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RESEARCH ARTICLE

Secondary Life of Electric Vehicle Batteries: Degradation, State of Health Estimation Using Incremental Capacity Analysis, Applications and Challenges

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ABSTRACT Electric vehicles (EVs) have created a revolution in sustainable transportation. The number of EV users has increased significantly within a short period globally. EVs running largely on the battery source require large-capacity battery packs to handle the range anxiety. The primary lifetime of such batteries in EV applications is said to end when their capacity drops to 80% of their initial capacity. This is termed as the end of-life of these batteries. These batteries can still be utilized for secondary applications based on their remaining capacity. Batteries undergo many degradations throughout their lifecycle which affects their capacity. This paper carries out a detailed study on the major degradation factors like solid electrolyte interphase and lithium plating which results in loss of lithium inventory. These affect the capacity of the battery in the long run. Remaining useful capacity must be accurately estimated to identify if the cells are useful for the next phase or must be recycled. Many estimation techniques are available with attention rising towards data derivational methods due to their accuracy and their sensitivity towards battery degradation which thereby makes it easy to track them. Incremental capacity analysis is one such method which is discussed in detail in this paper. The method starts from the initial stage of data extraction and extends to the training set of the models. This method is greatly beneficial as it can reveal the deviations in battery behavior with the help of the valley peak locations and alterations in the slope. The quantitative insights make it an advantageous technique in the field of battery health monitoring and diagnostics. These are discussed in detail and validated by experimental analysis and results. This paper also discusses the market prospects, developments, various ageing mechanisms in batteries, applications, comparison with other estimation techniques and challenges related to secondary life applications. The complete analysis of the estimation method along with the detailed steps also aims to serve as a foundation for the upcoming developments and research in this field.

INDEX TERMS Electric vehicle, incremental capacity analysis, second life of EV battery, state of health estimation.

I. INTRODUCTION

EVs have created a breakthrough from conventional internal combustion (IC) engines. Multiple sustainable advantages supported by advanced power electronics have helped in the rapid adoption of EVs in the market. Starting at a slow pace, the market has currently reached billions globally and is expected to rise by 40-50% by 2030 [Fig. 1].

Incentives are being provided to users from governments to promote the usage of more EVs [2]. EVs cannot be

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technically termed as pollution-free transportation as they only shift tailpipe emissions to the source side. This can be considered as a sustainable transportation when the source of electricity generation also becomes sustainable. More EVs in the market require higher grid electrification that eventually uses more fossil fuels to produce electricity. With the emergence of renewable energy along with the capability to tap into this energy using power electronics, electrification will become sustainable soon [3]. Charging stations are expected to be completely dependent on sustainable energy like wind, solar etc. EVs can run solely on battery packs (BEV), or in combination with ICE engines (HEV and PHEV). Two major types of energy storage systems (ESS) are present in the battery field. They are lithium-ion (Li-ion) and lead acid based. Li-ion batteries usually are more expensive than lead acid but manage larger cycles, less cost/cycles, lesser maintenance, and high total cost of ownership (TCO) [4]. Lead acid batteries usually are manufactured for 50 % depth of discharge (DoD) whereas Li-ion can provide up to 75-80 % DoD and support faster charging as well, which is critical from an EV application standpoint. Hence, if we require an actual battery pack capacity of 20 kWh, considering the 50 % DoD of lead acid, a 40 kWh battery pack is to be used whereas a 25-30 kWh pack is only required if using Li-ion batteries. This means the higher specific energy of the lead acid battery is not very advantageous. However, Li-ion batteries need a battery management system (BMS) to prevent overcharging/discharging, temperature management, cell balancing, etc. [5] Various batteries are used in EVs like nickel manganese cobalt (NMC) and lithium iron phosphate (LFP). However, LFP is gaining attention in the present due to its omission of the usage of cobalt. Cobalt has several disadvantages like fragile chain of supply, labor cost, volatile price etc. Although LFP has lower energy density, due to its high safety and temperature handling capabilities, they are widely being implemented in EVs and other applications. Figure 2 represents a comparison between three different majorly used Li-ion compositions concerning their safety, life cycles, etc. [6]

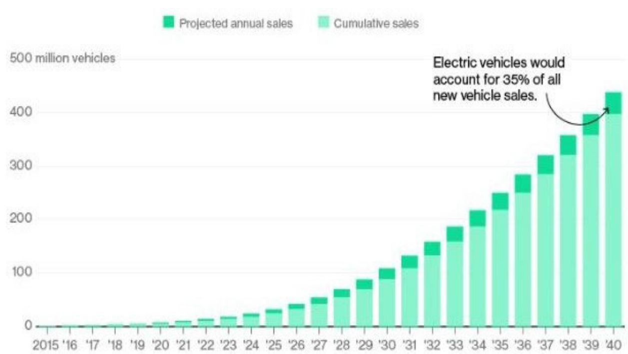

FIGURE 1. Projected sales of EVs by 2040 [1].

The demand for lithium-ion is also rising proportionally to the penetration of EVs into the grid. The estimated lifetime for Li-ion batteries during their primary application period is known as the EOL. The EOL of the battery in electric

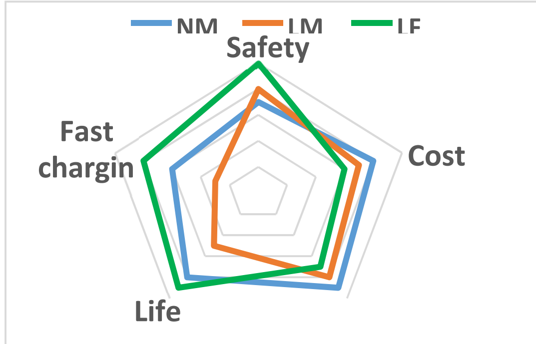

FIGURE 2. Comparison between various lithium-ion compositions.

mobility is said to take place when its capacity drops to 80 % of its initial capacity [7]. This retirement criterion set by the United States Advanced Battery Consortium (USABC) is widely followed at present. Research shows even a higher EOL is also possible since the battery capacity of most vehicles is also being increased annually. Once an EV battery is retired, three options are possible – Reuse, recycle or reject. Discarding these batteries is an environmental concern as their chemical chemistries make them harmful to accumulate in landfills. Recycling these batteries to get back the raw materials; is a good option, but the lack of high-functional facilities makes this a challenging task [8]. Recycling to get back the raw materials must be considered after finally utilizing the pack capacity to its maximum. The best option is to reuse/repurpose these batteries for other applications. This will help in gaining both economic and environmental benefits. By giving EV batteries a second life, the overall lifespan of the battery is extended, reducing the need for frequent manufacturing and disposal of batteries. This aligns with the Sustainable Development Goal (SDG) 12 (Responsible Consumption and Production) of United Nations Development Programme (UNDP) [9]. The primary goal of electric vehicles and their batteries is to reduce reliance on traditional internal combustion engine vehicles, thus lowering greenhouse gas emissions. Extending the life of EV batteries through their secondary use supports the reduction of carbon emissions, aligning with the SDG 13 (Climate action) [9].

Degradations occur throughout the lifetime of a battery. Batteries are electrochemical devices, and they undergo tremendous internal changes that affect their capacity. Many degradation mechanisms result in the power and capacity fading of these batteries. Solid electrolyte interphase (SEI) is the primary reason behind the degradation, and they ultimately take up the lithium which is critical for its operation [10], [11]. Other factors like loss of active material, graphite exfoliation, and electrode cracking are also types of degradation. State of health (SoH) estimation is a critical part of the secondary life of EV batteries. Once the EV batteries are retired and the healthy cells are taken out after inspection, the next step is to determine the SoH of the battery [12]. Based on its SoH, the optimum application in which the cells must be used is decided. Proper SoH estimation is a hotspot of research at present.

The beginning of SoH estimation was from the Raman microscopy used in batteries [13]. The insights from this study paved the way for a deep understanding of the electrolyte-electrode compositions in the battery. Model-based SoH estimations are also widely being studied [14]. Semi-empirical models that help to understand the relation between capacity and cycles were discussed [15], [16]. The loss of lithium is a major factor in the loss of capacity of the battery as it ages. Equivalent circuit models are a suitable method to learn about cyclic and calendar ageing. Extended Kalman filter with these models can also be used for state of charge (SOC) estimation which is essential in the battery management system [17]. These model-based estimations give a fairly accurate SoH value, but the time consumption is high. Data-driven models are another method to determine the SoH. The remaining useful life (RUL) prediction of these models is gaining high attention. A large dataset of battery cycles is required for these methods and accuracy depends on the confidence level of these datasets. Machine learning (ML) and data analysis (DA) based models are popular in these. ML-based Gaussian regression models and random forest models are discussed in the research. Data analysis models make use of prominent features from the data curves and train the model on this basis. Incremental capacity analysis and differential voltage analysis are some of the major SoH estimation techniques in this DA method [18].

