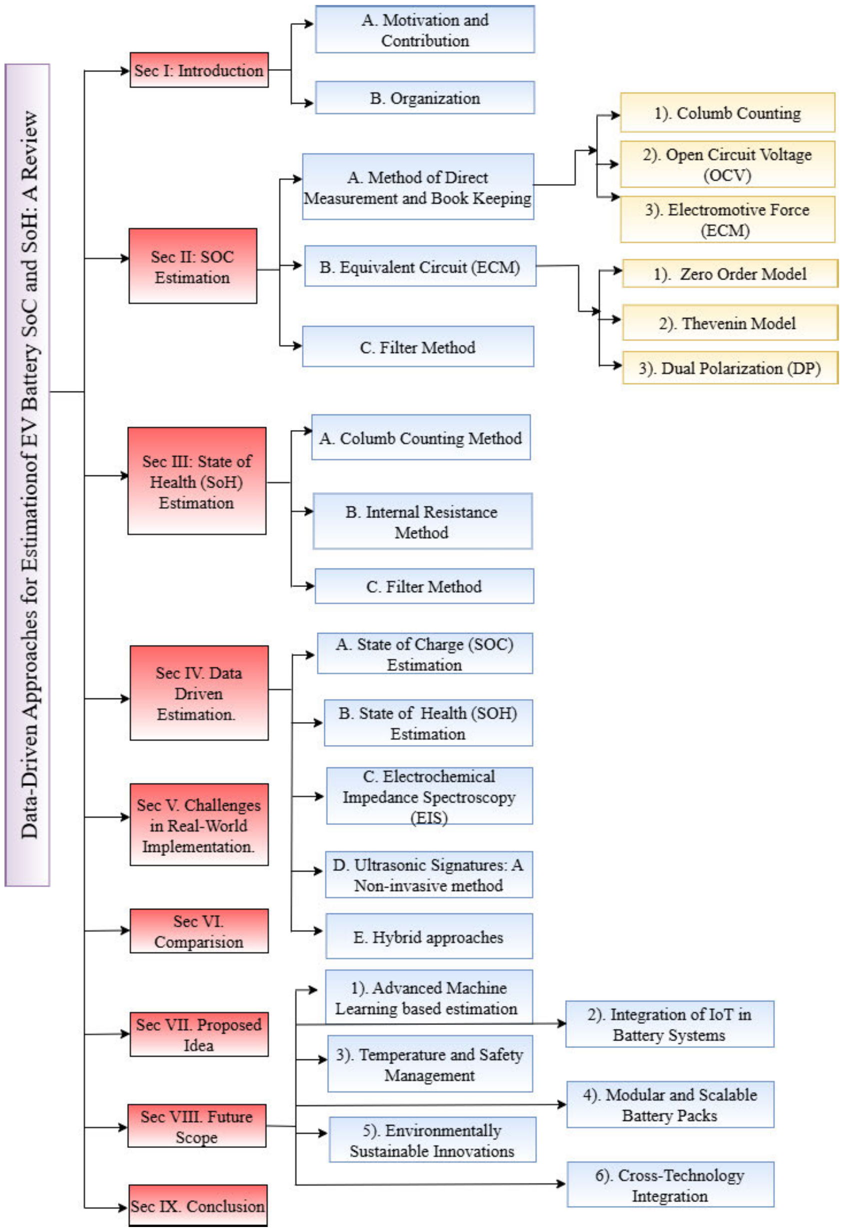

FIGURE 2. Structural organization of the paper.

provides a better result for varying conditions when compared to the CC method.

This method also suffers from some of the problems while calculating the SoC. Self-discharge and the aging effect were not taken into consideration. The enhanced Coulomb counting method considers these aging phenomena and thus gives us a better result as compared to Coulomb counting. As discussed in [18], the uncertainty of the initial SoC is the problem with the simple CC method and it is not considering self-discharge phenomena, aging effects, and temperature variation. To surmount the constraint of the CC method, the enhanced Coulomb counting (ECC) considers these phenomena and thus updates the SoC, which is crucial for light electric vehicles (LEV). Conversely, [19] presents an enhanced Coulomb counting technique for accurate SoC assessment in Li-ion batteries. This novel approach integrates numerical iteration and real-time error correction, significantly reducing the error accumulation inherent in traditional methods by employing a dynamic compensation coefficient and iterative calculation.

2) OPEN CIRCUIT VOLTAGE (OCV)

This is a simple method of mapping one-to-one OCV with the SoC and recording data, in a look-up table [20], based on the terminal voltage. To perform the test for the OCV-SoC curve, a compulsory relaxation time is needed so that the electro-chemical equilibrium is achieved. Usually, the relaxation time is of considerable duration to ensure that

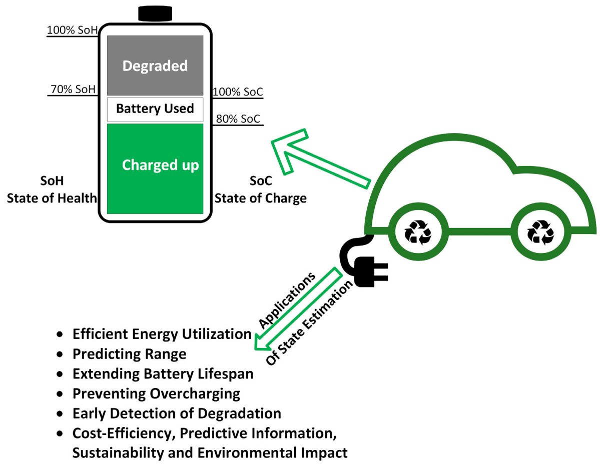

FIGURE 3. Estimation of battery state on EV application.

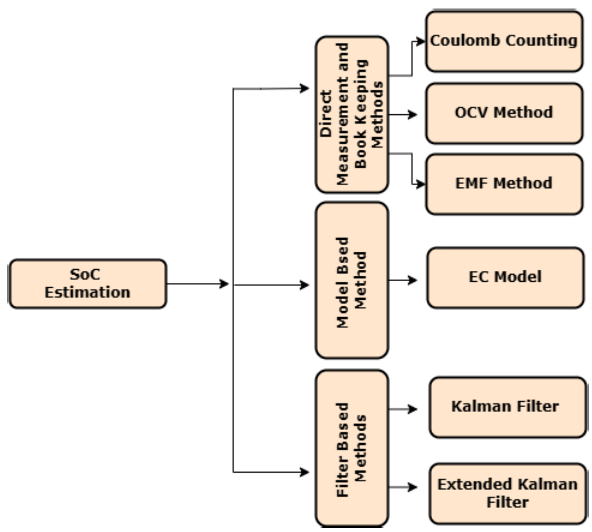

FIGURE 4. Classification of classical SoC estimation methods.

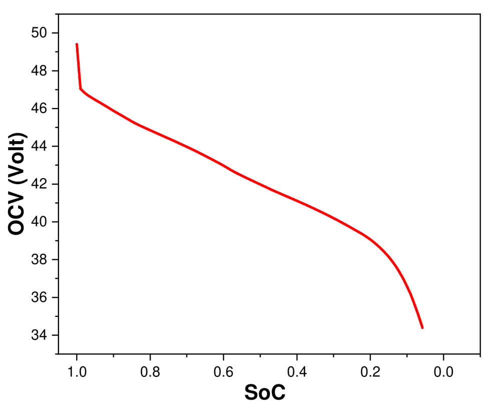

FIGURE 5. Mapping of OCV with SoC.

accurate OCV is achieved, which may then be associated with SoC. Usually, the OCV curve is given by the manufacturer in tabular or graphical form.

