Battery Hazards and Safety: A Comprehensive Review for Lithium -Ion Battery System

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Abstract: Lithium-ion battery systems (LIBS) have unique qualities like high efficiency, high capacity, better power, and low self-discharge. The fast development of the electric vehicle (EV) industry has created a huge market for LIBS to be used as an energy storage device and provide an eco-friendly transportation system. The high demands and market call for LIBS lag behind the safety concerns due to which the explosive incidents of LIBS take place. It is also seen that overcharge, deep discharge, lack of proper thermal management in two-wheelers, and poor selection of cell configuration are the key factors for the explosiveness of the LIBS. In this review, we have studied the reasons behind the occurrence of the above key factors and also analyzed the variation of electrical parameters like voltage (V), current (I), and internal resistance (R) with abnormal conditions. The aim of this study is to work for the betterment of the LIBS and contribute to uplifting the market's acceptability towards the enhanced EV industry.

Index Terms: Electric 2-wheeler, Li-ion battery, Overcharging, Deep-discharging, Thermal runway, Nail penetration, shocks and vibration, state of charge, state of health, Kalman filter, Extended Kalman filter+

I. Introduction

Green energy is always the point of attraction for various researchers across the globe. Basically, the commercial automobile industry used carbon-based fuels like petrol and diesel. Limited resources, an increased carbon footprint, and environmental pollution have led us to look towards ozone-friendly power sources. Windmills and solar power are the best options, but they are temperature- and environment-dependent. Hence, batteries, which are ozone-friendly, are the clear and best choice to run the auto-mobile sector smoothly. The use of LIBS in the EV industry is the most advanced and welcome step from an economic and environmental point of view **[1]**.

As per the Fortune business insight report (ID-FB100123) published in 2024, US$ 36.90 billion was the global market size of lithium-ion batteries in 2023, and it is expected that it will grow from US$ 38.82 billion in 2024 to US$ 103 by 2032, as shown in Fig. 1(a). Currently, India does not have a strong presence in the LIBS manufacturing field, but it has great potential. The business insight report reported on May 2024 valued the Indian market size of EV was about US$ 8.03 billion in 2023. The expected growth of the market is US$ 17.03 billion to more than US$ 60 billion by 2032 as shown in Fig. 1(b).

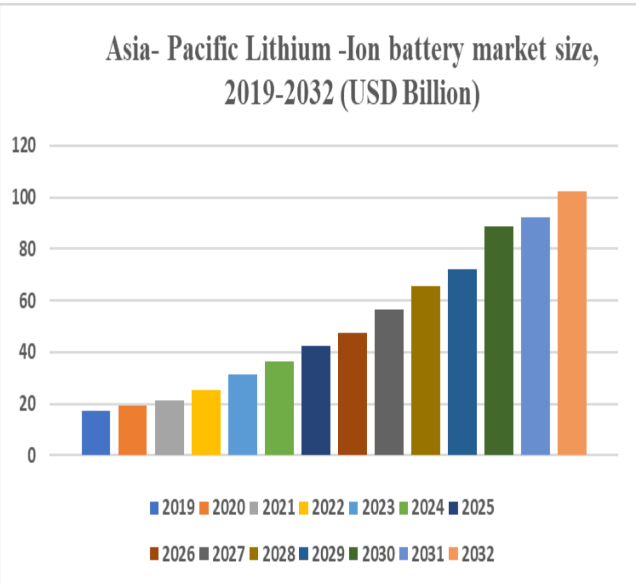

FIGURE1(a). market size of Lithium-ion battery by Fortune projection in business insight report 2024

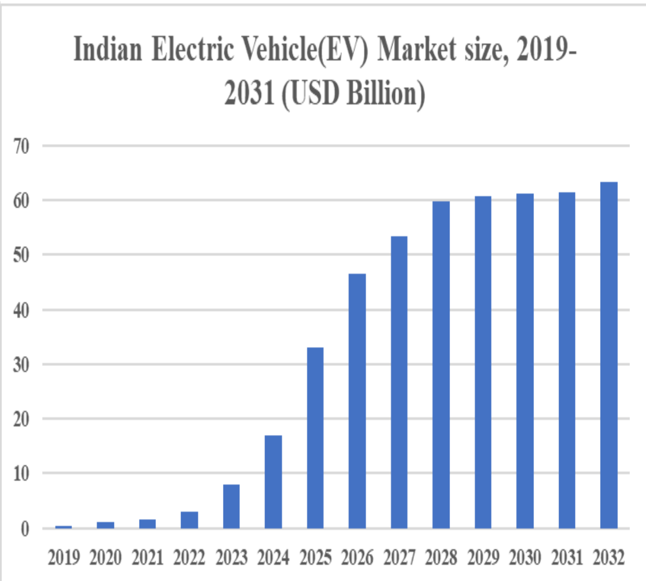

FIGURE 1(b). India: Lithium-ion battery expected market in USD Billion by business insight report 2024

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LIBS, although it has great trends and advantages in the market, faces lots of challenges and barriers to its upliftment. Since the last few years, various failures have been noticed in LIBS, due to which the energy storage system in LIBS has been a great field of research. Under various abnormal conditions, battery malfunction occurs, due to which mainly three abusive conditions occur inside the battery: electrical abuse, mechanical abuse, and thermal abuse. These abusive conditions at different temperatures of the running battery led to gas and smoke generation and explode the battery. The collective results of the three abusive conditions are thermal runways (TR). TR is a stage in which the whole battery pack explodes and gas and smoke come out of the internal portions of the battery.

Abusiveness in Lithium-Ion Battery System

There are various factors that are still barriers to the market acceptance of LIBS as shown in Fig.2. Overcharging, deep-discharging, no proper thermal management, and being incompatible with the roads and traffic systems of the different regions. The occurrence of internal short circuits (ISCs) is the most critical defect, which can be caused by overcharging, deep-discharging, and manufacturing defects and lead to the thermal runway of the batteries **[2]**. The LIBS internal chemistry is different in different cells, even if the cells are manufactured in the same unit at the same time by the industrial unit. There are basically three different types of cells used in the manufacturing of LIBS: 18650, 21700, cells, even if the cells are manufactured in the same unit at the same time by the industrial unit. There are basically three different types of cells used in the manufacturing of LIBS: 18650, 21700, and 26650. The specification sheets for the following three types of cells are given in the table 1

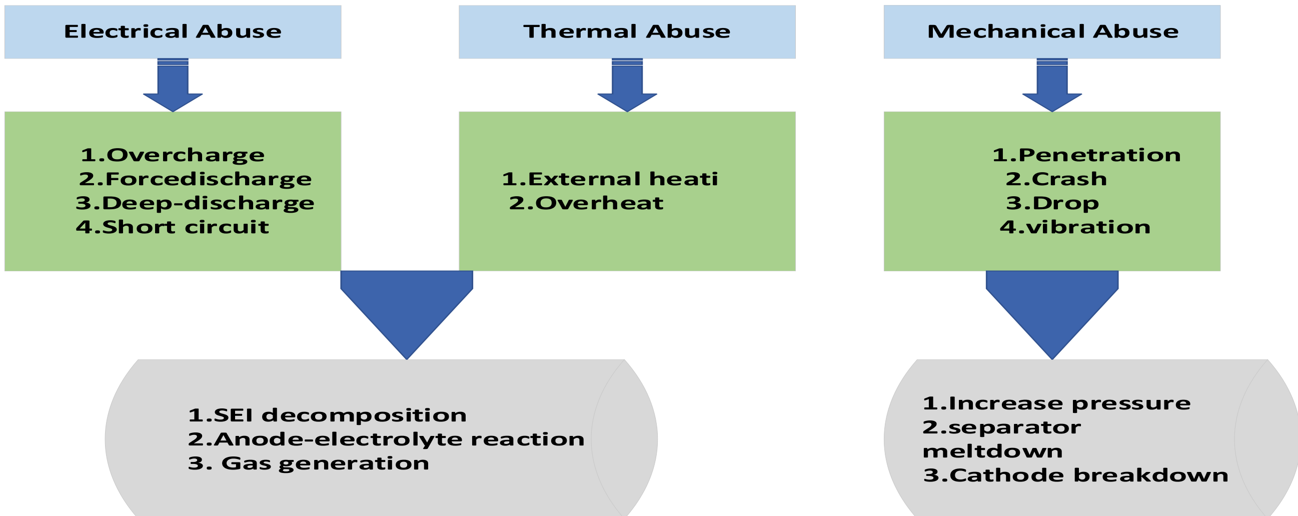

Figure.2. Kinds of abusiveness and their parts [2]

