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A Review of State of Health Estimation of Energy Storage Systems: Challenges and Possible Solutions for Futuristic Applications of Li-Ion Battery Packs in Electric Vehicles

Lithium-ion (Li-ion) battery pack is vital for storage of energy produced from different sources and has been extensively used for various applications such as electric vehicles (EVs), watches, cookers, etc. For an efficient real-time monitoring and fault diagnosis of battery operated systems, it is important to have a quantified information on the state-of-health (SoH) of batteries. This paper conducts comprehensive literature studies on advancement, challenges, concerns, and futuristic aspects of models and methods for SoH estimation of batteries. Based on the studies, the methods and models for SoH estimation have been summarized systematically with their advantages and disadvantages in tabular format. The prime emphasis of this review was attributed toward the development of a hybridized method which computes SoH of batteries accurately in real-time and takes self-discharge into its account. At the end, the summary of research findings and the future directions of research such as nondestructive tests (NDT) for real-time estimation of battery SoH, finding residual SoH for the recycled batteries from battery packs, integration of mechanical aspects of battery with temperature, easy assembling–dissembling of battery packs, and hybridization of battery packs with photovoltaic and super capacitor are discussed. [DOI: 10.1115/1.4042987]

Keywords: state-of-health, state of charge, lithium-ion battery, electric vehicle, energy storage

1 Introduction

In the recent past, the demand for oil, coal, and gas is increasing globally, mainly due to an increase in per capita energy consumption and demand for electricity in all the sectors [1]. Because of limited oil and coal reserve in the planet and stringent emission norms, researchers are forced to think for alternative methods for sustainable power generation and energy supply. In this aspect, energy storage can play a weighty role in the field of power generation and energy supply [2,3].

In the transportation sector, electric vehicles (EVs) can play a major role toward mitigating the environmental problems with sustainability [4–6]. An EV may be powered through the collector system, battery, solar panels, an electric generator, etc. There are mainly three types of electric vehicles such as hybrid electric vehicle, plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV) [7–9]. The main advantages of using EV are

- Electric vehicles emit lower amount of toxic gases, smoke, and other harmful particles during its operation; hence, EVs are considered as ecofriendly vehicles [9].
- EVs are more efficient than internal combustion engine drive trains, for example, the well-to-wheel efficiency of BEVs and incremental capacity (IC) engine vehicles are about 28% and 13%, respectively [10].
- Running cost of EV is less. The electricity to charge an EV is almost one-third of a petrol vehicle per kilometer [11].
- EVs are capable of capturing some energy (nearly 20–25%) that is normally lost in braking by regenerative braking [10].
- EVs have relatively negligible start up time and can achieve required high speed and acceleration very easily [10].
- In the case of safety, it has been seen that EVs tend to have lower center of gravity that makes them less likely to roll over [12].

In the recent past, the growth of sales of all EVs is increasing significantly [13]. Recently, the demand for BEV is increasing ever more. Figure 1 shows the growing demand for BEV over PHEV in recent years [14], and Fig. 2 shows the countries with most

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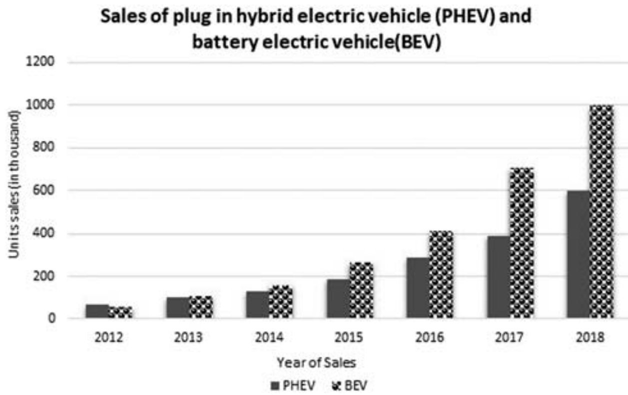

Fig. 1 Growth of the battery electric vehicle

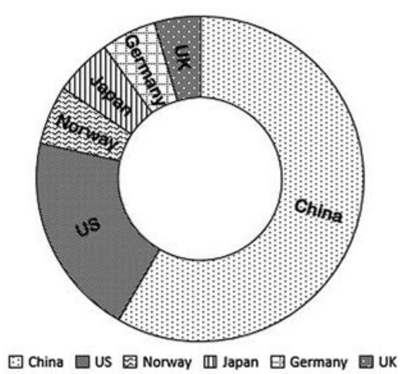

Fig. 2 Leading countries with electric vehicle adoption

electric vehicles, where China is leading with approximately 579,000 vehicles in the year 2017 [15].