Many research papers do not entirely explain the SLB topic from the fundamentals. They aim to cover wide areas of SLB without creating the foundation for the study which is important for budding researchers. SoH estimation given in research papers begins with a wide range of complicated studies which makes it difficult for the new authors to understand the essential points of the study conducted.

The major contributions of this paper can be summarized as:

1. The fundamental concepts of secondary life of batteries are discussed in detail along with the study of battery degradation. Major reasons for battery ageing are elaborated extensively. Aided by detailed images, this includes the present areas of focus such as solid electrolyte interphase and loss of lithium inventory.

2. ICA-based SoH estimation is analyzed from the fundamentals starting from the extraction of the physical data to the training of the model based on its analysis. The study on the ICA based SoH is later validated using test data and the effectiveness of the ICA is evaluated.

3. This paper also deals with the various applications and challenges faced in the implementation of secondary life batteries. Also, a comparison study of ICA method with the other estimation techniques is conducted.

II. SECONDARY LIFE OF EV BATTERIES – OVERVIEW

The secondary life of EV batteries in simple terms means repurposing the retired batteries that were used in the EV applications. Lithium batteries used in EVs are said to reach their end of application when their capacity drops to 80 % of their original capacity. The remaining huge storage capacity inside the battery gets wasted if they are discarded or recycled. This also creates a threat to the environment as well. It is necessary to completely utilize them before sending them for discarding.

Table 1 depict the major difference between recycling vs repurposing batteries for secondary life. Several factors like complexity, feasibility, efficiency are considered for the detailed comparison between both.

TABLE 1. Comparison between recycling and secondary life repurposing.

Factors	Recycling	Secondary life utilization
Process complexity	After dissembling process, Hydrometallurgy and other complex recovery processes are followed.	Capacity assessment and segregation is the complex process involved at present.
Efficiency	The efficiency of recovering the actual purity is high but with the cost of pollution addition. Separating cobalt and nickel is also a major task.	Efficiency for utilizing spent battery packs is high especially for stationary applications.
Economic implications	Metallurgical processes are highly expensive.	Initial cost will be incurred to segregate and assemble the healthy packs together. Overall, the process is economically beneficial in the long run with effective utilization of resources.
Technical feasibility	Bio metallic recovery is the greenest form of recycling but still in initial stage and has lower efficiency at present.	SoH estimation techniques have become a major field of research with the inclusion of predictive algorithm to proactively diagnose the battery capacity.
Environmental impacts	Recycling of lithium batteries using metallurgy comes with the issue of increased pollution, water resource depletion leading to ground subsidence.	Environmentally friendly with effective resource utilization and zero waste concept. These batteries can be taken to the stage of recycling after their secondary life is over.

As the number of EVs is rising exponentially every year, the number of retired batteries is going to skyrocket. This leads to a tremendous opportunity for the utilization of these batteries in other applications.

The steps that are conducted during the secondary life cycle are:

A. DISASSEMBLE

As the individual cells need to be taken from the used battery packs, the first step is to disassemble and obtain the cells [19]. Various cell types are present like pouch, prismatic, cylindrical, etc. and these cells can be segregated based on this or any other parameters [20], [21]. This dismantling should be done in a controlled environment to ensure that no oxidation of electrodes happens. The solid electrolyte interphase (SEI) developed on the electrode-electrolyte surface can be cleared to a small extent and this is said to restore its performance.

B. VISUAL INSPECTION

Cracks and other physical damage can be seen on the cells during visual inspection. These help to separate the good physical cells from the damaged ones.

C. RUL ESTIMATION AND PREDICTION

Various tests must be done to estimate the SoH and the RUL of cells. Once battery packs with such cells are designed, estimation for the number of years that it would sustain should be done. The life span of these battery packs is said to be 20-T years, where T is the original first life. It is important to ensure that the cells are in a good state of health before they are used for these secondary applications. Detailed testing of the retired battery packs is necessary to ensure proper functioning in their secondary life.

D. SAFETY CHECKS AND GROUPING

Cells must be organized into one homogenous battery pack based on their parameters after a safety checkup [22]. Homogenous cells can be later grouped into modules like ordinary battery packs and taken out for secondary applications.

After these four main steps, the batteries are taken for assigned secondary applications. After their secondary lifetime, they can be either recycled or discarded. Figure 3 shows the secondary life cycle flow of batteries which results in secondary applications followed by recycling or discarding finally after their secondary purpose.

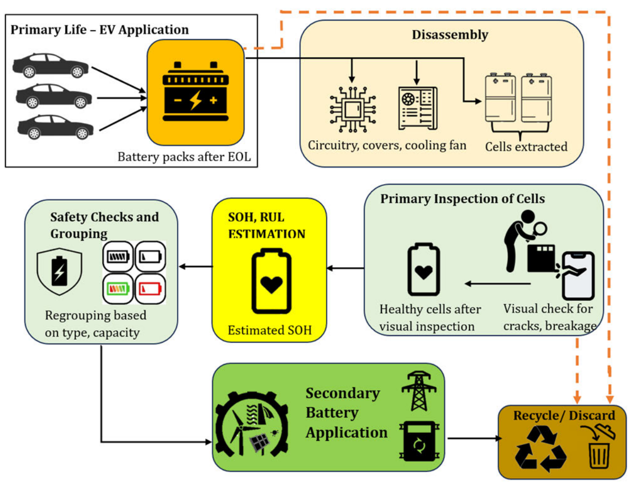

FIGURE 3. Secondary life cycle – Flow.

III. DEVELOPMENTS IN SLB – MARKET SCENARIO

Many companies are investing in joint ventures with battery companies to utilize the secondary life of retired batteries. These ventures help the companies to overcome the challenges of discarding these batteries, which could be difficult owing to environmental constraints as well. Table 2 shows the present developments and ventures in the field of SLB undertaken by EV companies.

TABLE 2. SLB initiatives by EV companies [23].

Sl. No.	Company-Venture	Details	Country
1	Mercedes Benz Energy – Lohum Cleantech	Agreed to offtake about 50MWh annually	Inda
2	Hyundai Motor – UL	Repurposing EV batteries to help combat environmental pollution, climate change	North America
3	Daimler – Beijing Electric Vehicle	Initiative for supporting China's electric grid while also aiming for secondary storage devices	China
4	MG Motor India – Lohum Cleantech	Initiative to build sustainable energy systems in urban and rural India	India
5	Renault – Connected Energy	Partnering to supply economic and innovative charging solutions	UK
6	Renault – Mobility House	Battery storage system developed from Renault Zoe retired batteries	France

Apart from these joint ventures, several other developments are also taking place in this field. Japanese automaker Mitsubishi uses their retired batteries to partially power the Okazaki City plant which is their EV manufacturing facility. Berlin-based company known as BELECTRIC used retired batteries from Audi to create a 1.9 MWh based energy storage system. Used batteries from Nissan Leaf were deployed to power up many stadiums in Europe.

Battery packs from Rivian trucks were used to create microgrid storage systems in Puerto Rico. These are a few of the many projects undertaken by many such companies. These examples prove that the market is ready for innovative developments in the field and the race for sustainable utilization of retired batteries has already been started.

IV. DEGRADATION STUDY OF BATTERIES

A battery's lifetime is the time for which it can handle the application that it is designated. The primary application of the lithium batteries in the EV is over when its capacity drops to 80 % of its initial value. The capacity of the battery keeps on dropping as the number of cycles increases. This is due to the degradation happening within the electrochemical parts of the cell. Two types of ageing are present in batteries. These are calendar ageing and cyclic ageing. Calendar ageing occurs due to the storage and natural degradation occurring between the electrodes and electrolyte over time [24]. These degradations become more concerning parameters like the state of charge (SOC), and storage temperature. Cyclic ageing occurs during the charging and discharging cycles. This type of ageing is affected by calendar ageing as well. As calendar ageing takes place, the charging and discharging capabilities of the battery are also affected resulting in cyclic ageing. The C rate of the battery, and charge discharge

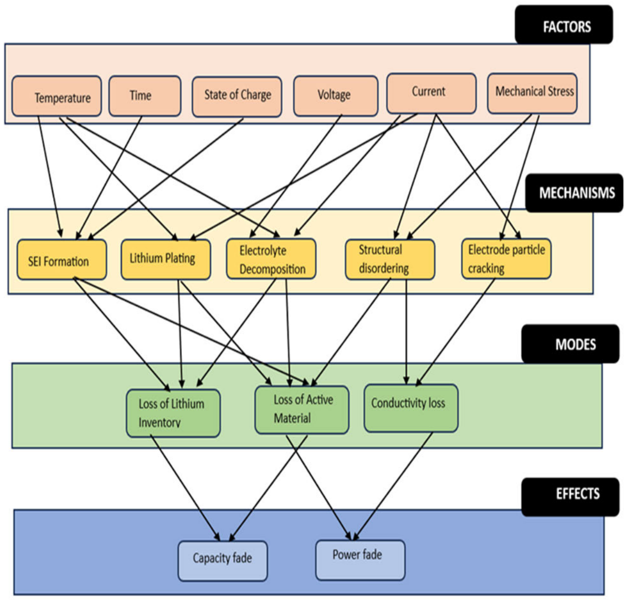

FIGURE 4. Battery degradation chart.

cut-off voltages are the major factors that contribute to cyclic ageing of the battery. Degradation of the battery is usually expressed as capacity fade or power fade [25], [26], [27], [28]. Capacity fade occurs due to electrolyte-electrode interactions within the battery, loss of active material, graphite destruction, lithium inventory loss etc. The factors leading to these are discussed in detail in the next section. Figure 4 shows the factors, degradation mechanism, modes, and their effects leading to either capacity fade or power fade.