Table.1. Specification Sheet of Libs Cells

Types Of cell	Nominal Voltage (V)	Max. charge Voltage	Discharge Cut-off voltage	Standard Discharge current	Rated Capacity (mAh)	Operating Temperature (degree Celsius) Discharging
186500	3.7	4.2	3.0	0.52	2600	-20-60
21700	3.63	4.2	2.50	0.61	3400	-10-50
26650	3.2	3.7	2.0	0	4500	-10-40

In India, 18650 and 21700 cells are commonly used to power electric two-wheelers. The most important factor is protecting them from damage, as thermal management is poor in two-wheelers due to economic and spacing considerations. Overcharging is the most prominent phenomenon resulting from the failure of LIBS. The overcharging of LIBS under different C-rates studied by author in **[3]** leads to a thermal runway. The journey of the thermal runway is divided into expansion, rupture, and combustion. In expansion, voltage and surface temperature increase with increasing C-rate. Lithium-ion cells are configured in three different modes (staggered, tapered, and rectangular) to provide high power, capacity, and energy demands. It is analyzed by the researcher that the abnormality of a single cell in the packs

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damages the whole battery; it may be due to overcharging, deep discharging, or high heat generation. Temperature rises inside the battery are non-uniform in nature, which could not even be recorded by the battery management system (BMS). Authors across the globe try to analyze the abrupt rise in temperature and its effects on the workability of the battery. Flame temperature was analyzed as an important parameter in **[4]** to examine the real working condition of the cell packs. It is analyzed with the help of a thermocouple placed over the cell packs. It is also seen in the operation of LIBS that with the overcharging at the upper cutoff voltage, the cathode material decays with the formation of solid electrolyte interphase (SEI); therefore, in **[5],** the author analyzed that the charging and discharging capacities of LIBS gradually decline with the proportion of the square root of the number of cycles. It is also seen that with the charging of the same source to two different capacity batteries, the battery with a higher capacity degrades faster than the lower capacity battery, and its capacity retention percentage is also lower than the later

battery **[6]**. The market for stationary charging stations is also emerging as one of the most challenging tasks in energy storage systems around the world. Germany is providing a large uplift and a base for such stations. In this way, the authors **[7]** collected data from home storage systems (HSS) and industrial storage systems (LSS) to provide transparency and system development throughout Germany. The world is facing huge challenges to meet the needs of required battery storage systems in the auto-mobile sector. The scarcity of availability of raw materials, proper investment, manpower, complexity in chain supply, and diversification are studied by authors **[8]**. The International Council of Clean Transport (ICCT) published in its current report that the demand for zero-emission heavy trucks in Europe is increasing now, but earlier it was low because of low range covering and mileage by EV heavy loaders **[9]**. BMS is the key device in Li-ion batteries to balance and manage the operational conditions of the running battery. Researchers across the world have used different techniques to analyze the behavior of the BMS and try to enhance its capacity. However, without a BMS, proper monitoring and operation of batteries raise problems like safety, reliability, durability, and cost. BMS-master and BMS-slave (the main modules of BMS) can work together with wiring communication. **[10]**. To extend battery life, BMS must provide critical information about the battery charging and ageing mechanisms through accurate calculations of the state of charge (SOC) and state of health (SOH). Author uses bagging and Extra-Tree algorithm which has best interquartile range (IQR) among other ML techniques **[11]** to estimate the SOC. However, the calculation of SOH is a tougher task than SOC because of the non-uniform ageing mechanism of the batteries. Electrochemical Impedance Spectroscopy is generally used to detect the ageing mechanisms of batteries. Today, with the increasing application of computer science tools in research applications, different technical approaches are being used by the authors in battery systems **[12]**. By utilizing cloud computing, author in **[13]** improved the power calculation and data storage capabilities of battery systems. Based on the availability of the tools, the battery system is basically divided into two states: model-based and data-based. In a model-based approach, the characterization of battery operation is based on selecting the parameters and analyzing the internal state of the model. Different filters have huge applications in this approach, but Kalman filters have broad applications in this category. Author in **[14]** Use different filtering techniques, like the extended Kalman filter (EKF) and smooth variable structure filter (SVSF), to calculate the SOC. Data-based methods use real-world experimental data to investigate the operational behavior of the system without concern for the internal behavior of the ageing process. This method necessitates a large amount of data as well as highly sophisticated computational tools. This method provides a more accurate estimation because it is totally based on a mathematical and statistical approach. Author shows Fuzzy-logic techniques as more versatile in this category of SOH estimation **[15]**. The remaining useful life (RUL) calculations of the batteries are accurately calculated by this method. The Box-Crox transformation algorithm and Monte Carlo methods are extensively used in this approach as in **[16]**. The data-driven method depends on health indicators (HI) to accurately predict the RUL. The general HIs like capacity and impedance cannot be measured in real-world running batteries due to complexity **[17]**. To frame this issue **[18]** The characteristics approach of the voltage, current, and temperature are proposed to obtain the HI of the battery with respect to its possible capacity.

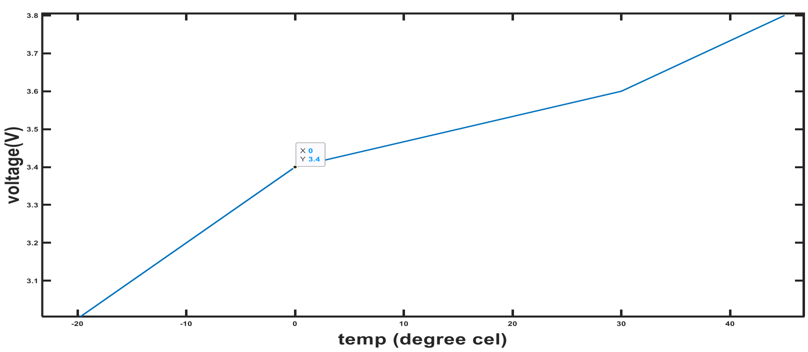

Figure.3. Variation of voltage with the temperature of the battery [19]

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Electrical abuse of Lithium-ion battery

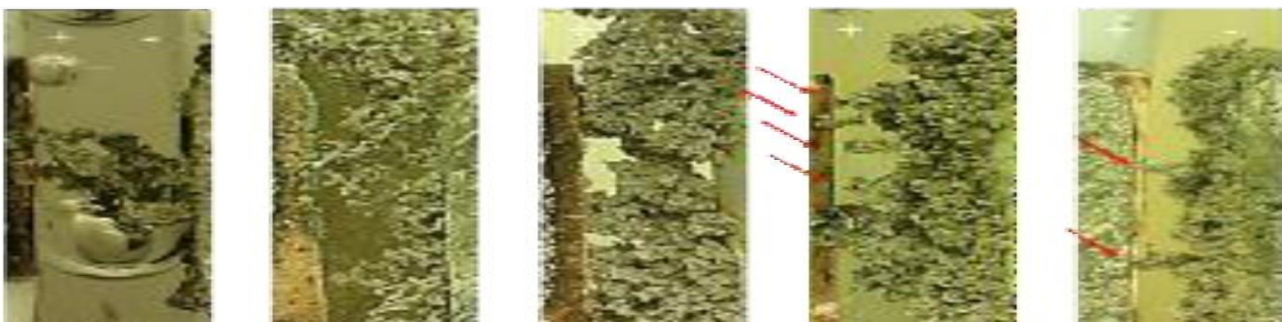
Electrical abuse is mainly related to improper charging and discharging of LIBS. Overcharging and deep discharging are the main factors in the electrical category that are responsible for the thermal runaway of batteries. Charging the battery over the specified limit is responsible for enhancing the rate of reaction inside the battery. It is the foremost duty of BMS to protect the battery from overcharging, deep discharging, and temperature variation. Ambient temperature has a significant impact on the battery performance. At low temperature, voltage of the battery declines faster than normal working temperature as shown in Fig 3. It is the duty of manufacturing companies to use better- quality or reliable BMS that cannot fail in real-time applications **[19]**. In EV two-wheelers, thermal management systems are not available due to space and installation problems; therefore, it is difficult to predict the internal abuse of the running battery, which leads to battery explosion

Overcharging and Depth of Discharge.