In [9], traditionally OCVs are derived through a labor-intensive experimental process that involves subjecting batteries to constant current discharge and allowing for rest periods at set SoC intervals. The OCV vs. SoC curve, as seen in Fig. 5, is plotted using the terminal voltage obtained from this test. However, these curves vary when subjected to different rates, charges, and (current rate) C-rate. To address these issues, the researchers have proposed a method to estimate dynamically the ECM parameters via the Recursive Least Square (RLS) algorithm for better estimation of the OCV [21]. This approach enables the concurrent refinement of the OCV-SoC curve while assessing other ECM parameters [22]. In [23], authors have discussed the problem of the OCV plotting method that needs to go offline to calculate the terminal voltage. We require a general model that works since the link between the OCV and the SoC is distinct and varies depending on the outside temperature and battery age.

An online approach is suggested to determine the relationship using the parameter estimation problem. The mapping is done for the non-linear model that increases as the SoC increases. Additionally, the Kalman filter is incorporated with this algorithm, which enhances the model precision by considering the noise as well. To improve the estimations, the authors of [24] suggested a new method that combined the increasing low current OCV for efficient OCV-SoC mapping. In [25], the authors discussed various models that define the OCV curve. The proposed model by the authors combines exponential functions with polynomial terms to capture the battery's behavior accurately. This model emerged to address the shortcomings related to complexity and real-time implementation.

The OCV reset method operates on the premise of recording the terminal voltage upon cessation of the current flow of the battery, with the assumption that this voltage is in close proximity to OCV [26]. Then, this voltage is used to reset the SoC. Thus, the name 'OCV-reset' came into formation. This reset process allows voltage stabilization, which can be fruitful with frequent stopovers. In [27], the authors state the various problems of the OCV reset method that require long rest time. Moreover, Direct Current Internal Resistance (DCIR) is not appropriate for real-world applications and only functions well with constant current. As a result, the authors proposed integrating the DCIR reset strategy with the enhanced OCV reset method in one algorithm. This method addresses the limitations of the previous methods by reducing required rest time and adapting to dynamic driving patterns.

3) ELECTROMOTIVE FORCE (EMF)

The voltage of a battery acquired when internal chemical equilibrium is reached and no current flows through it is called its EMF and is used to assess the SoC. This differs from the OCV approach, which measures voltage after rest but may include transitory effects [28]. EMF

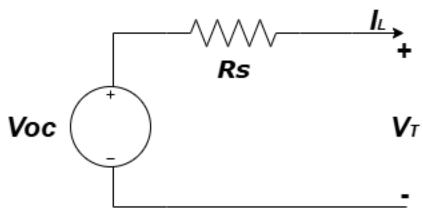

FIGURE 6. Zero order model of battery.

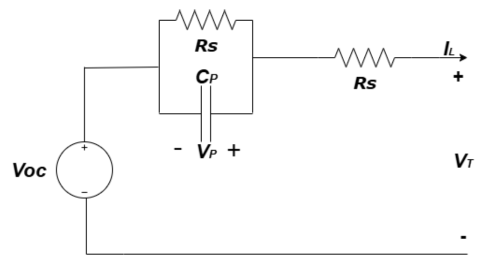

FIGURE 7. Thevenin model of battery.

accurately represents chemical potential without unnecessary influences, thus improving SoC estimation accuracy. In [29], authors discussed that when the Li-ion battery is disconnected from a load it does not settle immediately to the EMF as it relaxes over time. Thus, the authors proposed a method that can predict the EMF more quickly rather than waiting for it to get settled. For quick EMF prediction, the technique uses a nonlinear relaxation model in conjunction with a sequential linear least squares approximation process. The results showed that they perform better and outperform the conventional OCV approach.

In [30], the authors analyzed the characteristics of primary batteries that cannot be recharged and the difficulties in precisely estimating the SoC for these kinds of batteries. The authors focused on the EMF-SoC relation and thus proposed a piece-wise linear fitting approach. The proposed model is advantageous because it does not require the discharge method and load to be consistent, making it versatile for various battery types and conditions. It also eliminates the need for preliminary experiments to measure OCVs, saving time and resources. The authors of [31] presented a technique that divides the voltage curve into linear and hyperbolic sections for accurate analysis, hence predicting the EMF under load conditions. To improve SoC accuracy, the technique uses algorithms that take into account the rate of change in terminal voltage and impedance, especially in the hyperbolic region.

B. EQUIVALENT CIRCUIT MODEL (ECM)

To explain how the battery dynamics behave, lumped elements like a resistor and capacitor are combined. Due to its simplicity, convenience of usage, and low number of parameters to adjust, this method is commonly used in numerous studies. These models generally provide the behavior and not the exact chemical equations, which makes them useful for simulation purposes [32]. For better understanding, these circuit models are categorized further as explained below:

1) ZERO ORDER MODEL OR THE R_{int} MODEL

This is the most basic model, as depicted in Fig. 6, where the load current I_L is positive when charging and vice-versa, and the OCV V_{oc} is connected to a series resistance R_s. This model is not accurate for the calculation of battery state when any dynamic load is applied as it does not represent any transient behavior of the battery [33]. The terminal voltage V_T in Fig. 6 can be written as

$$V_T = V_{oc} - R_s I_L \tag{2}$$

Here, V_T is Terminal voltage, V_{oc} is Open circuit voltage, R_s is Series resistance, and I_L is Load current.

2) THEVENIN MODEL

The Thevenin model is an enhanced version of the R_{int} model, frequently referred to as the first-order model. The polarization resistance R_p and polarization capacitance C_p are the additional resistance and parallel capacitors that are part of it. As illustrated in Fig. 7, V_p represents the voltage across the polarization capacitance. These components are used to characterize the battery's transient behavior during operation [34]. The V_p and V_T can be written as

$$V_p = -\frac{V_p}{R_p C_p} - \frac{I_L}{C_p}, \tag{3}$$

$$V_T = V_{oc} + V_p - R_s I_L. \tag{4}$$

Here, R_p is Polarization resistance, V_p is Voltage across the polarization capacitance, V_{oc} is Open circuit voltage, I_L is Load current, and C_p is Polarization capacitance.

3) DUAL POLARIZATION (DP)

Often, a first-order model cannot adequately represent all of the polarization properties. Therefore, a dual polarization model is necessary, which includes an additional polarized resistor and capacitor. To accurately model the dual polarization of the battery, a combination of two resistors and capacitors is used. The accuracy of the model can be improved by using higher-order models [35]. Nevertheless, the circuit becomes more complex as the number of resistor-capacitor couples rises. Therefore, determining which model to prefer depends on the analysis to be conducted. In [36], authors compared two models, and it was seen that the 2RC model performs better, which consists of two RC networks. Additionally, many parameter estimation techniques were used, including Unscented Kalman Filter (UKF) and Recursive Least Squares (RLS).

In [37], authors used the RLS algorithm and combined it with the EKF for the parameter estimation, and is applied on the Thevenin model for accurate SoC estimation. The model was simulated as well as tested in a chamber at different

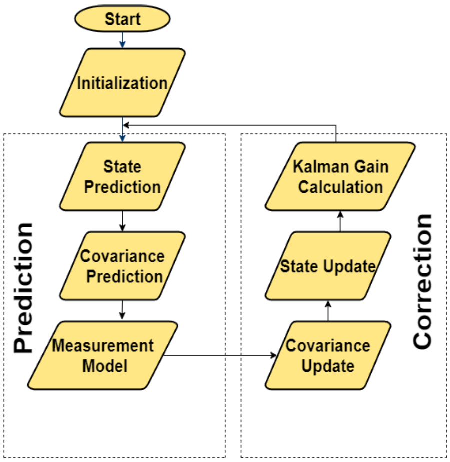

FIGURE 8. Flow Chart of KF method with prediction and correction.

temperatures. The experiment gave correct results only when the initial SoC was known; if not, the deviation may increase. In [38], the authors addressed the necessity of an enhanced ECM model that could predict the battery parameters well and thus help in estimating the SoC. It is seen that the earlier methods fail to calculate the parameters in large discharge current and over potential. The authors in [38] proposed an Extended Kalman Inverse Recursive Least Square (EKIRLS) algorithm, which is very practical and can be used in real-time and is tested on an automotive-grade microcontroller. The model is compared with earlier research such as [39], which uses ARMX as its basis and sequential Monte Carlo filtering (SMCF) for SoC estimate, and [40], which employs second-order EKF and ECM algorithms. In [9], authors discussed the problem faced in the OCV method and proposed a model that estimates the SoC using the RLS algorithm. The ECM parameters are defined, which further guides in estimating and plotting the OCV and OCV-SoC curves, respectively.