Loss of lithium inventory (LLI) which is characterized by SEI is the most important factor leading to degradation of lithium cells. Reduction of the lithium directly affects the capacity and performance of the battery to a huge extent. It is necessary to understand the charge and discharge mechanism of lithium-ion cells to understand the fundamentals of the formation of SEI.

A. BASICS OF LITHIUM CELL CHARGING / DISCHARGING MECHANISM

A lithium-ion cell, like any other electrochemical cell, consists of a positive electrode (i.e., cathode), negative electrode (i.e., anode), electrolyte, and separator (Fig. 5). The cathode consists of the current collector, and the cathode material which could be Lithium ferro phosphate (LFP) / LMO depending on the battery composition used [29]. Graphite is generally used as the anode in most cases. Lithium salt-based liquid composites are used as electrolytes. The electrolyte material is chosen in such a manner that it allows only the transfer of ions and does not allow the electrons to pass through it. This is done to provide a second path for the electrons to flow and thereby generate current in that required path. The separator is present for protection purposes in cases where the electrolyte may dry up and cause hazards. The lithium-ion atoms can be broken down into lithium ions and electrons through chemical reactions. The ions transport through the electrolyte, and the electrons go through the external circuit when they undergo charging/discharging. The electrodes can be considered as storage sites for the Li atoms.

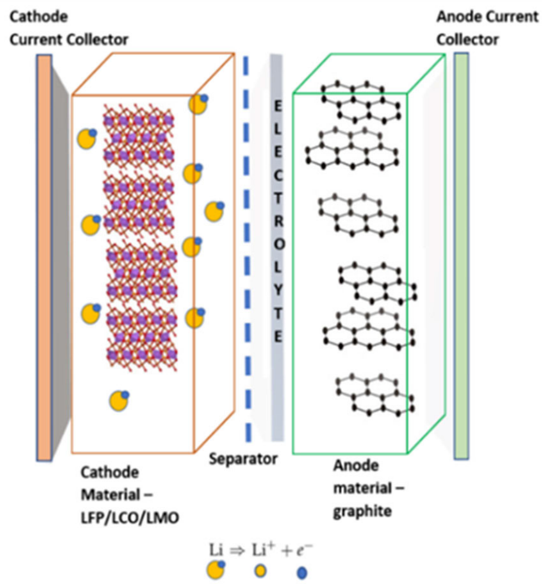

FIGURE 5. Li-ion cell chemistry.

B. CHARGING & DISCHARGING IN A LI-ION CELL [30], [31]

During the charging period of a Li-ion cell, as shown in Fig. 6, the Li atoms present in the cathode breakdown into an ion and an electron. The electron moves in the external circuit and reaches the anode whereas Li ions are absorbed by the electrolyte and transported to the anode. Both the ion and electron reach the anode and are temporarily stored in the anode material. This state of the cell is not considered to be very stable. Unlike lead-acid batteries, the electrode atoms do not react with the electrolyte material to produce ions (redox reactions). In a Li-ion cell, the electrolyte absorbs the atoms and merely transports them to the other electrode. The ions get stored in the lattice structure with the electron. This process is also termed intercalation. During the discharge (Fig. 7), the Li atoms stored in the anode are now separated and the same process that happened during the charging is reversed. This is called deintercalation.

C. LOSS OF LITHIUM INVENTORY (LLI) – FACTORS

1) SOLID ELECTROLYTE INTERPHASE [32], [33], [34], [35], [36]

SEI is one of the most important phenomena in a Li-ion cell structure. This layer is formed thinly during the first charging of the cell. The Li ions that pass through the electrolyte during the charging, will be combined with the electrolyte solvent. As they reach the anode, the solvent along with a small percentage of lithium forms a layer on the electrode-electrolyte interphase leading to the formation of SEI. (Fig. 8). Although

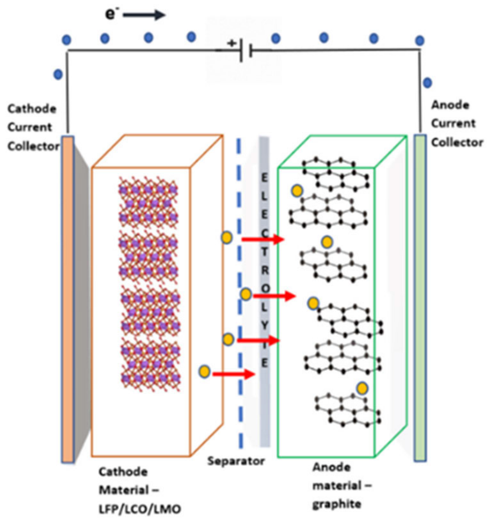

FIGURE 6. Li-ion cell charging.

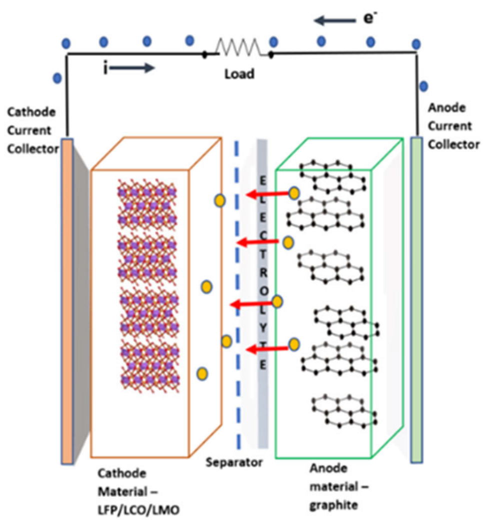

FIGURE 7. Li-ion cell discharging.

this layer was formed in an unplanned manner, it is a blessing in disguise as it prevents electrons from meeting electrolytes which may lead to its degradation. It is, at the same time, porous enough to allow intercalation. In the long run, however, SEI becomes one of the primary causes that leads to capacity and power fading in a cell. Most of the over limits of electrical and thermal parameters like SoC, voltage, temperature, and high C rate affect this layer. High temperature, SoC, voltage aids in SEI growth and thereby leading to the loss of active lithium for cell functioning. Frequent use of cells in higher C rates leads to the passing of solvent materials as well to the anode resulting in gas pressure building, swelling of cells, etc. Every major parameter of the cell directly or indirectly affects the SEI. The SEI growth is seen to be predominant in the negative electrode but can exist on the cathode surface as well.

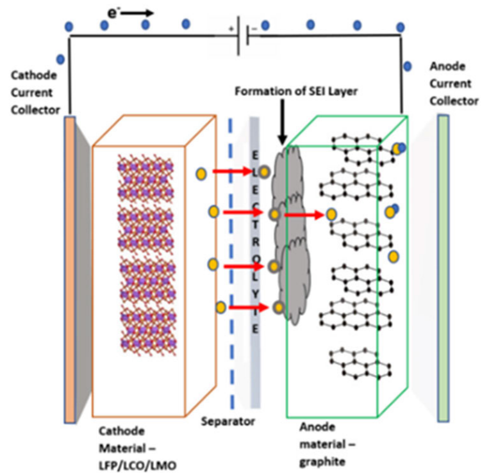

FIGURE 8. SEI formation in Li-ion cells on the anode-electrolyte surface.

2) LITHIUM PLATING [37], [38]

Lithium plating is the phenomenon where lithium instead of intercalating into the anode crystal gets deposited on the anode surface. These are usually formed due to charging at a high current or at a low temperature. During the fast charging, the rate of lithium deposition is greater than the rate of intercalation that results in this degradation. Lithium plating is one of the biggest challenges when dealing with fast charging. Physical and chemical properties of the anode also play a part in the level of lithium plating. The deposited lithium is difficult to remove. This plating can further aid in the development of secondary SEI and may result in loss of energy density and an increase in cell resistance. Dendrite formation is also a side effect of this kind of plating. An increase in the resistance at the anode or changes in the polarization of the electrolyte are possible indications of lithium plating in cells.

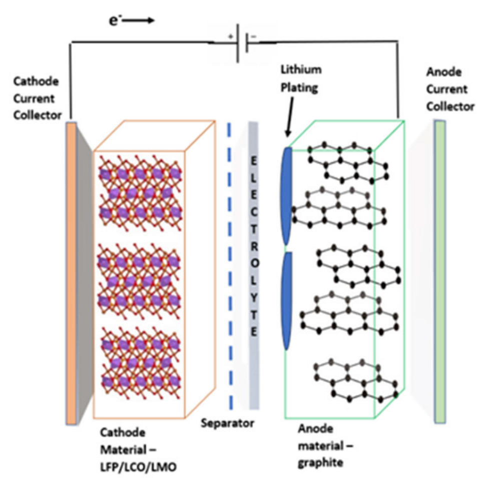

FIGURE 9. Lithium plating causes degradation.