In battery powered EV, the battery packs are the heart of the vehicle because it provides the primary energy to run the vehicle efficiently. A host of literature and experiments are reported to investigate the issues like safety, reliability, and viability in any operating conditions of the electric vehicle [16–18]. In the recent past, lithium-ion batteries are used as a major source of power supply in the battery electric vehicle [19–21]. The use of different kinds of batteries such as lithium cobalt oxide, lithium iron phosphate, lithium manganese oxide, lithium nickel–cobalt–aluminum oxide, lithium nickel–manganese–cobalt oxide, etc. has been reported by the researchers on their research work [22,23]. Table 1 compares these popularly used lithium-ion batteries that are commonly accessible to the market [24].

Lithium-based batteries have the highest cell potential and the lowest reduction potential compared to other elements. Lithium molecule is the third lightest element and has one of the smallest ionic radii of any single charged ion. This allows Li-based batteries to have high gravimetric and volumetric capacity and power density [25]. The energy density of the lithium-ion battery is in the range 200–250 W h/kg. Its columbic efficiency is very high with nearly 100% [26], and it has no memory effect [25]. Due to its high energy and power density, the lithium-ion battery becomes the most preferable choice over lead acid, nickel cadmium battery, and popularly used for various equipments such as portable electronics, power tools, and EVs [27–29]. The research on the lithium-ion battery is attributed to present trends to increase cycle life, safety (both abusive and normal condition) [30], and other performance characteristics. At the same time, researchers have utilized other types of electrochemical energy storage systems with higher energy density in EV. Some advantages of the lithium-sulfur battery over Li-ion are higher energy density, improved safety, a wider operating temperature range, and lower cost (because of the much availability of sulfur), which makes it a promising technology for EV application [31]. However, lithium-sulfur technology has not been widely commercialized yet as it has some limitations such as low columbic efficiency, poor cycle, self-discharge, and capacity fade due to cycling, high discharge current, uncontrolled dendrite formation, etc. [32]. As hybrid and electric vehicle technologies are continuing to the field of advancement, most of the car manufacturers have begun to use lithium-ion batteries as the electrical device of energy storage for existing and future vehicles. The use of the lithium-ion battery in an electric vehicle has been progressing at a high pace, and as such, it is important to provide current and timely updates of this emerging technology. While reviewing the papers, the following issues were discussed by many of the researchers as far as the use of battery in an electric vehicle is concerned: battery management system (BMS) [5], battery thermal management system of the battery pack [33], design and manufacturing of batteries, state of charge (SoC) estimation, SoH estimation, etc. [34].

Battery state-of-health (SoH) estimation is an extremely important issue for the performance and cost-effectiveness of EVs. In order to ensure efficient and safe operation, prevent the battery from over-charging and over-discharging, increase the lifespan of the lithium-ion battery system and forecast its end life, and it is necessary and important to estimate the battery's SoH [35]. Often, SoH of batteries is monitored for an efficient battery management system design [36]. But estimating the dynamic status parameters of a battery, such as SoH and related issues, will be useful in obtaining the best suitable method for battery health monitoring. Furthermore, by summarizing the methods, its advantages and disadvantages, there is a potential for developing a new method by hybridization of various methods and integration of nondestructive methods for battery condition monitoring.

In this paper, SoH and its estimation methods are discussed in Sec. 2. Section 3 summarizes the various approaches for SoH estimation adopted by researchers. The research drawbacks and their scopes of research have been discussed in Sec. 4. Finally, the conclusion of the paper is summarized in Sec. 5.

2 State-of-Health Estimation Methods

The SoH is a "measurement" that reflects the general condition of a battery and its ability to deliver the specified performance compared with an unused or fresh battery. It is defined as the ratio

Table 1 Most common Li-ion batteries available in the market

Name	Anode material	Cathode material	Nominal voltage (V)	Energy density	Cycle life	Safety	Cost
Lithium cobalt oxide	Graphite	Lithium cobalt oxide	3.6	High	Medium	Highest safety concern	Low
Lithium iron phosphate	Graphite	Lithium iron phosphate	3.2	Low	High	Safest lithium-ion cell chemistry	High
Lithium manganese oxide	Graphite	Lithium manganese oxide	3.7	Low	Low	Good safety	Medium
Lithium nickel manganese cobalt oxide	Graphite	Lithium nickel manganese cobalt oxide	3.6	High	Medium	Good safety	Medium
Lithium nickel cobalt aluminum oxide	Graphite	Lithium nickel cobalt aluminum oxide	3.6	High	Medium	Safety concern required	Medium

between full charge capacity of a battery in the current state and the full charge capacity of a battery when it is initially bought

$$\text{SoH} = \frac{\text{Current actual capacity}}{\text{Nominal capacity}}$$

State of charge (SoC is a short-term prediction while SoH is a long-term prediction) can be determined by measuring the actual amount of charge in the battery. SoH is a subjective measure in which different researchers derive different definitions by using a variety of different measurable battery performance parameters (current, voltage, resistance, temperature, self-discharge rate, stress, strain, etc.). Though SoH is a function of such parameters (which all affect the capability of the battery), for simplicity, it is generally expressed in terms of capacity, considering other parameters constant or keeping them unchanged during the moment [37]. An accurate estimation of SoH is important to forecast batteries' reliability, efficiency, and power delivering capacity and proper operation of the system [38,39].