Overcharging the battery beyond the specified limit enhances the chain reaction inside the cell. When the LIBS is overcharged, a large number of Li ions are transferred from the cathodes and deposit on the anode electrode's surface. This ion transfer process produces dendrites, which are spike-like structures on the anode that collide with the separator and cause a short circuit inside the battery. Ultrathin carbon nanomembrane (CNN) having sub nano-meter size(1.2nm) pores as an interlayer for the mass- transition of Li-ion regulation are emerged as the controller for the dendrites formation **[20]**. Various factors, like current density, temperature, and electrolyte convection, are responsible for dendrite generation. Author used the in-situ observation method as shown in Fig.4 to detect the dendrite formation at different current densities **[21]**

Table 2. Time Duration to Voltage Drop and Growth Rate [21]

Initial current density (mA/cm^2)	**Time to half of the gap(h)**	**Time to first voltage drop(h)**	**Growth rate (mm/h)**	**Cell voltage**
10	3.7	7.3	0.23	0.8
40	0.45	3.88	0.43	0.3
87	0.35	2.08	0.92	0.6
95	0.53	1.48	1.7	0.5
110	0.23	0.5	2.18	0.7
125	NA	NA	4.96	1.0



10 mA/cm^2 40mA/cm^2 87mA/cm^2 95mA/cm^2 110mA/cm

Figure. 4. Formation of dendrites at different Densities [21]

Estimation of average dendrites under various current densities can be calculated by dividing the length of dendrites over elapsed time to the first voltage drop as per the Table.2. The time required for a short circuit decreases as current density increases, implying that the rate of lithium dendrites increases as current density increases. Initially, the unstoppable growth of the lithium dendrites increased the surface area of the Li metal and enhanced the irreversible side reaction between Li metal and electrolyte **[22]**. The thermal runway mechanism due to overcharging has been studied many times. However, the exact processor to evaluate the internal failure of the battery still needs to be explored. Different

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

scholars use different techniques to evaluate the process; many of them conducted the overcharge experiment with LIBS and cathode metal. In **[23]** author introduced the fire alarm techniques and controller of the TR in the battery box of different length for different time duration during loading condition at a particular temperature. Anode loading during side reactions is responsible for the loss of cyclable efficiency and poor coulombic efficiency was absorbed by author in **[24]**. The marching rate is greater than the critical towards the anode, starts dissolving SEI, and effects SOC. A different modification approach has been applied by the researcher to analyze the degradation of the LIBS, therefore in **[25]** author develop the particle level model to analyze the phase transition structural degradation in terms of loss of active material(LAM) and loss of lithium inventory(LLI). A multilayer electrothermal model is developed to analyze the ISC and its further effects on the thermal runway **[26]**.

One of the worst results of the overheating of the battery is damage to the electrodes. Various approaches have been enhanced by the researcher to modify the physical chemistry of the electrodes. In **[27],** The author introduced the dimensionless SOH indicator for battery under different stages of charging and discharging to predict the failure conditions, in **[28]** author use the inverse heat transfer method to back calculated the heat generation during overcharge.

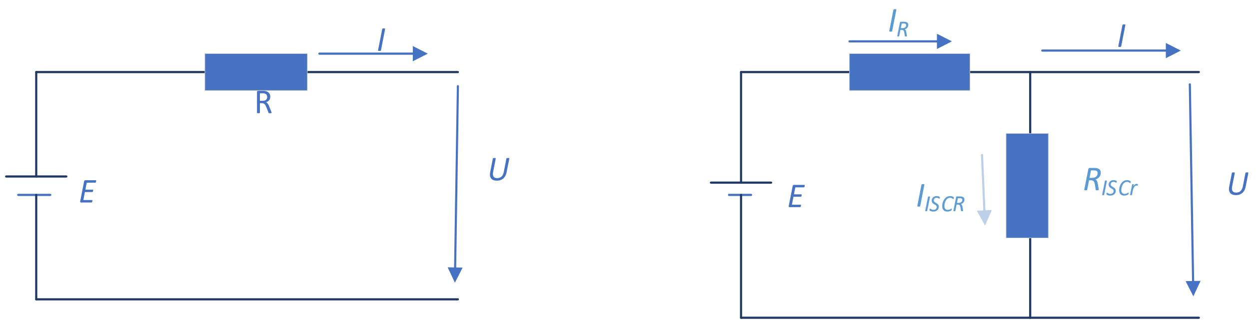
Apart from this, various techniques have been evolved by the researcher to detect the occurrence of an internal short circuit (ISC) as it is one of the important cause for the thermal runway (TR) of the battery **[29]**. However, if the indicators are visible, they are unstoppable; therefore, it is necessary to find out the initial indicators of the ISC. The equivalent circuit model (ECM) is a comparatively simple base for analyzing practical applications. If the capacitive parameter is neglected, the ECM is equivalently transformed into an electrical circuit, as shown in Fig. 5(a). The dynamic voltage is shown in equation 1.

$$U = E - I.R \tag{1}$$

Where,

U = measured value, E = open circuit voltage (OCV),

I = current, R= internal resistance



(a) (b)

Figure.5. Electrical equivalent circuit of battery [30]

Fig. 5(b) shows the condition of the ISC in the battery system. In this condition, the short-circuit resistance R_{iscr} is connected in parallel to the main circuit. Combination of electrochemical impedance spectroscopy (EIS) and deep neural network (DNN) are applicable for zero false positives detection of ISC with the accuracy of 97.5% and equivalent resistance range from 200 ohm -10 ohm **[30]**. Over-discharging is one of the serious problems in LIBS battery packs since cells connected in series are expected to discharge at the normal rate despite the different cell capacities. Let us suppose there are three cells: two fully charged and one at 60% SOC. If these cells are connected with a load in a series connection, a partially charged cell will be discharged first and start, which forces the electrodes to operate outside the normal potential range and effects the life cycle of the battery but does not cause any hazard conditions by single over-discharge. The depth of discharge (DOD) essentially represents the running battery's remaining capacity. It is an important parameter to understand the SOH and size of the battery bank required to meet the energy consumption. Every battery manufacturer provides a limit for DOD with their battery products. This limit allows for the greatest amount of capacity sacrifice while posing the least risk to battery performance in the future. Although normal discharging of batteries is a general operation and has no significant negative impacts on the battery's functionality, deep discharging and fast discharging have a non-uniform impact on the battery's cycle life. Normally, it is seen that the normal operating temperature of LIBS is 40–45 degrees as per the datasheet provided by the manufacturer; battery charging below this temperature always provides lower energy as an output due to lower output voltage and capacity. Discharge the battery at a temperature greater than 45 degrees, which provides more energy but reduces the battery's life.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

Mechanical abuse

In LIBS, mechanical abuse is basically studied in different forms, like nail penetration, shocks, vibration, and immersion as per the Fig.6. In this portion, we basically studied these forms one by one and also found out some of the latest innovations in the field