C. FILTER METHOD

Accurate SoC determination still remains a complex challenge due to the inherent non-linearity, hysteresis, and variability in battery behavior. To address these challenges, various estimation techniques have been developed, with filtering methods emerging as prominent contributors in achieving robust and reliable SoC estimates. The estimation of SoC is a complex problem that is affected by temperature changes, different discharge and charge rates, and battery aging. Conventional techniques, such as CC and OCV, are not as effective in handling the dynamic and nonlinear features of contemporary energy storage technologies. Consequently, the integration of advanced filtering techniques has become imperative to mitigate the impact of measurement noise, model uncertainties, and dynamic system behavior. Mostly, we can encounter two types of filter: the Kalman Filter (KF) [41] and the other is the Extended Kalman filter (EKF) [42].

KF is utilized in linear dynamic systems where the relation between various variables comes in linear equations. It works on two basic steps, as shown in Fig. 8, first is the prediction step, where the system predicts its next step based on the input and previous state. The prediction is modified depending on the actual measurements in the second stage, known as the state update. On the other hand, EKF is basically used for non-linear dynamic systems. Its key idea is to linearize the non-linear function using Taylor series expansion. Partial derivatives are used in the EKF to linearize the state and measurement models at each time step, producing Jacobian matrices. The nonlinear functions' local linear behavior is captured by these matrices.

The authors of [10] suggested an EKF technique for accurately determining the SoC of Li-ion batteries, which are utilized in EVs. The study addresses the non-linear properties of Li-ion batteries by employing a first-order Thevenin model [43] for battery behavior. The methodology involves parameter identification using the least square algorithm, followed by simulation and real-world testing.

The use of UKF and EKF [44] for accurate Li-ion battery SoC estimation was investigated by the authors in [45]. Utilizing a 1RC battery model [46] and the Levenberg-Marquardt algorithm [47] for parameter optimization, the study compares these advanced non-linear methods against the traditional CC method. The study demonstrates how well UKF and EKF handle the non-linearities of Li-ion batteries, which is important for improving battery management systems in EVs, particularly under varying operational conditions and temperatures. A novel Fuzzy Unscented Kalman Filter (FUKF) technique is put out in [48] to calculate Li-ion battery SoC. Fuzzy logic and the Unscented Kalman Filter (UKF) are used in this method [49] to increase the robustness and accuracy of SoC estimation, especially in unpredictable and dynamic situations. The FUKF method adaptively adjusts the measurement noise covariance using Fuzzy logic, effectively handling the non-linearity and uncertainties present in models of Li-ion batteries.

In [50], the authors introduced a new technique for determining the SoC of Li-ion batteries. A second-order RC equivalent battery model is used to improve the EKF by merging it with the Sage-Husa adaptive filtering algorithm [51]. This method overcomes the shortcomings of current SoC estimate approaches, especially with regard to accuracy and stability in the face of unpredictable and non-linear battery behaviors. Using the recursive least squares method with a forgetting factor for parameter identification is one of the key elements [52] and an improved EKF with a square root algorithm for error covariance decomposition [53].

III. STATE OF HEALTH (SOH) ESTIMATION

SoH is inferred as the capacity degradation of the battery compared to its initial charge-discharge cycle, and it is defined as:

$$SoH = \frac{C_i}{C_1}, \tag{5}$$

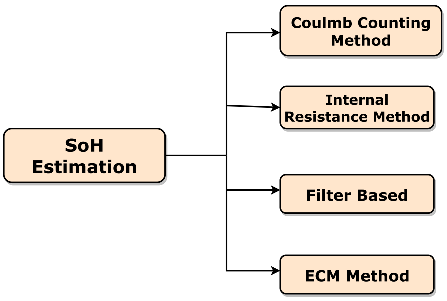

FIGURE 9. Classification of classical SoH estimation methods.

where C_i is capacity at i^{th} cycle and C_1 is capacity measured after 1st cycle by completely charging and discharging operation [6]. It is naturally a ratio of capacities and $SoH_{\%}$ is obtained by multiplying it with 100% [14]. Throughout their lifespan, batteries undergo a gradual degradation procedure that causes internal resistance to rise and capacity to decrease. This degradation is primarily attributed to both chemical as well as mechanical transformations occurring within the electrodes. Calendar and cycle aging are the two primary types of battery degradation [54], [55].

All deterioration mechanisms that are not dependent on charge and discharge cycles are included in calendar aging, relying on factors such as cell SoC, temperature, and elapsed time. On the other hand, cycle aging represents the degradation occurring with each discharge and charge cycle and is contingent on temperature, depth of discharge (DOD) [56], and current. A battery reaches EOL when its performance drops below a predetermined threshold [7]. SoH in terms of classical estimations can be classified as shown in Fig. 9, and the details of each method are discussed in the following subsections.

A. COULOMB COUNTING METHOD

The CC method determines the total electric charge by keeping an eye on the electric current that enters and exits the battery transferred over a cycle by integrating the current over time [57], [58], [59], [60]. Theoretical or nominal capacity is known for a new or healthy battery. The capacity loss or degradation can be assessed by comparing the actual measured charge with the theoretical charge.

In [61], authors proposed an enhanced Coulomb counting (ECC) method that integrates the Coulomb counting (CC) and Open Circuit Voltage (OCV) methods. This integration intends to revise the SoC estimation's initial value, which is a known limitation in the traditional CC. In order to estimate SoH, the method takes into account the change in battery capacity and uses power equations for the battery's input and output network to compute internal resistance.

The authors in [62], addressed the issue of accumulation of error over time in a simple CC method, which in place gives bad estimation for SoH as well. Therefore, to improve this, the authors proposed a new model and used Kalman filtering techniques to reduce these errors accumulated and thus improve the accuracy. To enhance the initial measurement of the SoC, the authors feed the voltage and current data to an Adaptive Extended Kalman Filter (AEKF), and after the Coulomb counting of the SoH measurement, the data is given to the Adaptive Kalman filter (AKF).

B. INTERNAL RESISTANCE METHOD

As a battery undergoes degradation over time, its internal resistance tends to increase. This is caused by a number of issues, including the age of the electrodes, modifications to the electrolyte's composition, and the development of resistive layers inside the battery. The concept shown in [6] depicts that SoH can be determined as:

$$SoH_{\%} = \frac{R_{EOL} - R_{current}}{R_{EOL} - R_{BOL}} \times 100\%, \tag{6}$$

where R_{BOL} is the initial internal resistance of the battery and R_{EOL} represents the internal resistance as the battery ages. Internal resistance $R_{current}$ at the current situation; if it were R_{BOL} at the beginning of life, then SoH would become 100%. which means the battery is fresh and completely unused. If $R_{current}$ is at the end of life, then the SoH becomes 0% that is when the battery is completely degraded.