It has been reported that capacity, internal resistance, power fade, and cycle life change with battery's age and hence these parameters are useful in predicting the behavior of the cell or battery [40]. Aging processes of a battery are irreversible changes in the characteristics of the electrolyte, anode, and cathode and the alteration in the structure of the components used in the battery. Battery aging can be divided into cycle aging and calendar one [41]. Cycle aging associates with the impact of battery utilization periods, and the calendar aging associates with the consequences of battery storage. Aging is considered for the estimation of SoH as it is highly related to change in capacity, internal resistance, and power fade [42]. Changes of these parameters help the researchers to find out which could be the best parameter for SoH estimation in accordance with the situations. For example, changes in the performance of battery's external behavior due to loss of rated capacity or due to an increase in temperature because of internal changes like corrosion.

Figure 3 shows the variation of cycle life with the cell operating temperature. From Fig. 3, it is evident that cycle life is maximum when the cell operating temperature is maintained between 10 and 50 °C. The cycle life gradually decreases if the cell operating temperature reduces below 10 °C and increases above 50 °C. With further increase of the cell operating temperature, the cycle life decreases sharply due to thermal runaway [5,16].

Formulation of battery modeling is necessary to relate the battery parameters such as charging and discharging voltage, cycle life, temperature, etc. Battery modeling (Fig. 4) is classified into emperical models, electrochemical models, and equivalent circuit models (ECMs). In the empirical model, model formulation is based on the data obtained from the experiments on the batteries where inside information of the battery activity is not known completely. In order to predict the unknown information of the battery, some methods like genetic programing, fuzzy logic, Kalman filtering (KF), neural networks (NNs), etc. are used to build the empirical model. In the electrochemical model, the models are based on the chemical processes that take place inside the battery. The electrochemical models are more accurate; however, these models are

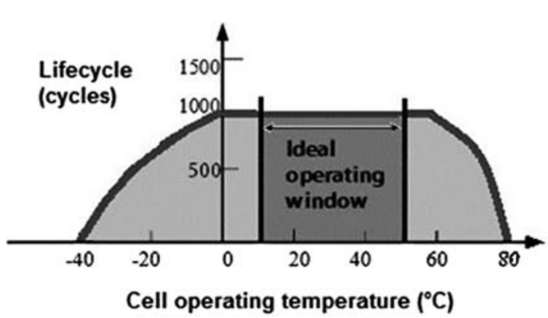

Fig. 3 Lithium-ion battery lifecycle versus temperature diagram

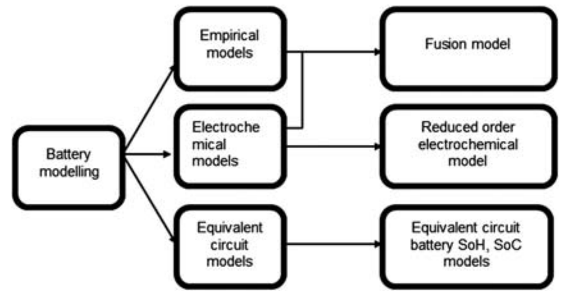

Fig. 4 Classification of battery modeling

complex to analyze. In order to reduce the comlexity of the model, some reduction models such as single particle model are used [43,44]. In the fusion model, the models are based on combination of empirical and electrochemical models. Data are obtained from the finite element simulation (electrochemical models) of the battery phenomenon. The quantification of data is then obtained by building empirical models using methods like fuzzy logic, Kalman filtering, neural networks, etc.

Some researchers explain the battery helath monitoring models/methods in different ways [45]. For example, Berecibar et al. [46] divided the methods of SoH estimation into two parts: experimental technique and adaptive method. In experimental technique, previous data were taking into account, whereas in adaptive technique, some parameters were introduced which had been sensitive to degradation or aging of the battery.

However, within these derived models, uncertainties and realistic conditions based on bumpy road, crash, and outside impact are not taken into consideration while estimating SoH or SoC. Generally, models work accurately when used as offline. But, the models do not work accurately when used in real-time and online; in this way, it is very difficult to model the SoH or SoC for the entire battery pack when compared to a single battery or cell. Therefore, designing of the best model considering all the necessary parameters is very much essential.

Distinct focus is given to the SoH and SoC estimation, and the methods or models were classified based on the given input conditions or parameters (charge, current, capacity, self-discharge rate, temperature, depth of discharge (DoD), time interval between full charge cycles, etc.). There are number of methods or models which are used by different researchers in different ways. Some of them that were used mostly are listed below.