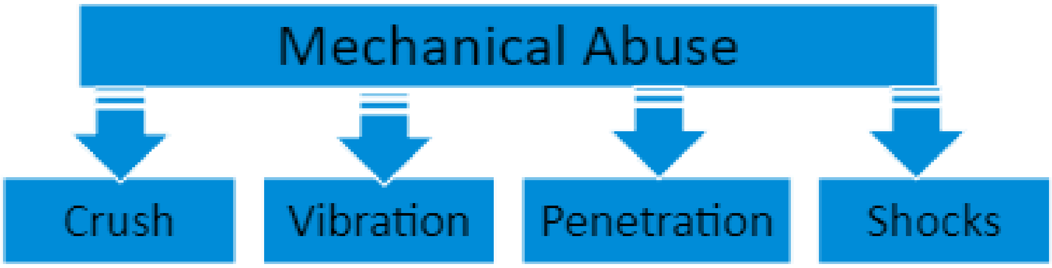


Figure.6. Mechanical abuse of LIBS and its parts

Nail- Penetration

Forcefully damaging the LIBS from an external source is known as nail penetration. This causes a change to the internal portion of the battery and results in some serious tasks. Out of all the internal damage due to nail penetration, short-circuiting is one of the major problems that can be triggered by any of the mechanical damage. Author demonstrates the Nail-test on different Lithium-ion cells (with similar conditions) monitoring the tabs voltage and surface temperature and concluded that tabs voltage shows comparable behaviors with similar reptations of ISC **[31]**. Nail penetration causes damage to the electrodes and separator, due to which the internal resistance increases and heat generation starts. In running a battery, further increases in temperature lead to exothermic reactions and around 90–100-degree temperature solid electrolyte interphase (SEI) meltdown, and at around 200–250-degree temperature, positive active metals start to decompose **[32].** Many of the researchers basically use nail penetration to test the safety of the LIBS. This technique is applied with a thin nail and a slow penetration speed on dry cells, wet dummy cells, and working cells. During the tests, ISC temperature and ISC current are also measured. It has been verified that during nail penetration, the ISC resistance alters significantly by several orders of magnitude. More significantly, it is discovered that the steady resistance following at earlier levels of nail penetration, the lowest dynamic resistance is substantially lower than full penetration. Thermal runaway during nail penetration testing would be understated in an analysis based on such a stable ISC resistance **[33]**. Author experimentally performed in the micro-short circuit cell structure of 18650; the thermal runway increased with SOC during penetration **[34]**. In **[35]** In the internal short circuit system, with the help of high-speed and high-precision X-ray inspection, the author clearly observed changes in nail tip, boiling of electrolyte, rate of gas generation, and the beginning of the thermal runway. Author captured for the first time the internal state of the LIBS during the process of pouch ballooning or when gas generation was observed outside the cell. The author conducted the optimized nail penetration test with the newly developed LISC scanner **[36]**. Basically, during nail penetration, the cell voltage decreases rapidly with the increase in cell surface temperature, as shown in Fig.7. The increase in cell temperature and cell voltage depends on the speed of penetration, thickness of the cell, and time to fully penetrate the cell. Author developed a new technique apart from conventional methods; he observed a number of peaks of local temperature ahead of the thermal runway **[37]**. The author tried a 3S nail penetration technique to separate the internal short circuit from the thermal runway of the battery.

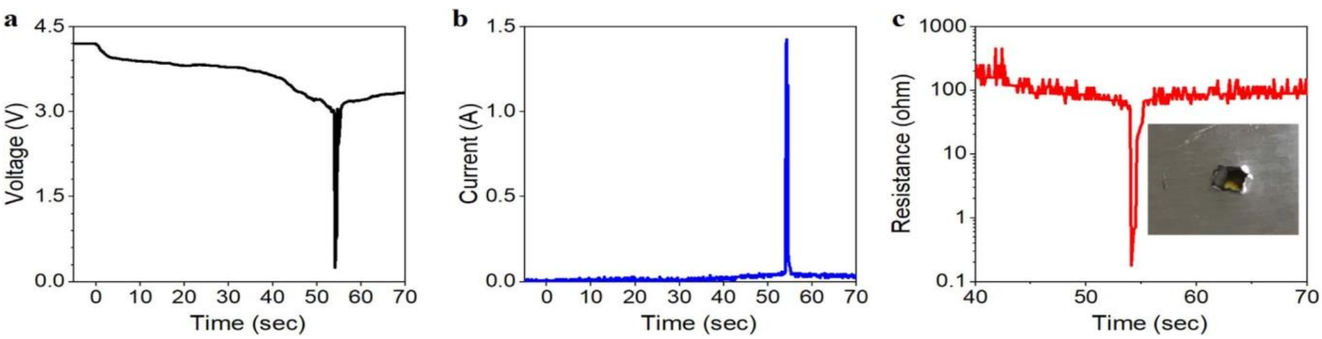


Figure.7. Li-Ion cell internal short circuit and thermal runaway through small, slow and in situ sensing nail penetration. [37]

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

Table 3. Comparative Study of Different Approaches in Libs

S.no	Author's Name	Methodology	Mode of study	outcomes
1	Xueyuan.Wang et.al.,	Multi-channel impedance spectra is used to measure the impedance of series connected cells	Experiments	CTR has a high sensitivity to the degradation of battery life
2	T.Reichl.et.al.,	Automated cyclic station H-tronic accumaster is used to evaluate the current, voltage and capacity at regular interval of time	Experiments	Cell Capacity(ct) test is more suitable for Isc detection
3	Yan-li Zhu.et.al.,	Different chemicals are used in different compositions in electrodes and in electrolyte for internal safety concern of the battery	Experiments	Lio_2Co_3 is and effective additive to reduce the safety problems of the battery
4	Mingyi Chen.et.,at.,	Video coverage recording of 6X6 and 10X10 array of lithium ion cells under the thermal propagation mechanism	Experiments	Flame temperature, ambient temperature of heat sensor probes and gas stream measurement are the important parameters for analyzing fire hazard.
5	Norihiro Togasaki.et.al.,	High-energy Panasonic cells are charged and discharged at different cut of voltage. Potentiostat was to measure impedance spectra at different number of cycles.	Experiments	EIS analysis is used in advance to prevent the second stage of capacity decaying.
6	Dongxu Ouyang.et.al.,	Battery capacity curves are investigated to depict the sensitivity of battery with different capacities.	Experiments	Battery degradation and battery nominal capacity are related to each other
7	Jan Figgener.et.al.,	Database of HSS, ISS and LSS has been build to estimate the market capacity and power range from KW/KWh to MW/MWh.	Market review	Development of operating and economic strategy of BSS. To evaluate the home storage system, industrial storage system to provide better transparency in market
8	Lorenzo Usai.et.al.,	ODYM-RECC model, based on the IAM-based survey to analyse the market driving development of EV,s fleet.	Market survey	Supply of key raw materials, recycling facilities and skilled workforce and climate target and sustainable resources strategy are required.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

9	Lutsey N.et.al.,	'White paper' survey on the government policies for spurring the EV industry.	Investigation	Investigation of light EV production, battery production and promotion policy.
10	M. Lelie.et.al.,	Optimum design of BMS with temperature acquisition, voltage acquisition and current acquisition.	Simulation	Hardware management of BMS for EV and stationary application.
11	K.Mehmet .et.al.,	SOC calculation has been done Bagging and ExtraTree algorithm	simulation	Better accuracy than other ML techniques with small IQR with 3 %.
12	L.Khaled .et.al.,	Different SOC estimation techniques and model has been evaluated. A new optimum, reliable and sustainable approach is in demand.	simulation	Non-linear behaviours of the battery at real-world aspects the better SOC calculation tools.
13	L. Weihan. et.al.,	All the necessary data of the battery are measured by IoT and transmitted to clouds, building up the digital twins for the BMS.	simulation	Cloud computing and IoT techniques has been evaluated to improve the computational and data storage capacity of BMS.
14	T. Kim, et al.,	2RC electrical model has been evaluated. The hybrid filter is introduced to online parameter identification.Comparative validation of HF and EKF has been done by using microcontroller.	Simulation/ Experimental validation	HF-based monitoring algorithm provide better result for real time embedded BMS. It can also used for fault diagnose and prognose.
15	J. Tang,et al.,	Different indicating parameters are mixed as a member functions, based on the fuzzy logic theorey are applied to estimate the effects of health indicators.	Simulation/ experimental	Mis based SOH estimation techniques has been introduced. MMF and AHP techniques integrate the estimation effects and predict capacity fading accurately with average error of 3 %.
16	Y. Zhang, et al.,	LSTM and RRN is employed to analyse the dependency of RUL on the degraded capacity of battery system	Simulation/ experimental	LSTM, RNN predict the battery RUL even when the offline data is inapplicable. Better result than SVM
17	Wei, J, et al.,	Novel support vector regression based capacity degradation model	Simulation/experimental	SVR-based SOH diagnosis model can provide accurate estimation of real measured battery parameters

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

18	T.Tang. et.al.,	Voltage, current and temperature characteristics are evaluated to obtain HI.ANN is used to obtain relationship between optimum HI and capacity.	simulation	Simple and accurate feature selection approach is designed for constructing capacity prediction.
19	R.Bollini, et al.,	Survey study of EV 2 wheeler battery thermal runway	survey	No battery is perfect at charging-discharging efficiency. Improper heat management system responsible for explosion.
20	R.Sathish, et al.,	CNM techniques is better suited to inhibit the formation of dendrites	experimental	Flat voltage profile with minimum polarization over 300 cycles indicate the low formation of dendrites
21	L.Kong.et.el.,	Optical cells was designed to analyse the condition of dendrites formation (In-situ)	simulation	the morphology of dendrites formation is directly proportional to the current density