Lithium plating can be homogenous or heterogeneous. When plating occurs at a larger area of the anode, it is termed homogenous lithium plating. Heterogenous are localized lithium plating that usually occurs at edges, corners or near separators.

3) ELECTROLYTE DECOMPOSITION

The decomposition of electrolytes during battery cell operation can result in highly complex mixtures. Fast charging initiates this degradation to produce different compounds. The molecule of the electrolyte decomposes into the surface of the electrode contributing to the further formation of solid electrolyte interphases. The SEI can later make the electrode surface passive and further results in more electrolytes being decomposed on the surface resulting in the significant degradation of the battery performance.

V. SOH ESTIMATION

Batteries undergo many degradations throughout their operating lifetime. The loss of lithium inventory and the plating of the lithium are the most prominent reasons that affect battery degradation. These issues arise more when the cells deviate from their operating parameters of voltage, current, temperature, etc.

The state of health of a battery can be expressed as the ratio of the present battery capacity (Q_p) to the initial capacity of the battery (Q_i) as shown in equation (1).

$$SOH = (Q_p/Q_i) \times 100 \tag{1}$$

The state of the health of the battery is, therefore, an indicator of the available capacity of the battery [39]. Accurate determination of the SoH is therefore a very crucial part of the BMS as well as in the application of the SLBs. Proper estimation of the capacity of the battery will help in prolonging the life of the battery as well as accurately predict the remaining useful life (RUL) of the battery in their secondary life [40]. SoH prediction and estimation has therefore become a key area of research in EVs and battery systems. The most widely used simple yet time consuming method for estimating the capacity is the Coulomb Counting Method (CCM). The battery is discharged completely and then charged again and later integrated to find the capacity as given in equation (2).

$$Q = 1/3600 \int idt \text{ Ah} \tag{2}$$

where Q is the capacity in Ah and i is the current. There are many types of SoH estimation techniques broadly classified as model-based estimation and estimation using data analysis and prediction. Model based SoH estimation is carried out by creating electrochemical and equivalent models of the cell/battery circuit and analyzing it by subjecting to changes in parameters [41], [42]. Data driven methods focus on collecting the data carried out from cycling testing and later using these data to understand a pattern that can be later used to train models to predict SoH [43]. Data driven methods are widely being researched due to the emergence of high-quality data analysis and machine learning features. A brief comparison between the model-based estimation and data driven estimation is given in Table 3.

TABLE 3. Advantages and disadvantages of estimation techniques.

Method	Advantages	Disadvantages
Model based estimation	• Less complicated. • Accurate battery capacity estimation based on quality of model.	• Models with little physical meaning lead to inexactness. • Uncertainty in circuit parameters affects real time SoH estimation [44]. • Generally, uses constant current techniques for SoH estimation.
Data driven estimation	• Requires less knowledge on internal battery parameters. • Capability to handle nonlinear and complex relationships between parameters [45]. • Helps to easily map between capacity and external features [47].	• Large data computation to be carried out where accuracy is vulnerable [46]. • Model requires extensive validation. • Methods like gaussian progression models helps to calculate the SoH under dynamic discharge conditions

The next factor that is considered during the SoH estimation is whether the current that is analyzed is under constant current or dynamic varying condition. Many studies focus on the constant current process during the degradation phase of charging because generally CC-CV charging is carried out in lithium-ion batteries. Model based SoH estimation techniques follow the constant current method due to its simplicity. At the same time, this method gives optimal results about degradation. Gaussian regression models are showing great potential to estimate the SoH under dynamic discharge conditions. Three fused health indicators i.e., discharge voltage integration, discharge time, net discharge energy are obtained from the experiments and given as inputs to Gaussian process regression model in [48]. Such dynamic operating conditions will help to create a robust and accurate model for battery capacity estimation. Six physical features that affect the degradation of battery were obtained in [49] where the cells were subjected to constant current-voltage tests. The physics based Gaussian model is then validated against testing cells operating under mixed conditions. The results proved to be effective even when the training data considered were constant current based. Cells were charged with CC-CV profile but subjected to dynamic stress/discharge tests to validate in [50]. Voltage curves are converted to trajectories with NN modelling with respect to their constant current profiles and these served as inputs to the training model. Error was limited to 2 % and the method proved to be working fine under dynamic operating conditions as well. Different current rates of 1C, 1.5C at different depths of discharge (DOD) were used for training data set in [51]. This method of SoH estimation using discharge curves using empirical linear model provided results with error percentage lying below 3 %.

Based on the numerous studies on the training set data, it can be concluded that the dataset which is taken from the experimental setups can be of cells which are subjected to constant current conditions. They are still validated or proven to give accurate results with error percentage below 4 % in many research studies. For the ICA in this paper as well, the cells are subjected to CC-CV and the data set during the constant current part is taken for study. This is done for ease of understanding the estimation technique in detail and for implementation.

A. SOH ESTIMATION USING INCREMENTAL CAPACITY ANALYSIS (ICA) [52], [53], [54], [55], [56], [57]

The ICA was developed to learn about the electrochemical interactions happening within a cell. These IC curves give valuable information about the reactions within these cells without requiring the necessity to open them. Both prognosis as well as diagnostic analysis is possible using the ICA curves. The ICA analysis comes under the differential analysis method of SoH estimation which can be considered as a subset of the data driven method. The ICA curves are obtained by differentiating the change in capacity with the change in voltage as given in equation (3).

$$\mathrm{ICA} = \mathrm{dQ/dV}[\mathrm{AhV}^{-1}] \tag{3}$$

where dQ is the change in capacity and dV is the change in voltage. The voltage and capacity determined through equation [2] are taken as the inputs to derive the ICA curve. These curves are measured and the noise within the derived data is eliminated and then the pattern is studied. Few indicators known as health indicators (HI) have been identified. These are susceptible to changes in the ageing of the battery. These HIs are identified and extracted. These are later beneficial to train the models and predict the value of SoH for a particular set of HIs.

The major steps in the study of ICA based SoH Estimation are:

1) STEP 1: EXTRACTION OF DATA

Extensive data of voltage, capacity, cycles of different cells are required for doing the analysis. The higher the data, the better will be the accuracy. The voltage and capacity for different ageing of the battery are taken as the inputs to the next step.

2) STEP 2: ANALYSIS OF EXTRACTED DATA

The V versus Q data is obtained and then the required parts of the graphs are interpolated for higher accuracy. The capacity data is then differentiated concerning the change in V using mathematical tools. The derived dQ/dV curves are bound to have noise which may affect the proper identification of health indicators. Filtering is carried out to eliminate the noise and obtain a smoother signal. The HIs of the signal are identified. These are usually the peaks and the location of these peaks in the curves. The data of these HIs are then given as inputs to the next step.

3) STEP 3: TRAINING AND PREDICTION

The HIs are taken as a set and given to a model to find the pattern/relation between them and the output variables which are SoH or cycles. Multiple regression analysis, recurrent neural network (RNN) with long short-term memory (LSTM), deep neural network can be used to train these models with the help of finding a relation. These models are then used to predict the output for the next set of possible HIs. Extensive computation and data extraction will help to increase the precision of the model tremendously. A detailed methodology about SoH estimation using ICA is depicted in Fig. 10. This figure includes all the steps mentioned along with their description.

The accuracy of the model can be determined by running test data and comparing it with actual data. The battery degradation test data can be obtained online by Oxford, CATL, NASA and these data can be used for studying ICA.

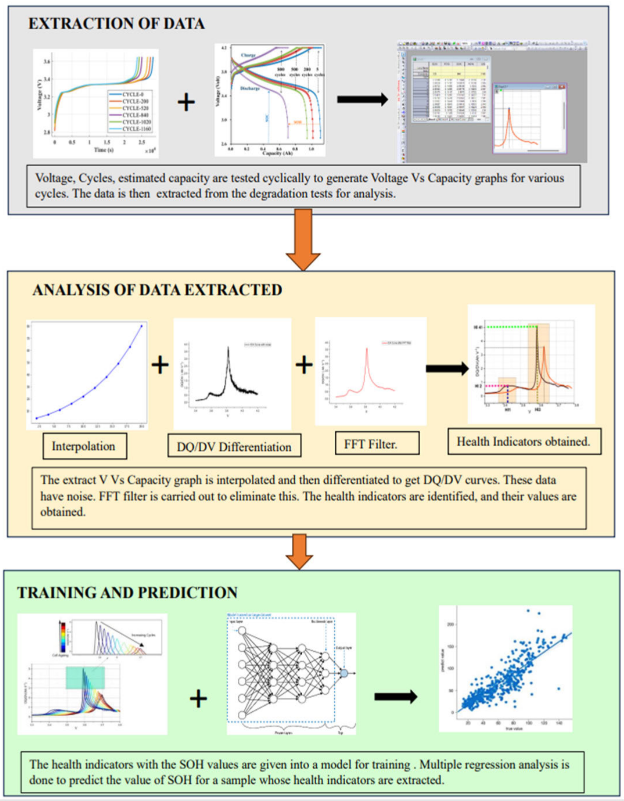

FIGURE 10. ICA methodology.