Another technique for determining the battery SoH was presented by the authors in [63]. Unlike other approaches, this method uses the internal resistance curve to estimate resistance growth and battery capacity fade. Compared to current techniques, which frequently rely on fitted functions, it offers a more reliable and accurate estimation. To determine the link between SoH and Equivalent Internal Resistance (EIR), authors presented experimental research in [64]. It offers a SoH estimate method that utilizes Support Vector Regression (SVR) [65], as well as a fast EIR extraction technique. To improve efficiency, the model uses representative EIRs from a given SoC range as inputs. The method's performance is evaluated using K-fold cross-validation [66], focusing on minimizing the mean error between observed and predicted values. Existing SoH estimation methods in embedded systems generally use a single health indicator, either representing capacity or internal resistance, due to hardware limitations [67]. A unique method for estimating SoH that takes into account both IR growth and capacity degradation was proposed by the authors. The approach involves extracting Health Indicators (HI) from battery datasets, utilizing a Recurrent Neural Network (RNN) [68], and analyzing the correlation between internal resistance growth and capacity fade.

C. FILTER METHOD

The KF is a strong state estimation recursive algorithm in dynamic systems. The key idea is to use the Kalman filter to update and refine the SoH estimate over time based on new measurements. The SoH of batteries for EVs can also be estimated with a unique method described by the authors in [69]. The existing laboratory methods for SoH estimation fail to account for real-world driving conditions like unexpected driver actions, challenging road and weather scenarios. To address this gap, the paper introduces a fusion method that combines the parametric modeling of OCV with an ECM. This method considers the connection between current, temperature, SoC, and OCV variations. The proposed model employs a Kalman filter, specifically an unscented Kalman filter approach [70], for SoH estimation.

D. EQUIVALENT CIRCUIT MODEL (ECM) METHOD

It helps us comprehend the behavior of the different battery parameters more precisely by representing the actual electrochemical battery behavior into the purely electrical model [71], [72]. Typically, these are RC filter circuits, which also indicate the battery's transient behavior. Thevenin or first-order methods are the most often utilized. These models use parameters such as internal resistance, capacity, charging-discharging rate, etc., and assist us in estimating the SoH using these parameters directly. The disadvantage here is that we need to have different circuit models, which does not maintain uniformity in the models.

In [73], the authors studied that most of the papers in the literature on this method were discharge pulse-focused and were using simple loading conditions. This study considers the dynamic conditions under which batteries operate, aiming to provide more realistic SoH estimations. The authors used the standard constant current and constant voltage (CCCV) protocol discharged at a specific rate and tried to construct a relationship between SoH and integrated voltage.

IV. DATA-DRIVEN ESTIMATION

Classical SoC and SoH estimations have progressed a lot in terms of accuracy, computational time, and noise filtering. However, there are limitations to these estimation techniques. In this section, we review modern-day techniques relying on historical or live data to analyze patterns and intelligence hidden inside the data, thus reducing the dependencies and computational time. Moreover, better estimation accuracy is achieved due to cutting-edge deep learning and machine learning models.

A. STATE OF CHARGE (SOC) ESTIMATION

A gradual rise has been seen in methods of SoC estimation over the years. The adaptive systems are the area of focus in the near future, and SoC prediction by self-learning and automatically adjusting the weight of neural networks according to the inputs. The neural networks that use Radial Basis Function (RBF) and Kalman filtering Back Propagation (KFBP) are included in this type of category [11], [74], [75], [76]. A study based on Deep Neural Network (DNN) has proposed a method of SoC estimation for the LiFeO4 batteries in [77]. Usually, it has been observed that the SoC is estimated using OCV, but OCV of LiFeO4 batteries is flat in between and consequently, for these kinds of batteries, the SoC estimation is inaccurate as the initial SoC calculation required for the Ampere-hour (Ah) counting method is not predicted properly and to overcome this problem, DNN is employed to predict the initial SoC thus help Ampere-hour counting approach for better estimation. The proposed DNN uses the current charging voltage as input, and it samples this data using the CCCV approach for ten minutes. Two types of battery are used in this paper namely LFP-20 and LFP-27. For different types of batteries and different aging styles, transfer learning [78] is used where the features are kept the same as a previous DNN, and the SoC can be estimated just by tuning the dense layer rather than creating a new DNN.

B. STATE OF HEALTH (SOH) ESTIMATION

BHUMP-Battery health and uncertainty management system [30] is able to estimate SoH in real-time and also handles uncertainties of the associated algorithm. Domain knowledge-based feature extraction is deployed to extract the 30 most essential features. The pipeline is employed on 179 Li-ion batteries, which takes the three most important designs into consideration -prismatic, pouch, and cylindrical. Lithium Iron Phosphate (LiFePO4) and Lithium Cobalt Oxide (LiCoO2) are two significant cell chemistries that are being researched. Both probabilistic as well as non-probabilistic models are deployed to check their individual performances which include Random Forest (RF), Gaussian process regression (GPR), DNN ensemble (dNNe) and Bayesian ridge regression (BRR) [79] and are evaluated using the calibration score, root mean square error (RMSE) and mean absolute error (MAE) [80].

Non-probabilistic machine learning techniques [81] are also an important elixir of SoH estimation of a battery. Sui et al. [81] have compared non-probabilistic methods. For battery SoH estimation, ensemble learning, k-Nearest Neighbor, Linear Regression, Support Vector Machine (SVM), and ANN are used. In this study, authors have compiled the results from 144 research papers on the basis of five performance evaluation metrics, which include implementation easiness, computational complexity, estimation accuracy, ability to deal with over-fitting, and data size requirement. It is observed that ANN [82] and SVM [83] are research hotspots for battery SoH estimation out of the other five reviewed methods. In a similar study [84] for SoH determination, the authors recommended the fusion of a bidirectional gated recurrent unit (BiGRU) and a 1D-CNN. For SoH estimation, the Bayesian optimization algorithm is used to find the optimal model. However, there are too many trained parameters when compared to a relevant study. In [85], authors have used only discharge voltage data and formed two-dimensional data out of it to train deep learning models. Models were tested for performance using three distinct datasets, taking into account the impact of sliding window and data size (training) for SoH estimation.

C. ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY (EIS)

One more popular and promising non-invasive approach for battery state information is EIS. Until now, EIS has not been extensively utilized for battery diagnosis. A battery forecasting system was created by Zhang et al. [86] by combining the Gaussian Process machine learning model and EIS. Dataset generation as well as evaluation is done for commercially available Lithium Cobalt Oxide (LCO)/Graphite batteries. Approximately 20000 electrochemical impedance spectra are captured for the given batteries at different temperatures, SoC and SoH respectively. The dataset generated is the largest of its kind for EIS. Twelve 45mAh Eunicell LR2032 Lithium-ion coin cells are used in the experimental evaluation, and they are subjected to a constant charge-discharge cycle. Three climate chambers of 25, 35, and 45 degrees Celsius are used for cycling with CCCV protocol. The battery is cycled until the EoL when capacity is below 80 percent. After completely charging, EIS spectra are gathered following a fifteen-minute resting state. In another similar study [87], the authors have used unsupervised Convolutional Auto-encoders (CAE) for the purpose of extracting features as 2D images from EIS data. A deep neural network (DNN) is fed these images to predict SoC and SoH, resulting in the CAE-DNN technique. To investigate the effect of parameters on neural network design, a study involving ablation is also carried out. Adding or removing filters yielded no change in results. On the other hand, increasing kernel size was not also fruitful because of the smaller input size. Reducing the dropout rate to a value of 0.01 leads to a decline in the model's performance.