2.1 Coulomb Counting Method. The Coulomb counting method is associated with monitoring the input and the output current continuously. Since capacity is the integral of current with respect to time, by measuring the input and the output current, change in capacity or capacity degradation of a battery can be measured easily [47]. In this method, SoH is calculated by dividing measured capacity (after discharging the battery to 0% SoC value) to its rated capacity. It is an extensively used method by researchers for its simplicity [48–50]. But, the accuracy of this method is not very high. Therefore, to improve its accuracy, for example, Ng et al. [50] proposed a smart coulomb counting method to estimate both SoC and SoH accurately. Similarly, an adaptive neurofuzzy inference system (ANFIS) was modeled in the paper [51]. It considered the cell's nonlinear characteristics to get the relationship between SoC and open circuit voltage (OCV) at different temperatures. During the estimation of SoC, at some random OCV and temperature, modeling of cell characteristics was done by ANFIS. The assessment was done on the cell level instead of the pack level for better precision.

2.2 Internal Resistance and Impedance Measurement Method. The relationship of battery internal resistance and the actual measured impedance with battery aging leads a way to battery SoH estimation [52–55]. As the aging process occurs gradually, the impedance value of the battery under different frequencies changes. Electrochemical impedance spectroscopy (EIS) helps in this context by measuring the actual impedance of the battery pack [56–61]. For example, Mu et al. [62] proposed a novel fractional order impedance model for the lithium-ion battery. EIS is a powerful technique which separates the electrochemical reactions and tracks the variations of the performance under a different SoH of a battery in a nondestructive manner. By combining electrochemical impedance spectroscopy and hybrid pulse power characteristic test (HPPT) data, a fractional order impedance model can be derived. Measuring the increase of battery internal resistance is also a direct tool for measuring the health of a battery [63]. Joule effect, HPPT, and other resistance measuring models are available for the measurement of internal resistance [46].

2.3 Neural Network. A neural network (NN) is a mathematical model whose parameters have no direct reflection of the physical or chemical structures of the original model. Feed forward and recurrent are the types of NN architecture design. They utilized a time series prediction system. Yang et al. [64] used maximum available capacity to indicate the battery's SoH based on a back propagation neural network. A direct parameter extraction method was employed to identify the parameters of the first-order ECM. Then, a three-layer back propagation neural network was proposed to estimate SoH, whose inputs were the parameters of the first-order ECM and output was the current value of SoH. From the experiments, it was found that when ohmic resistance increases SoH reduced and when SoC ranges between 20% and 90% ohmic resistance increases and SoC decreases. Artificial neural network (ANN) is known for its simplicity. It can handle nonlinear data, and it is not necessary to take all the details of the battery during modeling [65–68].

2.4 Support Vector Machine. This method depends on the given environmental conditions and load conditions. It is a Kernel function-based method, which uses regression algorithm to convert the nonlinear model in lower dimension to the linear model in high dimension [69]. To avoid degeneracy phenomenon in model building and keep the diversity of the particle, this method was used [70]. Klass et al. [71] measured capacities and instantaneous resistance over temperature and SoC range, and then, allow it for online estimation of battery degradation. By using the support vector machine (SVM) method, not only SoH but also many other useful parameters like SoC, remaining useful life (RUL), etc. can be measured accurately [70–73]. Nuhic et al. [74] had developed a SVM model to identify the SoH of battery for electric vehicles. Nuhic had divided the available data into two-third of the data being for training and one-third of the data being for testing and predicted SoH with less than 0.0007 mean square error in real driving conditions, considering temperature change, SoC, and C-rate.

2.5 Kalman Filter. Kalman filtering is a well-designed and time-proven method to filter the measurements of system input and output to produce an intelligent estimation of a dynamic system's state. In the KF method, both input and output data are experimentally measured which help in obtaining the minimum mean square error assessment of the true state [75]. In KF, linear optimal filtering happens. If the system is nonlinear, extended Kalman filter (EKF) is used. In this method, its nonlinearity is linearized by using a linear time varying system [75–83]. Claude et al. [82] presented mathematical equations to study the BMS of the electric vehicle and developed a battery electrical model. Mastali et al. [75] implemented both the extended Kalman filter and the dual Kalman filter where they used both the prismatic and cylindrical cell. Zheng and Fang [80] used relevance vector regression (a nonlinear time series production model) to give a prediction of the remaining useful life of a battery. Gholizadeh and Salmasi [84] proposed an inclusive and unobservable model for the determination of SoH and SoC. They developed multiscale EKF and used the macroscale to estimate the system parameter and the microscale to estimate the system state. Reliability and accuracy of this method were very high; also, this method largely reduced the computational cost of the control system. Andre et al. [85] had compared both EKF and NN to estimate the SoH of a battery. The comparison between EKF and NN confirmed that EKF was simpler to apply, required less input values, and required no functions of the dependencies to the working environment. Actually, NN needs recognized correlations among the input variables and internal states.