Shocks and vibration

The effects of stress and vibrations depend on the form factors of the cell. The mechanical cell design and internal component installation of cells determine whether they can withstand vibration or shocks. The author tested shocks and vibrations on 18 different 18650 cells of different manufacturer using random load profile based on SAE J2380. The ratio of mandrel diameter and inner jelly diameter are evaluated with the help of pre and post vibration test **[38].** The vibration profile of the cells is not related to the service life of the cells, nor is it suitable for the life estimation of the cells **[39]**. Since the last few years, researchers have been trying to analyze the effects of mechanical deformation on LIBs. Some researchers are trying to track the health condition of batteries with the help of a vibration profile **[40]** and energy consumption **[41]**. Aside from that, the battery array is configured in a variety of patterns to mitigate the effects of vibration on EVs **[42]**. In the last two to three years, the researcher focusing on the vibrational effects on a single battery has defined the effects in different aspects and provided different sorts of insight about the impacts of vibration on the electrical performance of the battery. In **[43],** author found that the LiCoO2 meso-carbon microbeads (MCMB) battery reduces ohmic resistance by about 3.77% and 1C capacity by 1.04% in vibration testing whereas in **[44],** author state that decrease in internal resistance and a slight increase in capacity with vibration testing. Author investigated the mechanical load effects in **[45]** on LIBS cells and concluded that mandrel dispatched the 18650 cells in the z-direction against the internal components with no electrical performance disturbances due to long-term vibration as shown in Fig.8

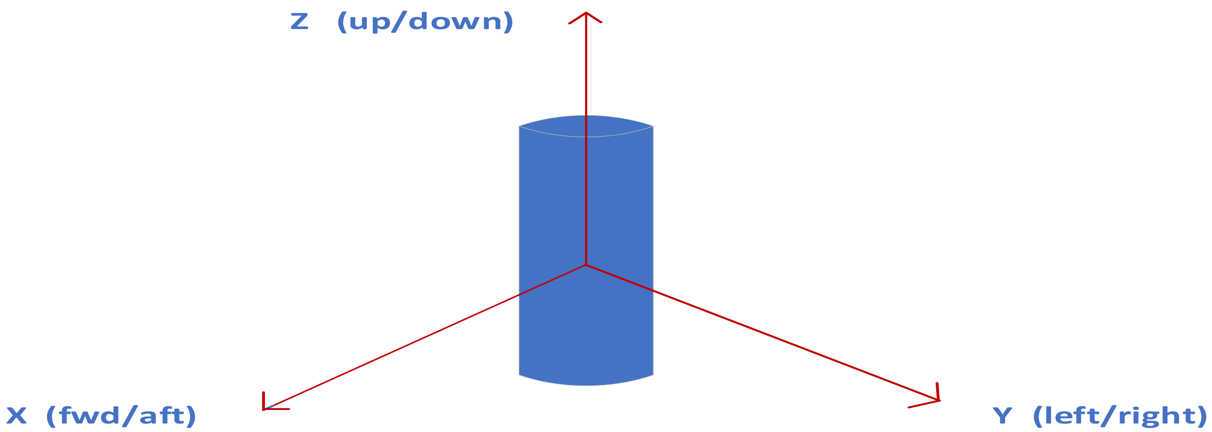


Figure 8. Three-dimensional vibration axis of Lithium cylindrical cell [45]

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

Batteries are assembled in packs to deliver the required power. Author studied the effects of loading and vibration on the battery pack enclosure and created the optimized design of the pack to increase the battery strength and decrease the weight of the body in **[46]**. The author develops a parametric reduced-order model (PROM) to analyze the cell-to-cell structural vibration of the battery pack **[47]**. He compared the PROM with the full-finite element model and concluded that the PROM is able to reduce the computational burden of vibration and fatigue. On the other hand, it is also seen that road conditions and driving patterns of the EV system are also major causes of random vibration, which directly affects the life span of the battery. The Crystal Instrument spider system worked on four different testing systems for random vibration and temperature control as shown in Fig.9.

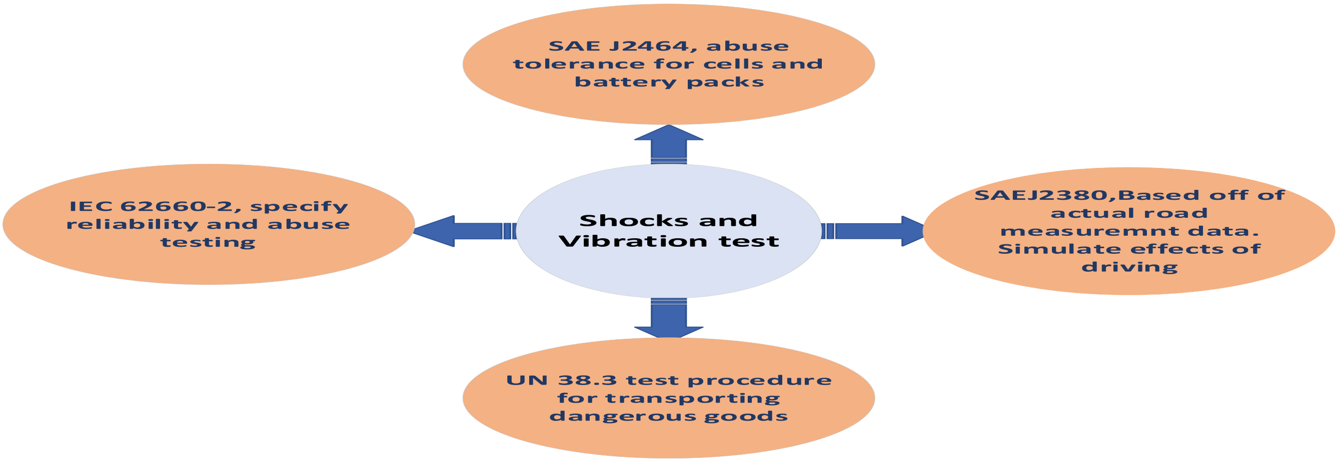


Figure.9. different testing procedure of crystal instrument spider system for vibration and shocks [47].

State of charge (SOC)

The state of charge is defined as the availability of charge with respect to the rated maximum possibility of charge a battery can store (nominal capacity). SOC is 100% if the battery is fully charged; SOC of 0% means that the battery has fully discharged. Researchers faced challenges with the SOC estimation because it was changing non-uniformly under different real-time running environments. Different approaches have been taken by scholars

across the world to estimate the SOC, such as conventional methods, model-based techniques, and machine learning (ML) techniques. An accurate modelling approach is required to provide safe, efficient, and smooth operation in LIBS. In the calculation of SOC, rapidly fading of capacity and decaying of internal resistance of the battery play a vital role; therefore, in the author develops the extended state observer technique (ESB) to combine the initial value of SOC and uncertainty on internal resistance was examined by author in **[48]**.

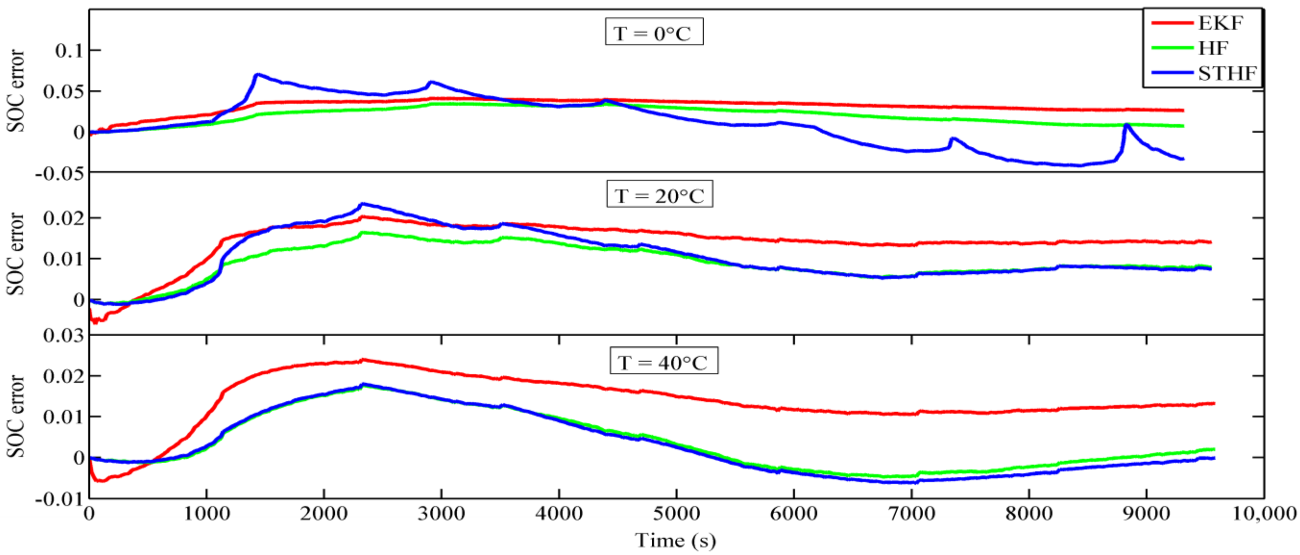


Figure 10. Comparisons of errors of STHF, HF, and EKF with white Gaussian noises [49]

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

Apart from conventional schemes, a model-based approach is also provided by the researcher to balance the simplicity and accuracy of SOC. The author used a novel errorless approach in SOC calculation. The authors have divided their work into three steps as in **[49]**, a second-order RC equivalent model, the calculation of model parameters using an exponential function filter, and the H-infinity algorithm. At last, battery SOC was calculated using STHF, and the results of HF and EKF were compared as shown in Fig.10.