B. EXPERIMENTAL SETUP

The experiment to estimate the SoH using the ICA is carried out in this paper at the cell level. The data for experimental cell is taken from the Oxford battery degradation dataset which is an open source dataset [Birkl, C. (2017). Oxford Battery Degradation Dataset 1. University of Oxford] The cycle ageing of the battery for various C rates is carried out and given as a dataset having voltage, capacity as the data variables. The experimental steps are carried out as per the methodological steps mentioned above.

1) STEP 1: DATA EXTRACTION

The Oxford Dataset 1 contains an ageing dataset from eight small 740 mAh lithium-ion pouch cells for every 100 cycles. The cells were all tested in a thermal chamber at 40° C. The cells were subjected to a constant-current constant-voltage charging profile, followed by an urban Artemis drive cycle discharging profile. One cell is taken for the analysis and the various cycles along with its SoH are plotted as shown in Fig. 11. The SoH versus voltage graph obtained from the data set for various cycles is shown in Fig. 12. The capacity of the cell is seen to drop as the cycles/ageing is increased.

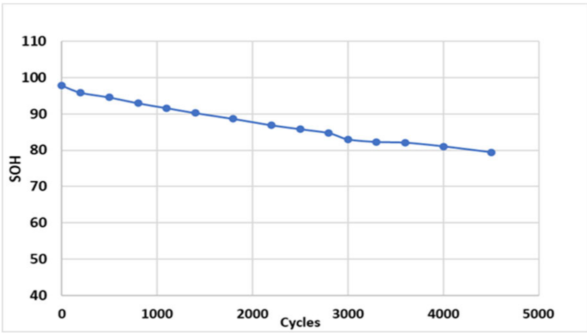

FIGURE 11. SoH versus cycles graph of the cell.

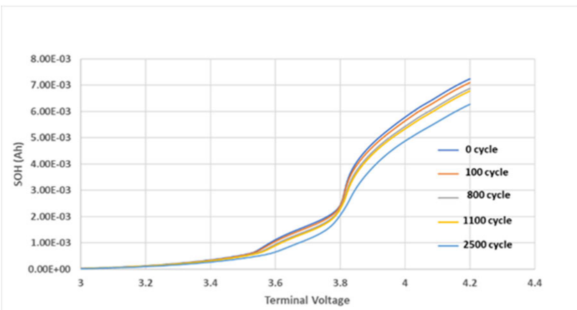

FIGURE 12. SoH versus terminal voltage graph of the cell.

2) STEP 2: ANALYSIS OF THE DATA EXTRACTED.

The capacity versus voltage dataset is first interpolated. Interpolation helps to increase the dataset between the points and helps to increase the accuracy of the set. Interpolation between two points (X_1, Y_1) and (X_2, Y_2) in a graph is given in equation 4.

$$Y - Y_1 = (Y_2 - Y_1)(X - X_1)/(X_2 - X_1) \tag{4}$$

After interpolation, differentiation of the capacity concerning the voltage is carried out and plotted as seen in Fig. 13. This is the ICA curve that is fundamental to the study.

The presence of noise in this signal is a negative trait that must be removed. Various filtering techniques can be deployed to filter out the noise and get a smooth waveform. Five-point FFT based filtering is carried out in this project to filter the noise. The DFT formula is given in equation 5.

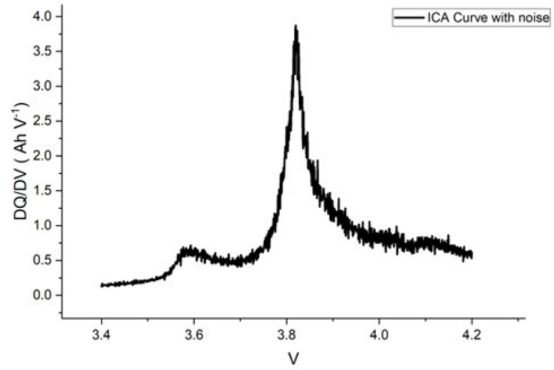

FIGURE 13. Projected dQ/dV versus voltage graph (ICA) of the cell.

$X(k)$ is the discretized frequency domain signal,W is the twiddle factor, N is the number of computations, k varies from 0 to N-1. The signal is decomposed into lesser short transforms and then recombination is done.

$$X(k) = \sum x(n)W_N^{nk} \tag{5}$$

Figure 14 shows the comparison between ICA curves with and without FFT filtering. FFT filtering provides a smooth signal for further analysis.

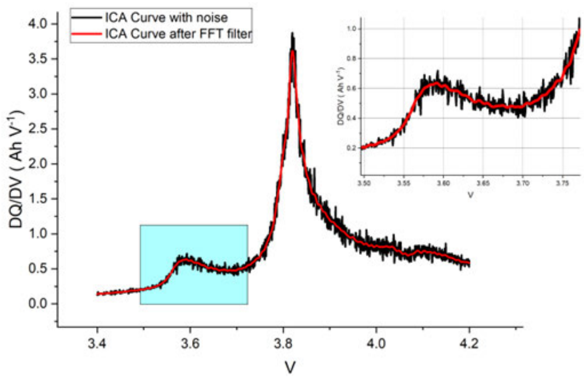

FIGURE 14. ICA curve containing noise.

Once the smooth ICA curve/data is obtained as shown in Fig. 15, the same process is carried out for other cycles/ageing of the cell.

Various cycles of the cell are taken and the ICA curves after the three steps of interpolation, differentiation, and filtering; are obtained. Figure 16 shows the respective curves as the ageing of the cell increases.

Two dominant peaks can be identified in the ICA curves where the second peak is superior. A zoomed version of the peak is shown in Fig. 17. As the cycles increase, the value of the peak is seen to be decreasing. The relationship between the peaks and the ageing of the cell is therefore seen to be inversely proportional and can be finalized as a main health indicator of the cell.

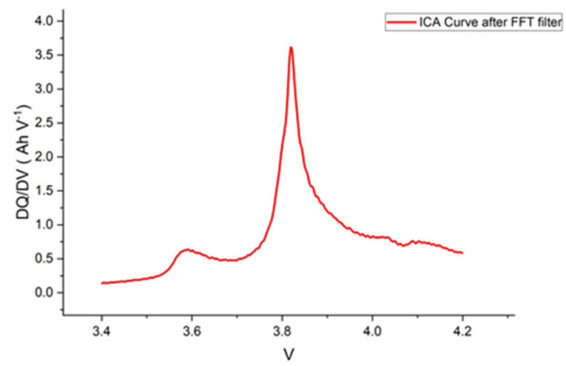

FIGURE 15. ICA curve after FFT filtering.

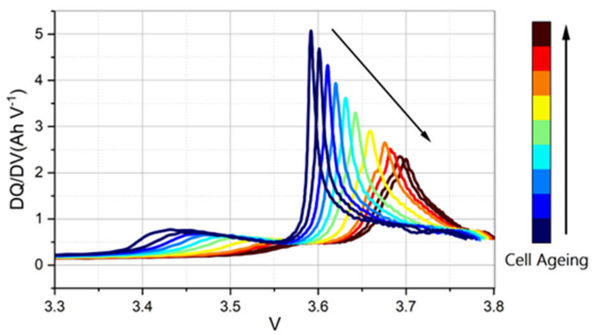

FIGURE 16. ICA curves' variation with the ageing of the cell.

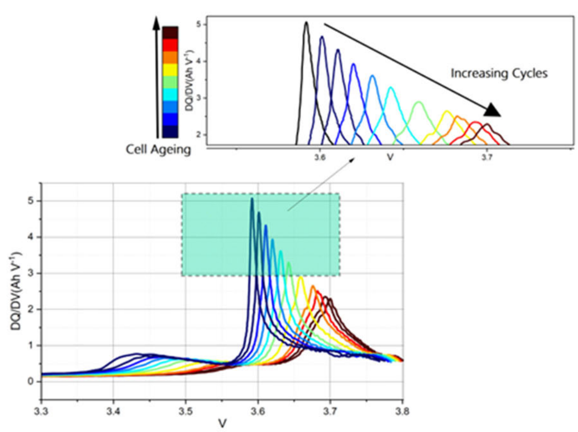

FIGURE 17. Peak variation with increasing cycles in the ICA curve.

3) DETERMINING HEALTH INDICATORS FROM THE ICA CURVE:

The curves are analyzed to determine the distinctive features that keep changing when the ageing of the cell takes place. Four health indicators were the most prominent ones in the study. These include the Y-axis values of the two peaks and the distance of these peaks from a starting position. All these four features were found to be changing when the ageing of the cell takes place. The Y axis health indicators, which are the peak of the wave, were found to be reducing concerning ageing whereas the X axis indicators which are the location of these peaks seem to be shifting to the right with the increased ageing. Figure 18 shows the four HIs numbered as HI 1-4 which are given as the inputs to the training model of the next step.