Similarly, Xiong et al. [79] proposed the multiscale extended Kalman filter, in which computational efficiency was less but they found higher estimation of accuracy. Thus, many researches have been done on the Kalman filter and made a number of suitable models for SoH and SoC estimation [75–83].

2.6 Sliding Mode Observer. In recent years, sliding mode observer (SMO) is becoming a popular method for its flexibility to adapt with system uncertainty and noise during the SoH estimation process. Lin et al. [86] proposed the estimation of lithium-ion battery SoC/SoH using SMO for the electric vehicle. A single particle model was proposed for modeling the lithium-ion battery ignoring the spatial distribution in homogeneity of local volumetric transfer current density and the Li+ concentration in solid phase electrode and electrolyte. SMO algorithm proposed the offline identification of the model parameters. The offline model parameters were identified by the urban dynamometer driving schedule (UDDS) test. This model showed good performance in estimating the terminal voltage and the model parameters. The SMO method is advantageous since it can elude chattering effects [87]. Kim et al. [88] projected a dual sliding mode observer model for estimating both SoH and SoC.

2.7 Fault Diagnostic Methods. The major faults such as overdischarge and over charge causing large model parameter variation are used to form a multiple nonlinear model for the detection of faults. Identification of such failure aids in the evaluation of health condition of the battery, as such failures are inversely proportional to a good health condition of a battery. The equivalent circuit methodology combined with impedance spectroscopy of lithium-ion batteries was used in the formation of the nonlinear model for fault detection of lithium-ion batteries in Ref. [89]. Estimation of the terminal voltage for generation of residual signal was done using Kalman filtering. Then, the probability of fault occurrence was predicted accurately from these residual signals using a multiple model adaptive estimation technique. Similarly, a reduced order electrochemical-thermal model of the lithium-ion cell was used and the electrochemical faults were modeled as parametric/multiplicative faults in the system [90]. Sliding mode methodology was used to design the observer and its convergence as well as design was verified via Lyapunov's direct method. The effect of modeling uncertainties may be considered to improve the fault diagnostic scheme. However, Marcicki et al. [91] proposed a larger faults diagnostic method which also helped in estimation of SoH in the lithium-ion battery. A modified nonlinear parity equation was used for fault detection on lithium-ion batteries in EVs. Input voltage to the battery was estimated by sliding mode observer, and output voltage estimation was done by the open loop model. Minimum fault magnitude was accessed by estimation error of the observers using real-world driving cycle data. Maximum allowable probability of the error was taken into consideration by selection of optimal threshold. Smaller faults are difficult to determine by the fault detection technique presented in this paper as these faults are smaller than the normal estimation error of the observer. These faults could be corrected by performing a constant diagnostic test.

2.8 Other Methods. Besides these discussed methods, fuzzy logic [92–95], incremental capacity analysis (ICA) method [96,97], Gaussian process regression method, Bayesian network, particle filter method, Thevenin model, and many other methods [98–111] are available which are used for estimation of battery health conditions. Many researchers have attempted to combine more than one method simultaneously for better result and accuracy of the estimations [80,83].

Fuzzy logic uses fuzzy logic theory (combination of true and false statement) for complex and nonlinear models. The measured data from the system is separated into crisp sets and fuzzy sets. The fuzzy sets contain data with uncertainty. The members of the fuzzy sets belong to a membership function, which determines the accuracy of SoH estimation [112]. Schweiger et al. [113] made an assembly of both fuzzy logic and EIS for estimation of SoH of the lithium-ion battery.

Weng et al. [114] proposed state-of-health monitoring of lithium-ion battery modules and packs by incremental capacity peak tracking. ICA is a popularly used technique for lithium-ion battery SoH estimation. Efficiency and effectiveness of this method were greatly appreciated by many researchers. For example, in an electric vehicle, the current capacity is directly related with the driving range of the electric vehicle; on the other hand, power output capability determines the dynamic property of the electric vehicle. Capacity (Q) and the resistance (R) of the battery determine the power output capability, so the main aim for the SoH monitoring is to estimate the Q and R online. This paper reported the extension of the IC peak tracking-based SoH monitoring framework from single cells to multicell battery modules. At the first model, simulation was done and then validated using experimental data. The experiments consisted of 30 $LiFePO_4$ cells with each cell having different aging conditions, and these test cells were combined into battery modules for estimation. Results obtained from it showed that the total capacity loss could be linked with the IC curve peaks, and it was for both single cell and pack of multiple cells.

Thevenin model was developed based on the Thevenin theory [115]. In this model, various electrical techniques were applied to the batteries where the load is more dynamic; the internal resistance model is not sufficient for making accurate estimation of the behavior of batteries. For simulating the dynamic behavior of batteries, the Thevenin model is used. This model can also be used with both the Kalman filter and the sliding mode observer [116].

Wu and Jossen [117] described a novel SoH indicator based on cell entropy and battery surface temperature at a constant current charging process.