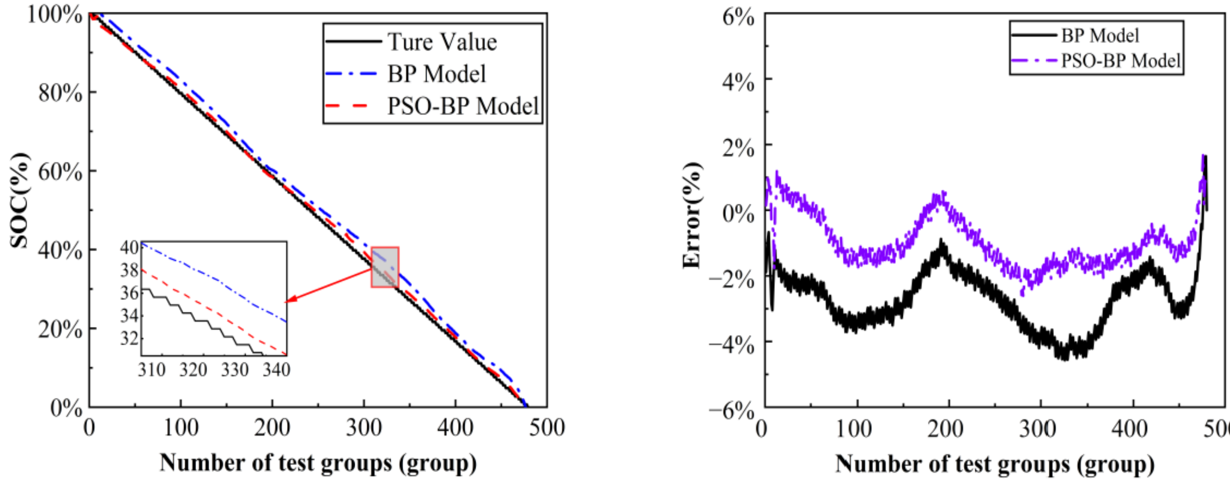


Figure 11. Evaluation of PSO-BP NN model (a) Predication of model simulation, (b) Comparison of the Error of the two NN model [50]

It is also seen that during the running condition of the battery, especially in a two-wheeler, the deep discharging effects the battery voltage, current, discharge current, and temperature, which are essential to the accurate estimation of SOC. ML techniques are useful to analyze the above parameters without consulting the inner chemistry of the battery. One of the major drawbacks of SOC estimation by various techniques is keeping track of previous data, which creates complexity in systems. In **[50],** author effectively proposed an estimation method with the help of PSO-LSTM algorithm for SOC and concluded that it has greater accuracy than the BP, PSO and LSTM neural network as shown in Fig.11.

The rated capacity of a new cell should be the reference point for SOC calculation instead of the current capacity. This is due to the fact that cell capacity reduces with cell life cycles. Unfortunately, the current capacity is taken as the reference point for SOC. In this case, at the end of life, if the SOC is 100% of a fully charged cell, its effective capacity would be 80% of the rated capacity, and various factors would have to be applied to calculate the capacity to compare it with the rated capacity. Researchers across the world use the current capacity as a reference point only to reduce complexity and design shortcuts.

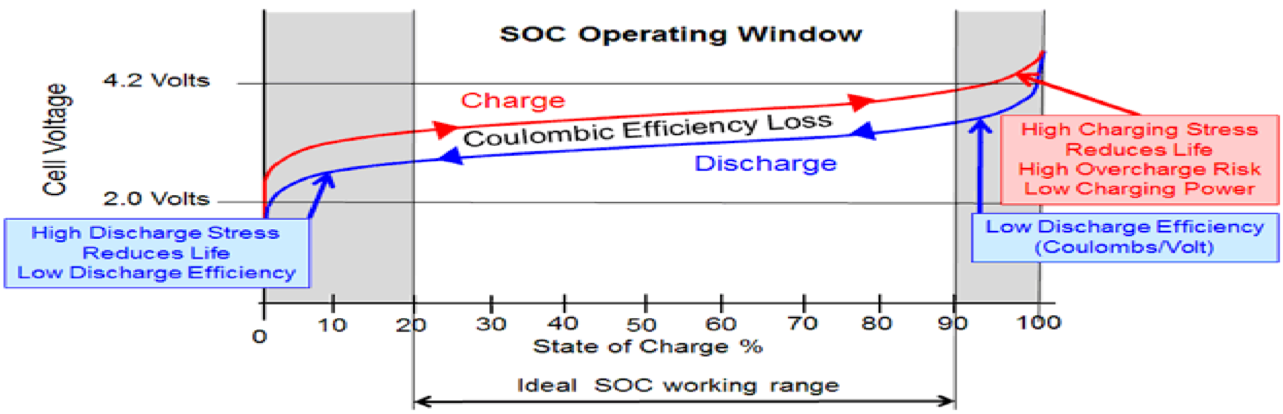


Figure 12. Safe Operating zone of SOC, battery and energy technology [51]

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

The concept of SOC plays an important role in large LIBS; a battery management system (BMS) is required to operate the battery in a safe zone and to ensure long life given in Fig.12. **(51)**.

The above discussion concluded that the calculation of SOC is an important task for the reliable operation of an EV system. The Fig. 13 shows some important methods for SOC calculation

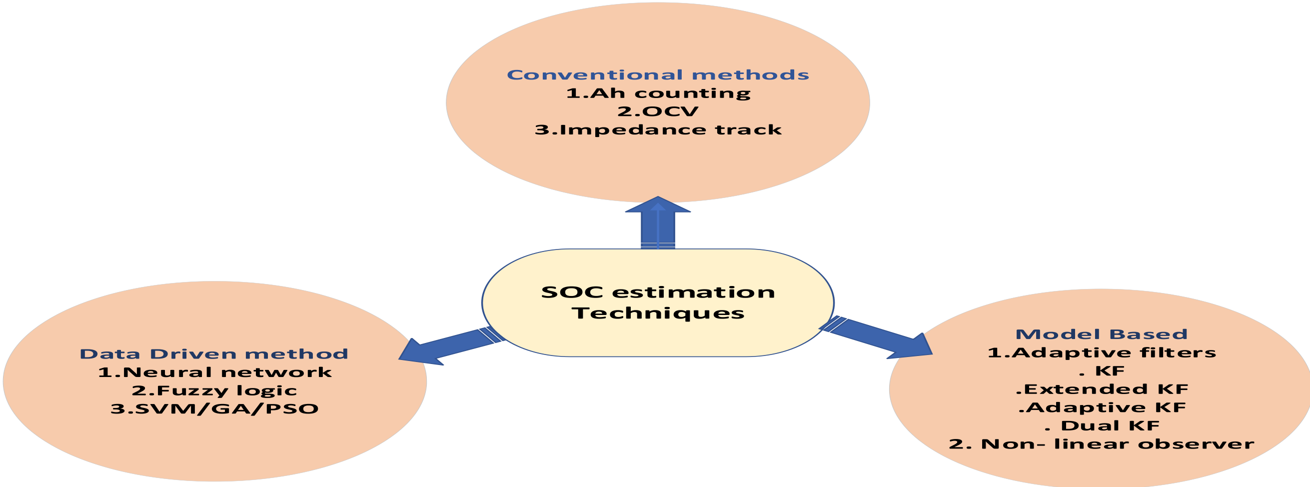


Figure 13. Important methods for SOC measurement.