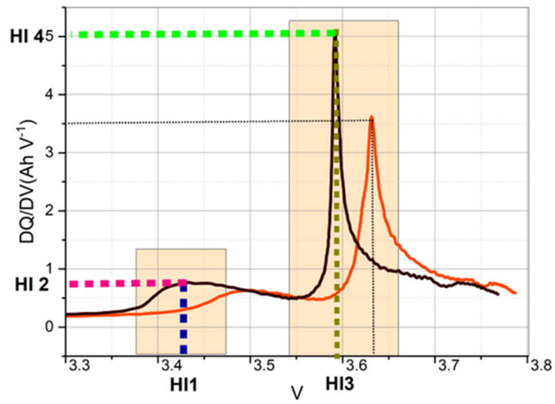

FIGURE 18. Projected ICA curves with health indicators detection.

4) STEP 3: TRAINING AND PREDICTION OF SOH

The relationship between the four health indicators and the SoH is made into a scatter plot and the trendline is plotted as shown in Fig. 19.

These data are taken for multiple regression analysis (MRA) to determine a relation between these four independent variables. The four independent variables in our case are the health indicators (HI1, HI2, HI3 and HI4). MRA is a statistical method which can be utilized effectively when the data set has a linear relation as seen in the Fig 19. The output variable will help to get a weighted relation between all the independent variables.

The model equation for the MRA is

$$Y = A_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 \tag{6}$$

where Y is the weighted output, $A_0$is the intercept, B_1, B_2, $B_3$and $B_4$are the coefficients associated with the independent variables. This method of regression is chosen due to its simplicity in the presence of linear data.

The goal is to estimate the coefficients that minimize the sum of squared differences between observed and predicted values. Hypothesis testing helps to determine the significance of each variable. Measures like R-squared assess the overall model fit. Interpretation of coefficients involves understanding the change in the dependent variable for a one-unit change in the corresponding independent variable, with other variables held constant. Multiple regression is a valuable tool for modeling complex relationships in diverse fields.

In this study, the health indicators are the X values, and the predicted SoH is the output value. MRA is considered for the analysis for easy understanding of the model. Ten sets of cycles were taken as the training inputs for the MRA, and three sets were taken as the testing for the model. After MRA, table 4 shows us the values of the coefficients obtained from it from an R^2 value of 0.9.

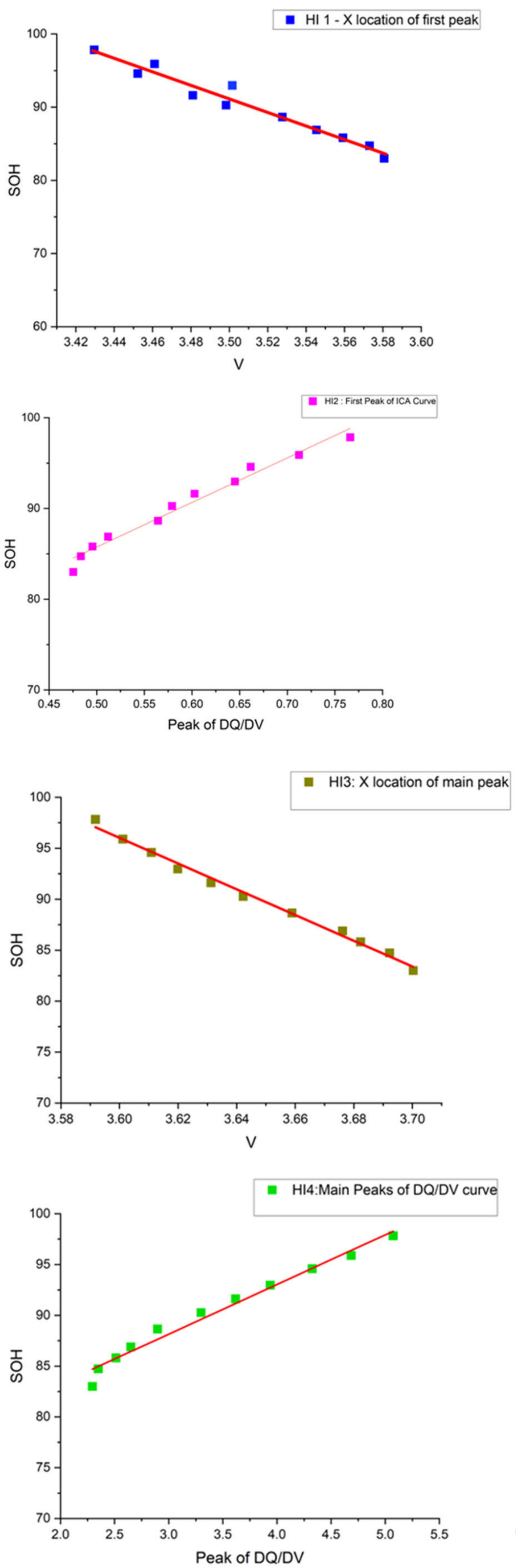

FIGURE 19. SoH versus selected HI plot.

These coefficients help in the prediction of the testing sets. The idea is to test new cells and find their health indicator location. These values are employed in the equation (6) along with the coefficients; to obtain an average estimated SoH based on the linear regression model equation. It is assumed that the HI positions will shift but will stay linear throughout the life cycle.

TABLE 4. Values of coefficients from MRA.

Coefficient	Value
A_0	400.4007
B_1	-12.5872
B_2	14.9954
B_3	-75.2791
B_4	-0.11599

Three sets of data are taken for testing and the results are shown in table 5.

From the experimental analysis, ICA is found to be a highly effective method for SoH estimation. The error percentage obtained for the testing data was less than 4 % and the accuracy can be improved further if a greater number of datasets can be used for training. Only 10 sets of training data were taken for easy understanding and experimentally analyzing the basics of the ICA-based SoH estimation. The experimental results prove that the method is highly effective. It gives significantly accurate results even when the study has a smaller number of training sets. The study focuses on building a strong fundamental on data-driven SoH estimation methods like ICA that can be carried out further in the future. Stepwise analysis helps in the clear understanding of creating a dQ/dV curve. ICA can be further developed for module level testing which will be greatly beneficial for applications like secondary life of batteries.

The results obtained in this case study are for a cell level analysis. Those can be extended to module level through extrapolation techniques.

VI. COMPARISON BETWEEN VARIOUS SOH ESTIMATION METHODS

Many estimation methods are present widely in research with emphasis given to model-based methods, data driven, machine learning, hybrid models etc. Each method has its own pros and cons. Table 6 highlights an extensive comparison between various established estimation techniques. Each method is provided with its advantages and disadvantages as well as their recent developments.

VII. STANDARDS ASSOCIATED WITH SLB

Policies or standards associated with repurposing of used EV batteries are not many. Few of the standards at present include:

A. UL1974

This standard, developed by Underwriters Laboratories (UL), primarily focuses on safety and performance evaluations for second-life batteries. It outlines certification guidelines and procedures to assess the safety and functionality of repurposed batteries. UL 1974 ensures that these batteries meet

TABLE 5. Results of the model using test data.

No.	HI1	HI2	HI3	HI4	Actual SoH	Predicted SoH	Error Percentage
1	3.643473	0.42227	3.74088	1.9383	81.1	78.63	3.04
2	3.63	0.468	3.8029	2.29493	77	74.78146771	2.83
3	3.633473	0.41227	3.85088	1.9183	72.8	70.33	3.39

specific safety benchmarks, like fresh battery systems, before they are repurposed or reintegrated into other applications.

B. IEC 62933-5-3

Part of the International Electrotechnical Commission (IEC) standards, this document specifically addresses safety concerns related to SLB systems. However, it requires adaptation to encompass systems using components sourced from used batteries. It aims to ensure that safety standards for these repurposed systems are aligned with those for new systems.

C. ISO12405

This International Organization for Standardization (ISO) standard provides testing procedures and requirements for lithium-ion batteries used in electric vehicles. While it does not focus solely on second-life applications, it sets benchmarks and testing protocols that indirectly influence the evaluation and potential reuse of batteries after their primary EV use.

D. EUROPEAN UNION BATTERY DIRECTIVE

This directive within the European Union aims to regulate the handling, collection, recycling, and disposal of batteries, including EV batteries. It emphasizes the significance of sustainable resource use and environmental protection in managing batteries throughout their lifecycle, including their secondary use. It says that 50 % of an EV LIB weight shall be recycled.