Measuring SoH with piezoelectric sensors is another method for determining SoH and SoC of the lithium-ion battery. Time-of-flight and signal amplitude of the guided wave are the main revealing parameters for this estimation [118].

Marcicki et al. [119] proposed a reduced order electrochemical model where a Pade approximation reduction process was used for reducing model partial differential equations (PDEs) to lower order ordinary differential equations. Moura et al. [43] used adaptive PDE techniques where Pade approximation was also done to identify the diffusion coefficient. Adaptive output fraction inversion technique was used to enable a linear state estimation design. Other adaptive techniques like a nonlinear geometric approach are grounded on nonlinear geometric models. Exponential stability of state and parameter assessment are the main plus points of this method [120], whereas electrochemical–thermal model-based nonlinear adaptive techniques are more beneficial in accuracy compared to equivalent circuit models [121].

Retrospective-cost subsystem identification (RCSI) is another method which was adopted by Zhou et al. [122] RCSI helps in identifying the film growth of the electrolyte. The relationship between voltage change and film growth was studied accurately in this method. Chaoui and Gualous [123] proposed a hybrid estimation technique for lithium-ion batteries. This technique makes use of state-space observer theory to decrease the complexity of the design and the stability analysis. The hybrid estimation technique consists of a state-space observer and an online parameter estimator with temperature compensation. SoC estimation was achieved with reduced order observer using OCV-SoC characterization. Similarly, Lyapunov-based method is a hybrid estimation method, where battery health and other internal parameters are measured with the help of battery terminal voltage and noisy currents [124].

In the smart grid scenario, energy storage systems played a very important role, which allowed decoupling production and usage times. Landi and Gross [125] developed measurement techniques for online battery SoH estimation in vehicle-to-grid applications. They allowed for a full exploitation of renewable energy sources that can be used to shape load curves and constitute the energy reserve in the battery electric vehicles. Moreover, if such vehicles were plugged into the power grid, they could act as the support system for electricity storage and could also support the vehicle-to-grid (V2G) system. That is why measurement techniques to estimate the SoH of batteries were needed. The authors in this paper stated techniques to determine SoH of a lithium-ion battery. There are many papers available on offline methods for lithium-ion batteries. Such offline methods were widely used for characterization of aging of super capacitors [126] and fuel cells. Yuan and Dung [126] had worked offline for the SoH estimation of high power lithium-ion batteries by a three-point impedance extraction method. As reported, this methodology was found to be computationally fast and efficient.

Thus, it can be seen that numerous research works have been carried out for the estimation of SoH of the lithium-ion battery. In Sec. 3, a qualitative and quantitative assessment of these methods is tried to put forward by summarizing them in a tabular format.

3 Summarization of Past Studies

The findings of various researchers related to SoH estimation methods and quantitative analysis with pros and cons of the various methods are presented and compared in Table 2, Table 3 [112], and Table 4, respectively.

4 Research Gaps and Future Research Directions

This work discusses the following new directions (Fig. 5) of research and extensions of the existing works on SoH of battery packs for electric vehicles.

4.1 Nondestructive Methods for Battery Condition Monitoring. Methods discussed in this paper have some shortcomings. By eliminating or modifying those shortcomings, the efficiency of the methods can be increased. EIS determination method is applicable for similar charging conditions only. Similarly, previous values of SoH/SoC are required for estimation of SoH in the Coulomb counting method. Fuzzy method is practically not suitable for the electric vehicle. The cost of this method is very high, and the battery parameters frequently change with battery lifetime. The existing methods such as those based on sensors (stress and frequency) may not be accurate enough because of sensors error and micro monitoring is required to make sure the laboratory conditions are uniform. In this context, the nondestructive test (NDT) methods such as those based on laser or ultrasound/infrared approaches can be used to investigate the temperature distribution, state of charge, state-of-health, etc. of the battery pack. For example, a light optical system can be used for determining the damage of separator; X-ray computed tomography for analysing microstructural properties, short circuits, or even to analyze thermal runway; multidirectional laser scanning for aging; etc. Multidirectional laser scanning investigates local reversible and irreversible thickness change of the cell and establishes corelation with capacity fade and impedance [140]. Furthermore, the use of signal features made up the elements of statistical analysis; pattern vectors can be inputted to pattern recognition paradigms (ANN, SVM, and K-nearest-neighbor) for decision making on battery damage characterization. Thus, the integration of NDT methods with supervised learning-based regression methods shall pave the way for the design of an efficient battery management system.