Traditional EIS approaches take a huge amount of time to obtain battery impedance information [88]. Moreover, it requires precise instruments, which are really expensive. To solve these problems, various approaches are proposed, such as calculations based on time domain signal processing, equivalent circuit model response by Laplace transform, Fourier transform method, impedance employing the Morlet continuous wavelet transform and transient response [89], [90], [91], [92], [93]. However, all methods are complex to calculate and thus Fu et al. [94] have devised a simplified method for impedance calculations employing an enhanced Fast Fourier Transform (FFT) to extract EIS data for every cell in a series setup significantly faster. 25 NCR18650A cylindrical Li-ion cells with good capacity gradient are used for experimentation and later evaluation is done on four other cells connected in series. A break of 3 hours is taken after the battery achieves 100 percent SoC to clamp it up for perfect EIS calculations as it achieves a stable internal state after this rest period. EIS feature/Health factor (HF) is of six types ranging from health factor 1 (HF1) to health factor 6 (HF6) and all are based on peak values and EIS spectra's amplitude. For 25 training cycles, the leave-one-out cross-validation approach [88] is employed. The SoH estimation error based on ELM is fairly reasonable, not surpassing 2 %. An improved Fourier transform approach that utilizes the Fourier transform's conjugate property and the relationship between the decomposition of real and complex signals reduces the computing cost of the signal spectrum. The model is evaluated on 4 other cells connected in series and both capacity as well as SoH estimation errors are below 1.5 % computed in a time frame of 35 seconds.

The battery's remaining life is the keynote pointer for the SoH of any battery. Saha et al. [95] have used particle filters and Relevance Vector Machines (RVMs) for estimating a battery's remaining life as well as for providing uncertainty bounds. SVMs lack the probabilistic capabilities for outputs and thus cannot be used for any type of diagnostic data as per the authors; therefore, they have proposed RVMs because of their Bayesian properties and generalized linear model. Additionally, it uses less number of kernel functions for exactly similar performance. On the other hand, RVM uses probabilistic kernels. It significantly lessens the detrimental effects of outliers and fluctuating data points over time, which can ultimately bias any least squares-based models or techniques. Passivation, sulfation, corrosion, and aging are the processes which alter the electrolyte resistance R_E and the charge transfer resistance R_{CT}. R_{CT} and R_E are very significant for battery SoH. The dataset used in this study is tested at Idaho National Laboratory in which 2nd-gen 18650 Lithium-ion cells are used.

D. ULTRASONIC SIGNATURES: A NON-INVASIVE METHOD

It is a prominent method that uses a non-invasive approach for SoC estimation without worrying about conventional external measurements of voltage, current, and temperature. A completely independent signal that provides rich insights into the internal structure and thus enforces rapid data acquisition [97], [102], [103]. The simplest conceivable setup for this technology is a single piezoelectric transducer combined with a pulser-receiver. The transducer vibrates due to periodic pulses produced by the pulser-receiver, and a mechanical stress wave is transmitted by it through the battery. With a pulser-receiver arrangement, reflections are captured as finite time series waveforms. Pouch cells are best in terms of ultrasonic inspection due to their flat form, which makes them most suitable for testing with flat-head transducers. The dataset used is from an earlier study [104], which uses a 210 mAh commercial graphite pouch cell for ultrasonic setup. CCCV protocol was used for acoustic measurements with cell cycling between 2.75V and 4.2V. Measurements were repeated after every 60s in which the temperature of the cell was observed to range from 24.9 to 29.9 degrees Celsius. A total of 5045 waveform samples are recorded from the setup experimentation. Two hidden layers and a single node output layer and with 100 nodes each were used in a feed-forward neural network (FFNN) [105] to evaluate and train regression models with every possible configuration of data. Frequency domain configuration resultant of Fast Fourier Transform (FFT) yielded a good accuracy of 75 percent for estimating SoC [97]. A reiterating point is that this method is completely voltage and temperature-independent.

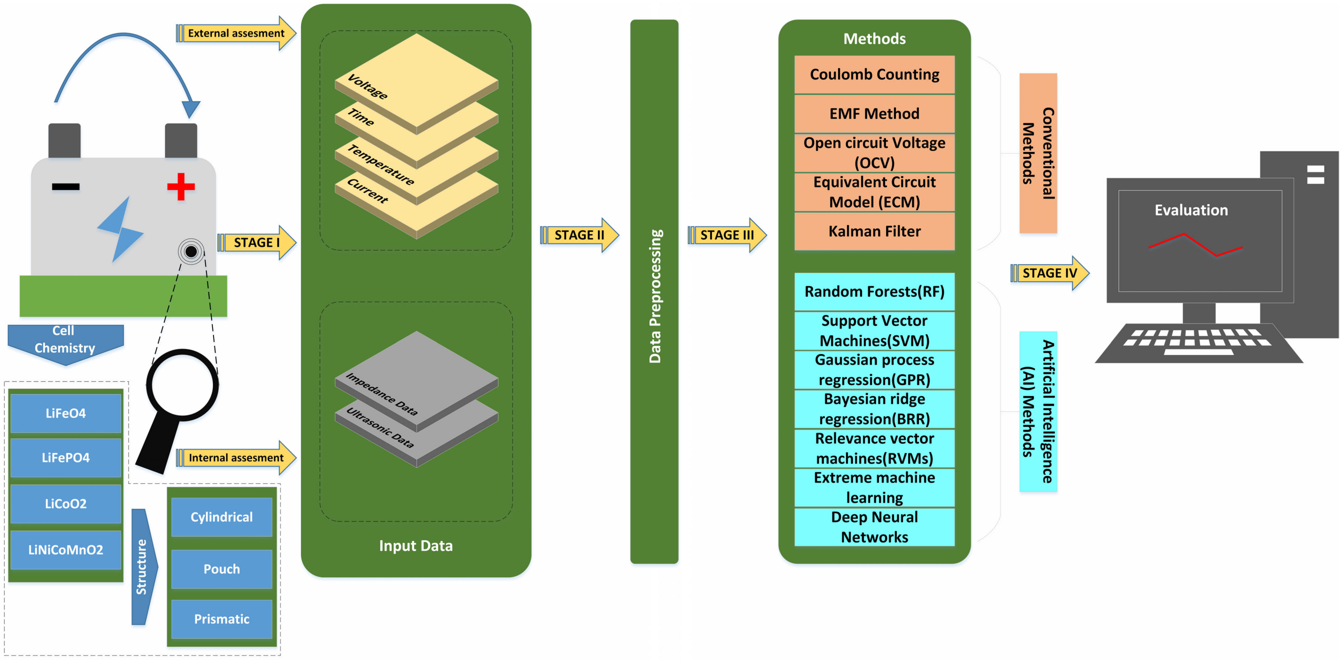

FIGURE 10. **Block diagram of the overall process for evaluation of battery parameters.**

E. HYBRID APPROACHES

Hybrid approaches focus on evaluating SoC as well as SoH under the same study or model. In [98], authors have put forth a versatile strategy built on a CNN, which calculates SoC and SoH utilizing short periods of charging data. The given method neglects feature engineering and has flexibility in terms of input data due to the data collection's reliance on voltage range. The dataset is based on eight 0.74 Ah batteries, and the model is validated on three datasets measuring battery degradation that represent various battery chemistries and operating situations. Assume a '**s**' times cycled battery and charging data that includes temperature, voltage, and current. An attempt to map such pieces of charging data to desired states of interest, i.e., SoC and SoH is achieved using CNN [106]. The global average pooling layer, activation function, batch normalization layer, and 1-D convolutional layer make up the proposed CNN model. Before the input is transformed into an appropriate distribution, the batch normalization layer normalizes it. Non-linearity is considered by using the ReLU activation function that increases the network capacity [107]. Reduced over-fitting risk is achieved by the global average pooling layer by reducing the dimensions of input data. This study utilizes the Oxford battery degradation dataset [108]. Using an EV driving profile, this dataset repeatedly charges and discharges eight commercial batteries in order to simulate battery degradation in EVs. All experimental tests were done in a 40 degree thermal chamber. The model is trained with the first six batteries, and its evaluation is done with the remaining two batteries. RMSE in terms of mAh is selected to determine model performance. 12.16 mAh, which accounts for 1.64 percent for maximum capacity (SoH), and 9.91 mAh, which accounts for 1.34 percent for remaining capacity errors, are reported, which are very nominal in terms of percentage.