VIII. COST ASSESSENT OF SLB

Secondary electric vehicle (EV) batteries, commonly repurposed for stationary energy storage applications after their initial use in electric vehicles, present an intriguing cost assessment challenge. One key factor to consider is the SoH of these secondary batteries, which reflects their remaining useful capacity relative to their original state. The cost of secondary EV batteries can be mathematically expressed as:

$$C_{\text{secondary}} = C_{\text{initial}}(1 - \mathrm{D})\mathrm{R} \tag{7}$$

where $C_{\text{secondary}}$ represents the cost of the secondary battery, C_{initial} is the original cost of the new battery, D is the degradation factor (a decimal between 0 and 1, representing the degree of degradation) and R is the remaining capacity factor (also a decimal between 0 and 1). D accounts for the wear and tear experienced by the battery during its initial use, while R reflects the portion of the original capacity that is still available for use. The cost assessment thus incorporates both the initial investment and the impact of degradation on the secondary battery's performance, providing a quantitative measure for decision-making in repurposing EV batteries for stationary applications.

The biggest benefit of the retired batteries over the new units is the price of procurement. The LFP battery that is decommissioned costs around \$0.5/kWh whereas the new one costs about \$1.3/kWh [78], [79]. Retired batteries are estimated to be only half of new battery price and almost close to the lead acid battery packs. As they are competing with the lead acid packs in terms of price, the potential for such batteries is huge since lead acid are widely used even at present in many applications. Their advantage of less price even when they are not environmentally friendly are overtaken by the retired lithium batteries that are both low in price as well as environment friendly.

The price for these retired batteries is determined considering the refurbishment expenses, cost incurred due to power electronics devices and operational expenses. Refurbishment includes sorting, dissembling, equipment costs and labor costs. According to [80], for energy storage applications, the price of SLB was \$72/kWh and the fresh battery pack costs about \$232/kWh. In [81], Mathew et al., suggested that for a PV-SLBESS system, the retailers sell the SLBs for less than 60 % of price of the fresh packs. Study in [82] showed that the revenue generated from the secondary batteries compensates for about 19 % of the fresh battery cost. Cost considerations cannot be precise as they may vary from application and could be variable depending on the storage, transportation, and uncertainties in replacements.

Economic models play a crucial role in assessing the profitability of SLBs across different applications. These models, as evident in existing studies, encompass various metrics such as net present value (NPV), levelized cost of electricity (LCOE), levelized cost of storage (LCOS), and the cost–benefit model [83], [84]. The NPV model evaluates cash inflows and outflows throughout the project, indicating profitability when yielding a positive result. However, conflicting conclusions arise based on specific analyses, as seen in studies comparing distributed solar PV systems in China and the European electricity market. The LCOE model facilitates a direct comparison between SLBs and fresh-life batteries (FLBs), demonstrating potential cost reductions in specific applications, such as fast charging. Additionally, the Cost–Benefit model proves beneficial in analyzing expenditures and gains in ESS for numerous services, including energy arbitrage and frequency regulation [85], [86], [87]. Notably, studies reveal that grid-connected applications

TABLE 6. SoH estimation methods.

Method	Estimation Technique	Pros	Cons	Recent developments
Electrochemical impedance spectroscopy [58-60]	Makes use of the relation between SoH and impedance. Uses a sinusoidal AC/voltage as an interference signal to test change in impedance.	Battery impedance can be measured over a broad range of frequencies. It is also possible to measure resistances like charge transfer resistance and SEI resistance.	Time consuming method. Information about the batteries requires to be extracted through complex analysis and calculations.	A multi-point impedance technology is proposed for monitoring LIBs, distinguishing resistance components, and simplifying calculations [61]. Fractional impedance model (FIM) is developed. This ensures a balance between model complexity and efficiency of computation [62].
Ultrasonic detection [63-64]	Emerging technology that utilizes reflection, refraction and obtains the transformation of wave pattern at the cell critical interface. Diagnosis is based on the reflected waves.	Method is compact and cost effective for SoH determination. Internal defect detection without dissembling can be achieved, which suggests a good prospect for this method.	Ultrasonic detection requires much more effective study and improvement. Since this method is based on incident and reflected wave theory, end users may find it difficult to analyze.	Ultrasonic guided waves based on piezoelectric transducers was proposed to monitor SoH [65]. A study about the decrease in ultrasound time of flight with the increase in cycles of cells was carried out in [66].
Equivalent circuit model (ECM) [67-69]	Model based SoH estimation, where equivalent circuit models for the battery cells are developed and tested.	Simplicity in structure results in lower computational costs compared to more complex models.	ECMs may lack the accuracy required for precise SoH estimation, especially as batteries undergo ageing and degradation. Precision of parameter identification is still a major task. Real time estimation is difficult	An electrochemical based ECM method was proposed which can simulate the voltage response in batteries as it considers electrochemical methods as well [70]. A recursive least square based parameter identification method with a variable forgetting factor was proposed in [71]. It has better stability and less complexity.
Artificial neural network method [72-73]	Data driven method. Uses battery historical degradation and monitoring data to train models to predict SoH. Gaussian regression, Wiener process, and Kalman filter are the variations of this method.	Prediction methods established on deep learning are proven to be superior to other machine learning (ML) methods. Long short-term memory (LSTM) based neural network is a highly effective method for predicting adaptive time series. The Gaussian filtering method helps to retain the characteristic values related to battery ageing.	AI/ML models rely heavily on quality and representative training data. Lack of diverse datasets may impact their performance. Overfitting risk if the AI/ML model is trained excessively on specific datasets.	Active states tracking LSTM based neural network was proposed in [74] to filter out useful information regarding battery capacity.
Incremental capacity analysis	Comes under the category of hybrid estimation. It is the combination of model and data driven methods. Utilizes the linear relationship between the residual capacity and IC peak.	Does not require the internal battery mechanism and the knowledge of the battery. Non-intrusive battery SoH estimation. Changes in the incremental capacity curve can serve as an indicator of ageing and degradation in the battery.	ICA might not provide detailed information about the specific degradation mechanisms causing SoH decline. Results can be influenced by factors such as temperature and discharge rates.	[75] concluded that ICA, differential voltage analysis, and probability density function had the same mathematical foundation. A probabilistic framework for predicting battery pack SoH was established in [76]. A method for obtaining the IC curves faster using finite time differentiation was proposed in [77].

tend to be more profitable than off-grid applications, particularly in peak shaving, area and frequency regulation and renewable firming. The efficacy of SLBs in reducing the cost of energy (COE) is emphasized in several studies considering local tariffs in different countries. These economic assessments underscore SLBs as viable alternatives to FLBs, highlighting potential reductions in capital investment and COE across diverse applications, including supply-side management. Investment costs can be significantly reduced, up to 60 %, when integrating SLBs with

PV panels, 70 % when used as energy backup sources, and 73.62 % in grid-connected renewable energy systems [81], [88], [89].

IX. APPLICATIONS FOR SLB

A. RENEWABLE ENERGY STORAGE SYSTEMS [90], [91]

Penetration of sustainable sources into the electricity grid is happening at a fast pace and energy storage systems are a vital part of any renewable source whether it is solar, wind, etc. The intermittent nature of such sources is a major problem and even though ESS is a solution, costs associated with such storage systems are remarkably high.

EV batteries in their second life can be repurposed for stationary energy storage. These batteries can store surplus renewable energy generated during periods of low demand and supply it during peak demand, aiding to balance the grid and encourage the use of renewable energy sources. This contributes to SDG 7 (Affordable and Clean Energy) [9]. To reduce the cost of associated ESS and thereby the overall system, SLBs can be utilized with these packages. SLBs can thus play a good role in the upcoming integration of renewables into the grid.

B. FREQUENCY REGULATION APPLICATIONS [92]

Mismatch between the load demand and the generation results in variation of frequency. To ensure the stability of the power system, the active and reactive power must be controlled by area regulation. ESS can be used for this purpose.

However, the usage of primary Li-ion battery is not economical. SLB can be used for such ancillary area frequency regulations.

C. LOAD LEVELLING APPLICATIONS [93], [94]

Storing electricity during off-peak time and supplying it during the peak period is a helpful way in reducing electricity bills, reducing grid stress, etc. SLB based ESS can be used for such arbitrage applications. Traditional battery ESS has a prohibitive cost and makes the application less economical. SLB having 80 % capacity remaining can be utilized effectively at a lower cost for peak shaving and valley shifting purposes.

D. ASSET MANAGEMENT [88]

The generation side requires maintenance from time to time but due to the high demand from the load side, backup sources like diesel generators need to run during the maintenance period. SLB based energy storage systems; when used in sufficient numbers; will have enough capacity to coordinate along with the diesel generator. This will also help to reduce the stress and fuel consumption of the diesel generators.

E. OFF GRID APPLICATIONS

Batteries are the most vital component needed in isolated microgrids. These types of grids run in renewable energy sources or other sources like fuel cells, diesel generators, etc. Power quality and its reliability with minimal cost can be achieved by integrating SLBs into such off-grid energy storage applications.

F. FAST CHARGING STATIONS

Using Li ion during their primary life in the EV charging station is not very economical due to their high price. However, SLB can be utilized in the charging stations for the fast charging off board application with or without coordination with the actual AC-DC converter supply inside the charger.