4.2 Comprehensive Design of the Battery Pack Considering Uniformity, Equalization, and Reuse Criteria Simultaneously. In this study, the uniformity criterion was considered for design of battery packs. However, this criterion is useful before the manufacturing stage of the battery pack. There is no guarantee that the

Table 2 Comparison of various models/methods for health estimation of the Li-ion battery

Authors	Thrust of the study	Model	Battery used and parameters/ conditions	Description	Results
Ng et al. [50]	Offline, numerical SoH estimation method	Coulomb counting method	Li-ion battery. voltage, current, and operating time	• Charging and discharging characteristics were investigated • DoD was used for SoH calculation • For better accuracy, charging and operating efficiencies were also considered	• The estimation error increased with charging and discharging cycle life of the battery
Chiang et al. [127]	Online estimation method of SoH and SoC	Internal resistance method	Lithium-ion battery	• Two simulations were performed • Two experiments were performed to facilitate algorithm and to determine the compatibility of the proposed method	• Internal resistance and OCV were accurately determined from the estimated parameters • For its simplicity, it is easily implemented by electronic circuit design
Weng et al. [128]	Offline estimation method of SoH and SoC	OCV model	Li-ion battery	• A unified OCV model which effectively captures aging information based on ICA was used for SoH monitoring • Parametric analysis and model complexity reduction were stated and experimental data were used to illustrate the effectiveness of the model	• The proposed parametric model was quite efficient in the determination of the OCV model parameters and establishing relationship with battery degradation • Electrochemical properties were clearly shown by the model in different temperatures and aging periods
Le and Tang [129]	Estimation of SoH	Ah–V characterization method	Battery capacity is the parameter	• Two models were established. One model was established by using Richard's equation and another one was by using quadratic fit. • Then, slope of the Ah–V curve was correlated with battery capacity	• This relatively simple method describes the relationship between the Ah–V slope and battery capacity. • Method was sensitive to minor errors and to continue its accuracy, complete charge–discharge cycle was required
Yang et al. [105]	Online experimental SoH estimation method	Constant voltage charging current analysis method	• All experiments were done at room temperature • Four lithium iron phosphate ($LiFePO_4$) IFR26650PC batteries were used	• Current time constant was found based on equivalent circuit method • A relationship between current time constant and battery capacity was established to indicate battery SoH	• By comparing all the battery's SoH, it was found that error was very less in spite of the large size of the data • Estimated absolute error is less than 2.5%
Zou et al. [42]	Battery health monitoring	First-order resistor capacitor (RC) model and nominal model	• Capacity • Internal ohmic resistance • LiMNC	• SoC dependent parameters were identified • Using those parameters, first-order resistor capacitor model was determined and the performance degradation of the nominal battery model over battery lifetime was found • Two extended Kalman filter methods with different time scales were used to combine SoC and SoH. SoC was estimated in real time and SoH was estimated in the offline mode.	• Use of extensive experimental data can give best result in the determination of accurate SoC and SoH estimation • The model accuracy deterioted in accordance with battery aging
Waag et al. [130]	Dependency of impedance characteristic on battery parameters and their variations over the battery lifetime	Electrochemical impedance spectroscopy (EIS) and current-pulse technique	Li-ion battery (40 Ah)	• Current pulses were used for battery impedance determination • Dependency of the impedance-related battery model parameters was checked by impedance spectrum • Changes on the battery impedance characteristic over the lifetime/time of the application were studied	• The SoC range during which the battery operates with high efficiency decreases due to significant aging
Yang et al. [64]	Experimental	Neural network	Ten $LiFePO_4$ batteries in different aging degrees of type IFP-1865140	• Used maximum available capacity as a parameter of battery health estimation • A back propagation neural network was used	• The method was accurate and suitable with low computational cost