State of Health (SOH)

SOH is one of the important parameters required to operate the LIBS in a safe and reliable mode. It is the analytical difference between the battery under consideration and the fresh battery. SOH is mainly defined in terms of the maximum charge of the battery to the rated capacity in terms of percentage. SOH control is necessary to balance the maximum performance and minimum degradation of the battery. In the reduction of Li-ions, the SOH of the battery is affected. The unavailability of the ions makes it necessary to monitor the SOH. VCT detector was used by author in **[52]** to estimate the SOC and temperature of the battery. Effects of the temperature is used by author to study the capacity degradation and further the SOH of the battery.

In the last few years, a lot of review papers have been published to provide a detailed and systematic view of SOH monitoring. Evaluation of various techniques for SOH predictions introduce the capacity balancing and regenerative methods for the battery. Former methods are ineffective in time-series handling and unable to track the health indexes. Attention based deep learning algorithm create the attention matrixes with the help of significant time series for the better result of SOH predictions **[53]**. In **[54],** author develop the mechanical and electrochemistry coupling to demonstrate the stress-SOH relationship with more accuracy. Accuracy in the SOH field is highlighted to reduce economic loss and provide better battery replacement of battery. A combination of TCMNN, CNN, and LSTM with an exponential smoothing algorithm is better suited to extract the data and estimate the SOH with the minimum error in Table.4 [**55]**.

Table.4. Execution Time for Proposed and Comparison Methods [55].

Method	**BPNN**	**Grey Model**	**CNN**	**LSTM**	**TCMNN**
Training Time (s)	147.57	234.451	77.008	1775.641	512.136
Testing time (s)	0.28	0.37	0.94	2.072	1.513

The author precisely enhanced the Kalman filter to UKF to predict the SOH with a RMSE value of 0.07% at 25 degrees **[56]**. In **[57]** The author introduces the most advanced version of KF, AUKF with STF, which calculates the SOH with more accuracy and consistency.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

SOH estimation is the prime demand for the smooth operation and life of the battery system. The variation of capacity and decline of SOC with time during the real-world condition of the battery alarmed the actual and correct estimation of the SOH. Various techniques have been invented over time by the experts as shown in Fig.14, but the most suitable method till date is the adaptive method, which includes the application of Kalman filter methods to estimate the SOH with the minimum error.

Figure 14. SOH estimation methods

Capacity Degradation Mechanism

The capacity degradation mechanism is one of the most important parts of the battery analysis scheme. The capacity loss phenomenon usually occurs when the current delivered by the battery and the voltage decrease with time. Capacity fading is mainly caused by various factors like ambient temperature, SOC, and different discharge rates. Temperature is the prime dominator in the degradation mechanism; below 25 degrees of temperature, the ageing rate starts increasing with a decrease in temperature, and above 25 degrees, the ageing rate starts accelerating with a rise in temperature. The capacity retention techniques fall down with the decrease in cycle N. Generally, it happens that the battery is supposed to reach its end of life (EOL) when the capacity degrades to about 80% of its initial value. Authors across the world are looking at the various schemes in **[58]** to determine the exact capacity of the real environmental condition of the battery. In **[59]**, the author develops the online estimation process of capacity. He developed the cascaded thermal dynamics model that decoupled capacity estimation with the help of SOC estimation techniques as given in Fig.15.

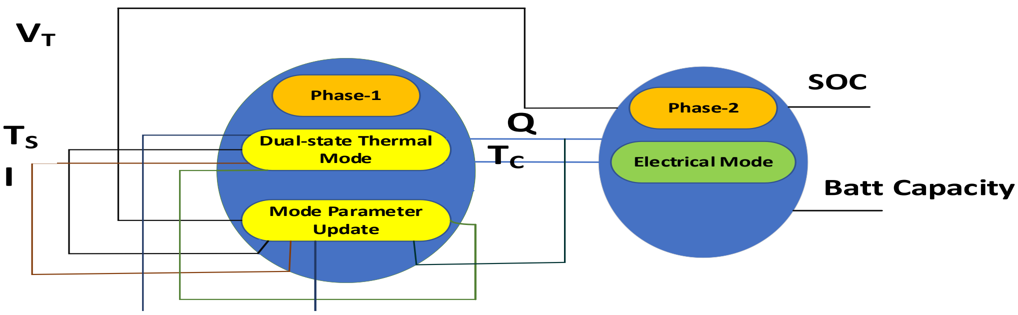


Figure 15. Cascaded capacity estimation model. [59]

In the real-time application of batteries, the calculation of parameters is typical, and the chances of battery failure are higher. SOC decreases rapidly with time and affects the SOH and capacity of the battery. Capacity estimation plays an important role in SOC and SOH estimation. The researcher used different model-based and data-driven techniques to estimate the capacity and estimate the SOC and SOH. A CNN-based method with the raw impedance spectra as an input provides a flexible and end-to-end framework for capacity estimation **[60]**. The author analyzed the differential thermal volumetry curve (DTV) in the on-going ageing process. He suggested that art from the battery inconsistency, noise, and measuring resolution have a great impact on the capacity estimation **[61]**. Capacity degradation improvement is required to prolong the life of the battery; therefore, these days, it is foremost in demand to model the battery so that the frequency of degradation is required. Model-based, data-driven, and AIML techniques are in use. In real-world conditions, the power fade and energy fade processes are mainly reflected in the capacity loss and rise of the battery. The ratio of C_{loss} to R_{in} with respect to the initial value at the beginning of life indicates the condition of SOH in BMS **[62]**.

Remaining Useful life.

The remaining useful life (RUL) of the battery is the difference between the total discharge-charge cycles of the actual capacity and the threshold capacity of the battery. RUL is one of the important parameters that is used to predict the

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

remaining working capacity of the battery. There are various parameters that directly or indirectly impact the life of the battery. Temperature is one of the important aspects that impacts the RUL. At low temperatures, LIBS has low power and energy capabilities, and at high temperatures, it has a high internal temperature, which directly impacts the working capabilities of the battery. It is found that temperature increases with the increase in capacity of the battery and decreases with the increase in thermal conductivity and heat transfer rate of the battery Temperature has directly affected the life and consistency of the battery **[63]**. At higher temperature above 60 degrees Celsius the life of the battery decreases and the operational consistency of the battery is worse **[64]**.

Continuous operation and charging of the LIBS also have negative impacts on the life of the battery. In **[65]**, the author experienced experimentally that copper foil dissolution and dendrite generation are the main outcomes of the overcharging condition of the battery. Author incorporated channel attention (CA) algorithm and LSTM to propose new CA-LSTM technique for RUL prediction **[66]**. In **[67]**, the authors used a bidirectional approach and a network on the lithium battery. The method was useful to decrease the uncertainty in the multi-step prediction of RUL. ML techniques seem to be very useful for battery safety and the prevention of resource wasting. The author used the LSTM approach to select and optimize the hyperparameters of the battery to predict its life. The study shows better accuracy with other ML techniques **[68]**. Based on the adaptively segmented empirical degradation data, the author used a hybrid model using the PF algorithm and the SVR algorithm to decompose the data-driven part. The model effectively utilizes the cycling capacity degradation data to predict the RUL **[69]**. In **[70],** author uses the V, I, and T curves for feature extraction and designs the HCNN network. A multiscale charge attention algorithm was used to estimate RUL with a 3.6% test error. Current deep learning techniques mostly fails to cover the relations among data due to complexity in model. TCN-DCN fusion mode provide the smooth and denoising correlation for RUL prediction **[71].** Data analysis techniques are also helpful for the prediction. Pre-processing, modelling used by the author in simulation using model includes decision tree, non-linear autoregression, RNN and LSTM provides the better performance among all data model **[72].** Author prepares a novel transformer model based on the deep learning spatio-temporal characteristics for RUL prediction. This model somehow reduces the complexity of the model **[73]**