Table 7 gives insights regarding some of the projects undertook in various countries regarding SLB and a brief overview about their approach to the work.

X. MARKET OPPORTUNITIES OF SLB

Based on the various SLB capacities available, a plethora of opportunities for their utilization is present. Brief details about their applications were given in section IX. Technical details regarding their purpose in those applications are given here.

Many studies present several practical applications of SLB in various fields like load leveling, renewable firming, backup systems, etc. [99] concluded that the best possible application for SLB at present is in the renewable firming field in the grid application and the automated guided vehicles in the mobility application. Table 8 depicts details about the capacity required, C-rating, and their potential of usage in the application with the * representing the effectiveness.

XI. CHALLENGES TO SLB

Various challenges are faced in incorporating lithium-ion batteries for secondary life applications. Although the cost of secondary life batteries would be lower than the primary ones, the economical standard for pricing SLBs is not yet developed. The price could include dismantling, testing, refurbishing, etc. in the overall cost of the SLB based ESS. Globally, the recycling and reuse of Li-ion batteries are in the developing stage. In India, many start-ups and companies are focusing on the recycling of Li-ion batteries to recover the raw materials, at present. Several challenges related to SLB are given below [100], [101], [102], [103], [104].

A. BATTERY DISMANTLING ISSUES

Battery disassembly is an important stage to accurately determine SoH. It usually involves disassembling to module level since at cell level, the process is difficult and complex. The main challenges behind this are the labor-intensive manual processes which inflates the cost of labor though these rates vary based on the local labor rates. The difficulty of the disassembly process largely depends on the battery's structure, interconnections, and factors such as the number of bolts, fasteners, and accessibility, all of which contribute to determining the overall expenses of disassembly and repurposing. When it comes to dissembling into individual cells, it becomes a tiresome task and can pose safety issues. This is owing to the thermal runaway; which could be hazardous. Lack of skilled workers and automation in the field of battery dismantling also is a major challenge and makes this initial stage difficult. As more electric vehicles hit the roads and their onboard batteries have a limited lifespan, there is an increasing need for disassembling and screening second-life batteries. This situation offers a chance to create a scalable

TABLE 7. **Applications of SLB in various fields.**

Application	Location	Approach to the work	Outcome
Fast charging Off-grid PV stations [95]	United States	Equivalent circuit modelling of the battery was done. Battery model considered was NMC. Feasibility study based on the residual capacity of the SLB to be used in off grid fast charging station with PV system.	SLBs opted as an excellent and cost-effective choice for off-grid-based fast charging stations.
Residential management [96]	Spain	The SoH of the battery packs in both life periods was measured using internal impedance and residual capacity. A study on the various effects of Li-ion batteries for residential management based on their SoH was done.	SoH is a particularly crucial factor that is necessary to verify the health and capacity remaining in the SLB. Internal impedance is a parameter that plays a role in the cycle and calendar ageing of the cell.
Gas turbine systems [97]	Spain	Study to find the expected lifespan of SLB when used for secondary applications such as gas turbine systems. Calendar and cycle ageing of SLBs based on SoC, temperature is also studied	SLB can be used effectively in gas turbine systems. SoC and temperature; if kept in overlimit for a long time; will adversely affect the cycle and calendar ageing of batteries. Storage temperature is important to ensure extended lifespan of the SLB.
Energy management and network deferrals [98]	United Kingdom	Different applications of SLB in frequency response, energy management were studied after their primary life data was captured.	Open circuit voltage tests, impedance tests help to determine the residual capacity of the SLBs.

TABLE 8. **Application specific considerations of SLB [95], [96], [97], [99].**

Application field	Subset	Capacity	Power / C rating	Effectiveness
On-grid	Load leveling	50 MWh	10 MW	**
	Peak shaving	3-4 MWh	1 MW, 0.5C	***
	Backup system	30-45 MWh	< 5 KW, 0.2C	***
	Renewable firming	1-10 MWh	1 MW, 0.25C	****
Off-grid	Residential load following	3-4 kWh	1 kW, 0.3C	**
	Power quality	Variable	Variable	*
Mobility applications [4]	Automated guided vehicles	10 kWh	0.2C-0.5C	****

automated machine that combines robotic disassembly with automatic screening processes.

B. EV BATTERY PACK VARIANT DIFFICULTIES

Battery modules differ significantly between vehicle lithium-ion batteries, including variations in form factor and chemistry. This diversity might not be right for mixing modules in a second-life application due to increased variability and potential mismatches. Present day EVs have high capacity and power to handle range anxiety. But many EVs use different variants of batteries which makes it difficult to segregate and reassemble faster. Diverse battery compositions require different handling and treatment methods, increasing the complexity and cost of establishing effective secondary life strategies. Moreover, different cells will have different SoH and capacities and must be made into a homogeneous pack. Otherwise, the SLB pack will not have its expected capacity and performance.

C. TECHNOLOGICAL CHALLENGES IN BATTERY REPURPOSING

Accurately determining when EV batteries retire is crucial for planning repurposing and recycling. To seamlessly integrate batteries from different manufacturers into energy storage systems, research must focus on understanding their degradation rates within limited supply windows. Flexible control systems enabling communication with diverse second-life batteries and their management systems are vital for optimizing these systems. Various methods like Kalman filters, fuzzy logic, parity relations, etc. are available for SoH measurement. There is a trade-off between various methods. Proper SoH assessment is necessary for the proper utilization of SLB in the market. The BMS designed for an electric vehicle's Li-ion battery might not suit its second-life application. Each new use requires a specifically engineered BMS to effectively monitor and regulate the battery modules for that particular purpose.

D. LACK OF POLICIES AND STANDARDS

Defining clear standards for regrouping batteries, especially regarding cell-to-cell variation, remains unclear in repurposing efforts. Understanding how these variations impact overall pack performance is crucial. Establishing a standardized quantitative approach considering self-balancing mechanisms among cells is essential. While certain cooling structures can reduce cell-to-cell variation, there is a cost trade-off. Stabilized cell-to-cell variation could serve as an upper limit for second-life battery parameters. New regulations and testing standards, like UL 1974, address safety and performance evaluation for used batteries. UL 1974 applies the same certification standards for second-life battery systems as it does for those built with fresh components. However, standards such as IEC 62933-5-3, focused on the safety of second-life battery systems, need adaptation to cover systems using components from used batteries. Yet, uncertainties remain regarding how testing standards can accommodate the variable quality of used batteries and accurately represent their performance in these systems.

E. EVOLVING ENERGY SOURCE MARKET

Various research works are being carried out to develop new energy sources for storage applications. Superconducting magnetic energy storage (SMES), hydrogen fuel cells, supercapacitors are being developed and there are many uncertainties whether Li-ion will be present in the long run. The present scenario, however, predicts a massive upsurge in the usage of Li-ion batteries by 2030. Solid state batteries are also an area of research and are claiming to be safer than lithium batteries. The energy market is constantly diversifying to create the next best energy source. But extensive research must be carried out in any field before being brought into the market. Lithium-ion batteries have already taken their place in the industry and are expected to stay for more than a decade at least.

F. SAFETY CONCERNS WITH SLB

Electric vehicle batteries vary in chemistry and configuration, requiring a deep understanding of capacity fade, impedance increase, and potential ageing issues like dendrite formation. Mitigating this degradation caused by ageing mechanisms to optimize the second-life potential of EV batteries is crucial. Operating second-life batteries safely without extensive historical data poses challenges, underscoring the importance of collaborating with original equipment manufacturers (OEMs). Such collaboration facilitates insights into battery history and safety guidelines, aiding in ensuring safe operations.

G. LOGISTICS CHALLENGES

Efficient reverse logistics for used batteries is a critical challenge in the battery supply chain. Safe transportation of end-of-first-life batteries requires specialized technologies. The availability of retired EV batteries drives the development of stationary energy storage systems. Forecasting the supply of used batteries is vital for a sustainable second-life battery ecosystem, ensuring stability for stakeholders amidst market price fluctuations.

XII. CONCLUSION

The EV battery's secondary life has become a major area of research and is expected to skyrocket as more electric vehicles enter the market. Discarding these batteries should only be a last resort and utilizing them in secondary applications ensures zero wastage of their energy capacity. Utilizing these discarded high potential batteries will also reduce their carbon footprint. The industry's success on secondary battery life hinges on proper testing, estimation, validation, pricing, and global efforts toward reuse and recycling. Studies show that repurposing batteries for secondary applications can reduce the overall cost by around 20-25%. Standards, expertise in thermal management, battery compositions, and predictive SoH methods are critical to this achievement. Accurate SoH prediction methods are pivotal for both primary and secondary battery applications. This paper presents a comprehensive data-driven SoH estimation approach in detail along with the degradation mechanism, challenges, and applications which can pave for any new researcher aiming to start their journey in secondary EV battery life as well as SoH estimation. The ICA technique accompanied with graphical understanding helps to get a clear idea about the importance of this method in the SoH estimation. Comparison study of the ICA with other estimation methods also conveys the reason why such data derivational methods are becoming the need of the hour.

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