V. CHALLENGES IN REAL-WORLD IMPLEMENTATION

In the above subsections, we explored various methods that can be deployed to estimate the SoC and SoH for efficient and safe battery operation inside electric vehicles. Classical SoC and SoH estimations are the foundation for determining state and paving a path towards more advanced techniques. Coulomb counting is very simple and straightforward to deploy but can lead to accumulation errors in current measurements, has a strict initial SoC requirement, limited SoH estimation accuracy during dynamic operation, and battery aging and capacity variations due to external conditions can lead to inaccuracies [109]. In [110], authors have discussed many model-based methods and have drawn various outcomes for challenges faced in OCV because it necessitates the rest period with no load and exhibits hysteresis effects, which can lead to complicating the State estimations. To accurately model the EMF requires a deeper understanding of the battery's electrochemical properties and can be complex for different environmental conditions, calibration, and battery conditions [111]. On the other hand, factors like temperature and aging can pose challenges for accurate modeling [112]. While modeling in the ECM method, real-time parameter identification is crucial under different operating conditions, such as temperature and aging. Moreover, computational complexity can increase with higher-order models, and the method is limited to specific battery chemistries [38], [113]. Kalman filters offer an optimal estimation with effective noise reduction, but there is a strict dependency on accurate covariance matrix values, sensitivity to initial conditions, and model inaccuracies

TABLE 1. Comparison of recent data-driven estimation methods.

Reference	Year	Cell-type	Data-type	Dataset	Estimation covered	Models used	Error
J. Tian et al. [77]	2021	LiFeO4	Current and Voltage	Proprietary	SoC	DNN with Kalman filter	2.03 %
D. Roman et al. [30]	2021	LiFePO4/ LiCoO2	Multiple features from the respective datasets	CALCE, NASA, TRI, Oxford	SoH	Random Forest (RF) Gaussian Process Regression (GPR) Bayesian Ridge Regression (BRR) Deep Neural Network ensemble (dNNe)	RF- 0.97% RMSPE dNNe- 0.45% RMSPE
Y. Zhang et al. [86]	2020	LiCoO2/ graphite	EIS data	Proprietary	RUL, SoC	Gaussian Process Regression (GPR)	R2(Coefficient of determination) - 0.88 for SoC R2- 0.96 for RUL
Y. Fu et al. [94]	2022	NCR18650A Li-ion	EIS data	Proprietary	SoH	Extreme Machine Learning	1.5 %
D. Zhou et al. [96]	2020	LiNiCoMnO2	Volatge	CALCE, NASA	SoH	Convolutional Neural Network (CNN)	RMSE-2% MAE-1%
B. Saha et al. [95]	2009	18650-2nd gen	EIS data	Idaho National Laboratory	RUL	Relevance Vector Machines (RVMs) Particle filters	NA (RUL pdfs estimation and fitting)
E. Galiounas et al. [97]	2022	LiCoO2/ graphite pouch cell	Ultrasonic signatures	Proprietary	SoC	Feed Forward Neural Network (FFNN)	0.75%-MAE
J. Tian et al. [98]	2022	LiCoO2	Multiple features from the respective dataset	Oxford, NASA	SoC SoH	Random Forest (RF) SVR Gaussian Progress Regression (GPR) MLP EN	RMSE of max capacity (LR1865SZ) - 38.04mAh RMSE of max capacity (NASA) -72.10mAh RMSE of remaining capacity (LR1865Z) - 38.27mAh RMSE of remaining capacity (NASA) -57.78mAh
Z. Chen et al. [99]	2018	LiNiCoMnO2	Voltage, time and current	NASA	SoH	SVM	RMSE∼ 0.5% MAE∼ 1%
J. Obregon et al. [87]	2023	LiCoO2/graphite	2D Images from EIS Data	Zenodo	SoH	Convolutional Autoencoder - Deep Neural Networks (CAE-DNN)	35°C RMSE- 0.0129% MAPE- 0.0128% $R^2 - 0.9657\%$ 40°C RMSE- 0.0112% MAPE- 0.0118% $R^2 - 0.9723\%$
Y. Mazzi et al. [84]	2024	18650 NCA cell	Voltage, temperature and current	NASA	SoH	CNN-BiGRU	MAE- 2.080% RMSE-2.516%
V. Safavi et al. [85]	2024	18650 NCA cell	Voltage	NASA	SoH	CNN-LSTM	RMSE- Case 1: 0.007% RMSE- Case 2: 0.008% RMSE- Case 3: 0.008%
C. Wang et al. [100]	2024	LiNiCoMnO2	Voltage, temprature and current	NASA	SoC SoH	GPR with Firefly Algorithm	RMSE- SoC: 0.16% RMSE- SoH: 0.92%
B. Dou et al. [101]	2024	18650 NCA cell	Voltage, temprature and current	Oxford	SoC SoH	Multi-timescale dual features-based network (MFN)	RMSE∼ 1.31%

pose another challenge [114]. Internal resistance tracking is challenged by temperature shifts, load variations, and measurement noise [63], [64]. Reliable fitting needs stable conditions and quality data, while aging irregularities and model-specific calibration add complexity [115].

Data-driven estimation is very popular and has a strong hold for getting better accuracy, but data quality and availability are a challenge because it is very difficult to collect data under diverse operating conditions. Also, there is a requirement of large quantity as well to cover every possible driving condition [116]. Moreover, model generalization is very difficult to achieve, as a model trained on a specific dataset may not perform well across all cell chemistries and driving conditions [117]. Finally, advanced algorithms can be computationally hungry, thus restricting real-time applications in battery management systems [118].

TABLE 2. Comparison of traditional SoC and SoH methods.