End of life (EOL) is defined as the threshold limit of the battery when it is not able to deliver the required power and energy for its permitted function. EOL is also known as the dead condition of the battery system, as the battery is no longer available to deliver power to the load. It is practically impossible to accurately estimate the stage of EOL in a real-world application. Assumption-based prediction and practically enhanced techniques are used by researchers to maximize the accuracy of EOL estimation. In **[74]**, the author used the OCV cathode drift techniques during the shallow DOD to predict the EOL limit. Rapid growth of the LIBS system led to a huge quantity of money spent within 5–10 years. A proper method is a challenge for advanced technology to find an alternative method of EOL recycling, pyrometallurgical or hydrometallurgical direct recycling, to suggest potential improvements to EOL recycling **[75]**. **[76]** and **[77]** provide extensive analysis on the recycling of lithium-ion battery for EV two-wheeler. The EOL LIBS still have the useful capacity of about 70 %-80% once it is removed from the EV **[78].** Second life application of the LIBS EOL can help to extend the battery capacity before it is seriously recycled **[79]**

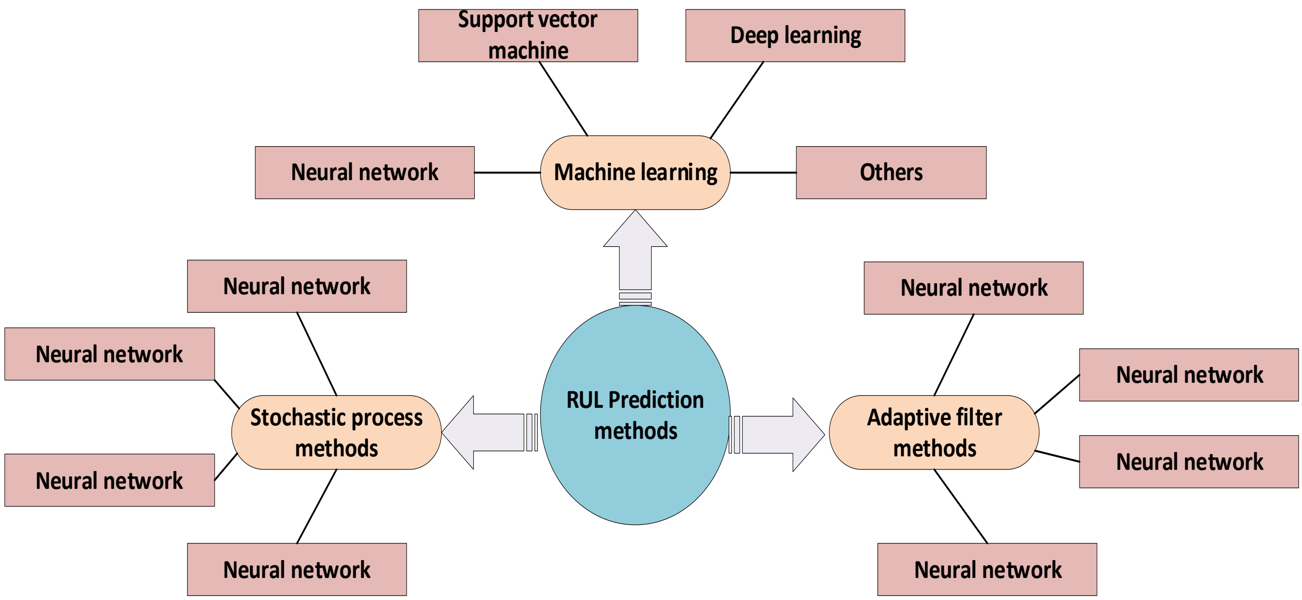


Figure 16. Different RUL prediction methods of LIBS.

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ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

Table 4. Comparative study of techniques and methods used in parameters estimation.

authors	**methods**						**Models/ network**	**Algorithm**	**Estimated values**				**Internal parameters/ Internal chemistry**	
	OCV	CC	Filters	OCV +CC	ML	Chemical composition			SOC	SOH	RUL	EOL	Z_{in}	Thermal imaging
W. Xueyuan (1)		✓					ECM					✓	✓	
C.Mingyi (4)		✓					6x6 / 10x10 array			✓				Servomex gas analyser
T.Notihori (5)		✓								✓				EIS
T.Kim (14)			✓	✓			Real-time On-Board model		✓	✓				
Z.Yongzhi (16)	✓		✓				LSTM-RNN				✓			
W.Jingwen (17)		✓	✓		✓		SVR/ State spacem model			✓	✓			
T.Tang (18)	✓				✓		ANN				✓			
L.feng (25)	✓				✓		ECBE			✓			✓	EIS
L.Sun (48)	✓						ECM	ESO	✓				✓	
X.Bizhong (49)	✓		✓				ECM	STHF	✓					
L.H.Molla (50)		✓					NARX ANN	Lighting search	✓					
Z.Chunxiang (55)		✓			✓		TCMNN	Data augmentation		✓				
M.Lili (56)			✓				Fractional-order	MIUKF	✓	✓				✓

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

L.shulin (57)			✓				2-RC	AUKF	✓	✓				
X.Rui (60)		✓			✓		CNN	Semi-supervised		✓				✓
Y.Jufeng (61)		✓	✓		✓		DTV curve method			✓	✓			
S.M.Jackleen (63)				✓			Thermal model		✓	✓				
L.Yiwei (68)	✓						LSTM	Improved Sparrow search(ISSA)			✓			
G.Kaidi (69)			✓				NED	PE/DWT/SVR			✓			
Y.Yixin (70)					✓		Hybrid CNN	MSCA			✓			

II. Discussion

It is apparent from the literature review that the LIBS system, although it has privileges over the other energy storage systems in EVs, suffers from various abnormal working behaviors. The development of better BMS technology is still in progress, but till now, TR and explosions of batteries seem to be barriers in the path. From the literature review of this paper, some gaps have been highlighted below that are still in existence in LIBS operations.

The increase in demand for the EV industry and the complexity of the supply chain in the LIBS sector, coupled with the lack of geographical diversity, can create a future threat to the chain as the system is still not in stable conditions even in developed nations.

SOC and SOH estimation techniques are growing for the various operating conditions of the battery, but precisely calculating the lifetime and optimizing the battery system is still a challenging task.

The surface temperature of the LIBS is used by many researchers to incorporate it with the ageing mechanism. The fluctuation and rapid increase of the internal temperature during various abusive conditions and its effects on various working parameters and health indicators still need to be found out properly.

Although various parameters are used to analyse the robust estimation of SOH, very little work has been done to investigate the sensitivity of health indicator parameters under environmental and mechanical loading conditions.

There are different charging and discharging techniques available for LIBS, but CCCV methods are generally used for charging and discharging the battery system. No battery system is perfect when we are talking about charging and discharging efficiency. Overcharging and deep-discharging are the most abundant problems in this context. Overcharging is the problem that arises when the charging voltage rises above the set value (4.2 volts). Thermal runway, and finally the explosion of the battery, always seen due to the overcharging. Although researchers have built various techniques to analyse and stop the overcharging of the battery, it is still seen, especially in the two-wheeler system, that due to the poor heat management system, the non-linear behaviour of internal and surface temperatures of the battery mostly damages the battery system. There is still a gap in fast and accurate methods for having a proper management system in an EV 2-wheeler.

With the continuous working of the battery and the practical declination of the charge-discharge cycle with time, safety concerns for the battery as well as the vehicle arise. RUL represents the remaining life of the battery until its EOL, but it is not clearly verified how safe the battery is to operate in that remaining life domain. State of safety (SOS) is the most

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

prominent factor to exactly evaluate the smooth working of the battery till EOL and also an important factor to estimate the health condition of the battery.

III. Conclusion

The rise of the EV industry provides a huge market for lithium-ion batteries due to their high current density, long life, and zero carbon emissions. Instead of having such a huge application and advantages, LIBS suffers great challenges in its path to being fully commercialised and providing a better runway to the EV industry.

The most basic requirement of the LIBS system is to have an accurate estimation of SOC and SOH. Real-world application and practical implementation of battery systems generally suffer from non-linear behaviours that fluctuate the battery's health and affect its life. Researchers across the world used various tools and models to get an accurate estimation of SOC and SOH. KF, EKF, UKF, and sinusoidal Kalman filters were used to have noise-free estimation methods. RNN, ANN, and machine learning tools are the most advanced tools to provide the minimum error estimation techniques.

Instead of having some enriching work in the field of LIBS, there is some future scope that needs to be evaluated to further enhance the operating conditions of the battery system.

The novelty and main conclusion of this study are to analyse the various working schemes and reasons for the failure of LIBS. The internal behaviours that affect the electrical parameters and their contribution to the battery conclusion are covered. The main aim is to point out the contribution of electrical parameters to abusive behaviour in LIBS working conditions so that one can extract the parameter value at the point of abusiveness

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