Method	Advantages	Limitations	Application
Coulomb Counting Method	SoC: 1) Simple and Straightforward 2) Low computational complexity 3) Real-Time Estimation	SoC: 1) Accumulated Error over time. 2) Sensitive to variation in capacity. 3) Requires Accurate Initial SoC.	1) Portable Application 2) Short-term SoC estimation
	SoH: 1) Simple and Non-Intrusive 2) Low computational requirements 3) Provides information about battery health	SoH: 1) Accuracy Affected by changes in battery conditions 2) Limited Accuracy during Dynamic operation 3) Dependency on accurate resistance measurement.	
Enhanced Coulomb Counting	SoC: 1) Improved accuracy through error compensation. 2) Reduced sensitivity to capacity variations. 3) Mitigates Drift issues.	SoC: 1) Require Sensor for correction. 2) Complexity increases 3) Calibration Challenges	1) EV 2) Renewable Energy System 3) Longer term SoC estimation.
	SoH: 1) Improved Accuracy through error compenstation. 2) Reduced sensitivity to cacpity variation. 3) Mitigates Drift issues	SoH: 1) Requires additional sensor. 2) Complexity increases with error correction method 3) Calibration challenges.	
OCV	SoC: 1) Simple and Non-Intusive 2) Applicable to a wide range of batteries. 3) Low computational requirements.	SoC: 1) Affected by termperature variation. 2) Accuracy decreasing during dynamic operation. 3) Limited accuracy during high-rate discharge.	1) Low Power Devices 2) Periodic states estimation 3) Low-computational SoC estimation.
	SoH: 1) Simple and non-intrusive. 2) Applicable to a wide range of batteries 3) Low computational Requirement	SoH: 1) Accuracy affected by changes in battery conditions. 2) Limited accuracy during dynamic operation. 3) Requires calibration.	
EMF	SoC: 1) Non-intrusive and minimal impact on battery. 2) No additional sensor required. 3) Suitable for intermittent measurement	SoC: 1) Sensitive to changes in internal resistance 2) Limited accuracy during rapid discharge 3) May require callibration for accurate results.	1) Remote monitoring. 2) Real Time monitoring
	SoH: 1) Non-intrusive and minimal impact on battery 2) No additional sensor required 3) Provides insights into battery aging.	SoH: 1) Sensitive to changes in internal resistance. 2) Limited accuracy during dynamic operation 3) May require calibration	
Equivalent Circuit Model (ECM)	SoC: 1) Detailed Modelling of Battery Behavior. 2) Can capture complex Electrochemical Phenomena. 3) Suitable for Predicting Long-term Battery Behavior.	SoC: 1) Requires Knowledge of Circuit Parameters 2) Calibration requiredd for accurate results. 3) Limited to Specific battery chemistries.	1) Research and Laboratory studies. 2) Understanding battery Degradation.
	SoH: 1) Detailed modeling of the battery behavior. 2) Can capture complex Electrochemical phenomena 3) Suitable for predicting Long-term Battery behavior.	SoH: 1) Required knowledge of circuit parameter. 2) Calibration required for accurate results 3) Limited to specific battery chemistries	
Kalman Filter (KF)	SoC: 1) Optimal estimation 2) Effective Noise reduction	SoC: 1) Cant model non-linear model. 2) Computational Complexity. 3) Sensitive to Model inaccuracies.	1) EV 2) Dynamic non-linear load
	SoH: 1) Optimal Estimation. 2) Effective Noise Reduction	SoH: 1) Cant handle non-linear model 2) Depends on the quality of the model. 3) Sensitive to initial conditions.	
EKF	SoC: 1) Handles non-linear system dynamics. 2) Adaptable to shifting system circumstances	SoC: 1) Depends on the quality of linearization. 2) System complexity increases.	1) EV 2) Real-time systems
	SoH: 1) Handles Non-linear system. 2) Adaptable to shifting system circumstances	SoH: 1) Depends on the quality of linearization. 2) Complexity of the system increases.	
Internal Resistance	SoC: 1) Simple and non-Intrusive 2) Low computation	SoC: 1) Accuracy affected by changing the battery conditions. 2) Limited accuracy during Dynamic operation. 3) Depends on accurate resistance measurement.	1) State of health estimation 2) Automotive application.
	SoH: 1) Simple and Non-intrusive 2) Provides information about the battery health. 3) Low computational requirement	SoH: 1) Accuracy affected by changing battery conditions. 2) Depends on the accurate resistance measurement.	

EIS provides deeper insights of battery behavior, but it is sensitive to temperature and SoC. Further, it requires expertise, time-intensive and costly equipment, thus limiting real-time use [119], [120]. On the other hand, the Ultrasonic method requires consistent physical contact and is prone to temperature changes and vibrations, which is impractical for EV applications [121], [122]. Lack of standardization for the ultrasonic method leads to inconsistent results and improper validation [123].

VI. COMPARISON

Table 1 demonstrates the recent Data-Driven estimation approaches and indicates the type of battery used in the proposed or cited study, the dataset name, and the inputs used for the training purpose. It also indicates the estimation technique and model or algorithm used for estimation. Lastly, for comparison, the results in terms of percentage error are indicated.

Table 2 evaluates all of the conventional techniques for estimating SoC and SoH found in the literature, outlining each one's benefits, drawbacks, and potential uses. We see that the CC method is simple and straightforward, but the error accumulation turns out to be a big disadvantage in the long run. Therefore, an enhanced Coulomb counting method reduces this accumulation problem to some extent. OCV method directly compares and needs just a lookup table but this method doesn't take into account the other variations like temperature and dynamic nature of the load. ECM method captures the parameters of the complex circuit easily, which makes it easy to estimate the SoC or SoH. The disadvantage is that we need different equivalent models for different types of batteries, which is not convenient. KF is a commonly used method that reduces the noises, but it is a complex model and requires good computational power; extended KF is an extension of the KF, which linearizes the non-linear parameters. The most common method for estimating

FIGURE 11. Discharge plot of 'battery 5' of NASA battery degradation dataset.

SoH is internal resistance; as batteries age, their internal resistance rises, making internal resistance a valuable source of information. Fig. 10 provides the overall architecture of the steps and methods involved during SoC and SoH estimation.

VII. PROPOSED IDEA

In the current scenario of emerging EV technologies and the evolution of battery management systems, the longevity of battery health, as well as the prediction of SoH and EoL, plays an important role in the EV industry. Our approach, which is based on machine learning, has the ability to predict any battery's EoL based on the temperature, voltage, and current data. We have used the NASA battery degradation dataset [124] to train our model for predicting EoL. We also tested the same trained model on an external dataset generated from LG Li-ion cells at McMaster University [125]. We evaluated our results using popular and classical machine learning approaches, i.e., SVM, RF, Decision Trees, and Logistic Regression, all address ensemble learning strategies in addition to regression. Table 3 provides a comparison of the recent review articles with our approach in which we cover various dimensions of battery state estimation.

Datasets used in our method are based on Li-ion battery degradation cycled at different scenarios. For the NASA battery degradation dataset, it is considered that below 1.4 Ah capacity, the cell has reached EoL, and above that threshold, it is in a Healthy State (HS). EoL and HS correspond to labels '1' and '0', respectively. In other words, if there is a fade in capacity from 2.0 Ah to 1.4 Ah, which sums around 30 percent fade, the battery can be considered as a degraded one. In Fig. 11, we have drawn a plot of 'battery 5' of the NASA battery degradation dataset segregating the healthy and degraded condition of the battery after certain cycles. The orange line in the given diagram denotes the threshold of 1.4 Ah. We have taken 'battery 5' degradation data and initially performed Exploratory Data Analysis (EDA). The original format of the file was. mat, and we converted it into a pandas dataframe using a Python script for easier data interpretation and analysis. There were a total of 50285 records and 10 features, which are listed in Table 3. We performed checks for any null values so that these can be handled as well, followed by hunting for outliers, duplicates, and unique values using established data-handling techniques. After all the above steps, we removed the unnecessary and weakly correlated features from our dataset. As machine learning models can be affected by non-scaled and non-encoded data, we scaled our dataset accordingly. Encoding was not required as all the data was numerical, but categorical data would have needed it necessarily. Finally, we trained our machine learning models with the prepared data after its proper EDA. In the testing phase, the SVM and RF models outperformed the other two with an accuracy of 86 and 85 percent, respectively, and with better precision and recall scores as well. On the other hand, Logistic Regression and Decision Trees gave an accuracy score of around 72 percent and 74 percent, respectively, as given in Table 4. Moreover, we also visualized true positives and negatives (TP-TN) and false positives and negatives (FP-FN) given in Table 5. These provide a deeper insight into how each model performs and are very crucial for evaluating the metrics. We used the better-performing algorithm to evaluate the performance of external data taken from McMaster University (LG) battery dataset [125], and it performed well for this unseen data and gave an accuracy score of 73.85 percent in external evaluation of the trained model.

VIII. FUTURE SCOPE

Advancing EV battery technology will focus on boosting efficiency, safety, and sustainability. Key areas include the use of machine learning for better performance and IoT integration for smarter management. Modular designs and improved cooling systems will also help extend battery life and enhance safety. Combining insights from various fields, future innovations will support greener and more reliable energy solutions with a rich data library generation. The subsections below cover a range of fields that are a future direction for EV battery advancement and management.

A. ADVANCED MACHINE LEARNING BASED ESTIMATION

Machine learning methods are being used to enhance the accuracy of determining the State of Charge (SoC) and State of Health (SoH) for batteries. Future advancements in this field will focus on refining these models to predict battery behavior more accurately under real-world conditions and drive cycles. A promising direction involves hybrid systems that integrate data-driven techniques, electrochemical impedance spectroscopy (EIS), advanced neural networks, and Ultrasonic signatures, thus setting a new benchmark for battery monitoring and data libraries.

B. INTEGRATION OF IOT IN BATTERY SYSTEMS

The application of Internet of Things (IoT) technology in battery systems is set to transform monitoring and

TABLE 3. Comparison of existing review articles with this review based on different functionalities '✓': corresponding issue was addressed in the work, '✗': not addressed.

Reference	Year	Main topics	SoC estimation addressed (Classical & Data-driven)	SoH addressed (Classical & Data-driven)	EIS estimation	Ultrsonic estimation	ML based EoL evaluation	External Validation
[126]	2024	SoC estimation methods, Machine learning methods	✓	✗	✗	✗	✗	✗
[127]	2023	SoC estimation methods, Traditional and data-driven methods, BMS	✓	✓	✓	✗	✗	✗
[128]	2021	SoH estimation methods, Fusion technology methods	✗	✓	✓	✗	✗	✗
[129]	2023	SoH estimation methods, EIS, Neural networks, GPR	✗	✓	✓	✗	✗	✗
[130]	2023	Data driven SoH estimation methods, ML and Deep learning	✗	✓	✗	✗	✗	✗
[110]	2019	Model based approaches, Data-driven approaches	✓	✗	✓	✗	✗	✗
[131]	2024	Direct measurement, Model based, Data-driven and Hybrid methods	✗	✓	✓	✗	✗	✗
[132]	2024	Traditional and data-driven methods, Sliding mode observers (SMOs)	✓	✗	✓	✗	✗	✗
[136]	2021	Traditional and data-driven SoH estimation mthods	✗	✓	✓	✗	✗	✗
[133]	2023	Introduction to SoH and RUL, Data-driven estimation	✗	✓	✗	✗	✗	✗
This review	-	Conventional and Data-driven SoC and SoH estimation, EIS, Ultrasonic signatures, Comparative analysis, Hybrid methods, EoL estimation	✓	✓	✓	✓	✓	✓

TABLE 4. Feature description of NASA battery degradation dataset.

No.	Feature name	Description
1	cycle	holding the charge, discharge and impedance processes
2	ambient_temperature	The outside temperature (degree Celsius)
3	datetime	The cycle's beginning date and time
4	capacity	Battery capacity (Ah)
5	voltage_measured	Voltage at terminals (V)
6	current_measured	Current at output (A)
7	temperature_measured	Measured temperature of battery (C)
8	current_load	Current at load (A)
9	voltage_load	Voltage at load (V)
10	time	Time in seconds for a particular cycle(secs)

management capabilities. IoT-powered power buses will enable real-time data collection, fault detection, and efficient cell balancing [134]. These developments will enhance safety and improve the overall lifespan of batteries.

C. TEMPERATURE AND SAFETY MANAGEMENT

Excessive heat remains one of the leading causes of battery failures. Future designs are expected to feature smart temperature management systems that use automated cooling and dynamic switching to address overheating [135]. Advanced algorithms, particularly Reinforcement Learning, will ensure that overheated cells are promptly isolated and substituted with reserve units, ensuring seamless operation [136].

TABLE 5. Summary of the results for ML algorithms.

Logistic Regression	**precision**	**recall**	**f1-score**	**support**
0 (HS)	0.73	0.96	0.83	9284
1 (EoL)	0.12	0.01	0.02	3288
macro average	0.43	0.49	0.43	12572
weighted average	0.57	0.72	0.62	12572
accuracy	**0.72**			12572
Decision Trees	**precision**	**recall**	**f1-score**	**support**
0 (HS)	0.76	0.96	0.85	9284
1 (EoL)	0.56	0.15	0.23	3288
macro average	0.66	0.55	0.54	12572
weighted average	0.71	0.75	0.69	12572
accuracy	**0.75**			12572
Random Forest	**precision**	**recall**	**f1-score**	**support**
0 (HS)	0.89	0.91	0.90	9284
1 (EoL)	0.74	0.69	0.71	3288
macro average	0.82	0.80	0.81	12572
weighted average	0.85	0.85	0.85	12572
accuracy	**0.85**			12572
SVM	**precision**	**recall**	**f1-score**	**support**
0 (HS)	0.88	0.95	0.91	9284
1 (EoL)	0.81	0.62	0.70	3288
macro average	0.84	0.78	0.80	12572
weighted average	0.86	0.86	0.85	12572
accuracy	**0.86**			12572

TABLE 6. Results of the confusion matrix for different algorithms.

Model	TP	FN	FP	TN
Logistic Regression	8955	3243	329	45
Decision Tree classifier	9284	3287	0	1
Random Forest classifier	8400	1030	794	2258
SVM	8793	1256	491	2032

D. MODULAR AND SCALABLE BATTERY PACKS

The trend towards modular battery pack designs will facilitate scalability, simplify maintenance, and optimize energy use [137]. Future systems will prioritize modular construction to improve load distribution and dynamic energy control, while smart circuits will play a critical role in meeting power requirements.

E. ENVIRONMENTALLY SUSTAINABLE INNOVATIONS

Sustainability will remain a cornerstone of battery technology development. Innovations in recycling processes, extended lifecycle management, and waste reduction will play a vital role in supporting a circular economy [138].

F. CROSS-TECHNOLOGY INTEGRATION

Future battery management systems will integrate insights from various fields, including artificial intelligence, IoT, and materials science. Different cell chemistries should be used to collect data in every possible scenario. Linking state-of-the-art techniques from every domain can result in a rich data library for future experimentation.

IX. CONCLUSION

This study thoroughly investigates various approaches for assessing the SoC and SoH of batteries, constituting a substantial advancement in the domain of EV technology. It is crucial to examine methods, such as CC and OCV, which have laid the foundational principles for battery estimation. On the other hand, filter-based techniques, particularly the Kalman Filter technique, which has shown considerable potential in real-time battery monitoring and estimation, are also explored. Eventually, this study transitions into a critical analysis of more sophisticated, data-driven approaches, highlighting their enhanced accuracy and adaptability in dealing with the complexities of EV battery management. Among the advanced methods discussed, machine learning algorithms emerge as a promising avenue. These algorithms can adapt and learn from data and offer a dynamic approach to estimation, enabling more accurate predictions of SoC and SoH. We underscore the importance of these advancements not only for the technical aspect of battery management but also for their broader implications in the field of sustainable transportation. The evolution of these methods reflects a growing need for reliable and efficient battery systems, which are vital for the widespread adoption of EVs. The study emphasizes that continuous innovation and research in this domain are imperative for addressing the challenges of environmental sustainability and energy efficiency.

In future endeavors, this study will continue to explore the potential research problems that will enable researchers to compare conventional ML techniques proposed in this study with cutting-edge deep learning models for automatic feature extraction and more accurate results. Moreover, we will explore better sensor fusion inside/outside the battery pack to evaluate different parameters precisely and to develop a dataset rich in terms of accuracy. Finally, we can design our own battery pack with a cooling management system in order to detect any temperature hotspots inside a battery pack, followed by a smart switching mechanism in order to avoid any mishap. This can prolong battery health and also help in developing a reliable system that has switching capabilities.

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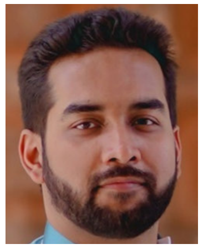

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