Table 2 ***Continued***

Authors	Thrust of the study	Model	Battery used and parameters/ conditions	Description	Results
Rufus et al. [131]	Health monitoring	SVM, dynamic neural network, confidence Prediction neural network and usage pattern analysis	Space application batteries/ Li-ion battery (4 A h)	• Experiments were performed on the battery parameters like voltage, current, temperature, etc. • Online estimation of the SoH and RUL of Li-ion batteries by using available data of parameters were evaluated	• Health states, energy state, depth of discharge, and RUL were obtained from this method
Xiong et al. [79]	Battery parameter and state estimation	Extended Kalman filtering method	Li-ion battery	• Multiscale EKF approach was proposed and employed to execute battery parameter and SoC estimation • The accurate estimate of battery capacity and SoC was obtained in real-time through a data-driven multiscale extended Kalman filtering algorithm	• The proposed data-driven multiscale EKF approach was quite efficient with minimum errors and high precision • Computational cost value was low
Lin et al. [86]	Experimental	SMO	2.3 A h high power $LiFePO_4$/ graphite cells (1) Constant current charge or discharge (2) UDDS	• Two separate SMO models combined with reduced order electrochemical model were studied	• The maximum SoC and SoH estimation errors were found less than 3% and 2%
Schwunk et al. [132]	Online SoC and SoH estimation	Stochastic modeling or particle filter (PF) approach	Li-iron phosphate batteries	• Monte Carlo sampling technique used particle filters to determine the SoC and SoH	• High accuracy was observed
Weng et al. [133]	Determination of capacity fading as the loss of capacity and aging of battery	ICA and support vector regression (SVR)	Li-ion battery	• ICA was used to correlate capacity fading with the IC curve • Using SVR, an SoH monitoring technique was developed to provide a definite and quantitative link between IC peaks and faded battery capacity	• Prediction of capacity fading of cells was done accurately
Andre et al. [107]	SoH and SoC estimation	Advanced mathematical methods	Li-ion battery	• Minimum variance estimation and machine learning were used to estimate the SoH and SoC of a Li-ion battery • Standard Kalman filter and an unscented Kalman filter was used to predict internal states of battery • SVM algorithm was implemented and coupled with the dual filter	• The estimations results were found to be satisfactory
Hu et al. [134]	Health management of battery	Enhanced sample entropy	Li-ion battery	• Sample entropy-based capacity estimator for Prognostics and Health Management (PHM) of Li-ion batteries in electric vehicles was described • Hybrid pulse power characterization profile was adopted as the input of the health estimator • The calculated sample entropy and capacity of multicells at three different ambient temperatures were employed and validated	• The estimations results were satisfactory for further application of the method
Liu et al. [135]	SoH determination	Gaussian process regression (GPR) (data-driven approach)	Li-ion battery	• A battery SoH estimation approach based on different models of GPR algorithms was presented • The prognostics were performed using offline data • In order to improve the poor performance of prognostics based on GPR, the Gaussian process functional regression (GPFR) algorithm was applied. Later a combination of covariance functions and mean functions for GPFR was applied for improvement of result	• The proposed method can be effectively used for battery monitoring and prognostics by quantitative comparison with the GPR and GPFR models
Chen et al. [136]	Online battery SoH estimation	Genetic algorithm	Li-ion battery	• Genetic algorithm was employed to estimate the battery model parameters including diffusion capacitance of a two-order RC circuit model using measurement of current and voltage of the battery • Temperature influence was considered to improve the robustness and precision of SoH estimation results	• SoH varies proportionally with the reciprocal of diffusion capacitance of the battery

Table 2 ***Continued***

Authors	Thrust of the study	Model	Battery used and parameters/ conditions	Description	Results
Cannarella and Arnold [137]	SoH and SoC measurements	Mechanical stress	Li-ion battery	• Mechanical stress was used to monitor SoH and SoC • The linear stress-SoH relationship holds over a range of cycling conditions • Irreversible volumetric expansions of the electrodes were observed which was responsible for the stress-SoH relationship	• Mechanical measurements (stack stress or strain) can be used to provide real-time measurements of SoH and SoC in Li-ion cells as stack stress is linearly related with SoH
Saha et al. [138]	Battery health monitoring	Bayesian framework Relevance vector machine (RVM), particle filter	All kinds	• Inference and estimation techniques are applied to determine RUL of a battery • Bayesian statistical approach and models of electrochemical processes in the form of equivalent electric circuit parameters were combined with statistical models • RVM approach and different PFs or Rao–Blackwell zed particle filter framework were used for battery prognostics	• This method can be used explicitly to exploit the uncertainty in battery aging
Landi and Gross [125]	Online battery SoH estimation in vehicle-to-grid applications	Fuzzy logic, neural network	Li-ion	• Two techniques to determine SoH of a Li-ion battery with particular reference to vehicle-to-grid applications were proposed • The techniques were based on fuzzy logic and the neural network method	• Li-ion batteries were suitable for grid support services • They can constitute the energy reserve in BEVs and which after plugging into the power grid can be used as a distributed electricity reserve and to provide ancillary services
Li et al. [44]	SoH estimation critically	Model is based on chemical mechanical degradation physics	• Voltage • Current • Temperature	• This model was formed by developing Solid Electrolyte Interface (SEI) layer formation which was coupled with crack propagation due to stress generation in the active material • Due to SEI formation, lithium-ions were lost for which battery resistance increased • For particle stress calculation, realistic boundaries were considered. This was then linked with capacity degradation.	• In future, addition of lithium plating could make the model foundation for important fast charging protocol
Zhang et al. [139]	SoH estimation	Artificial intelligence optimization algorithm	• Li (Ni1/3Co1/3Mn1/3) O2 battery • Nominal capacity 38 A h, nominal voltage 3.7 V	• To predict battery SoH optimization, genetic algorithm was applied • A particle filter was employed to avoid the noise occurring in battery terminal voltage estimation • A recursive least-square method was used to update cells' capacity • The proposed method was verified by the profiles of New European Driving Cycle and dynamic test profiles	• The experimental results indicate that the proposed method could estimate the battery states with high accuracy for actual operation

Table 3 Quantitative analysis of various methods for state-of-health estimation of Li-ion battery

Method	True SoH (experimental) (%)	Estimated SoH (approximately) ()%	Prediction error (approximately) (%)
Coulomb counting	63.85	69.78	<10
Electrochemical impedance spectroscopy	85	86.27	<2.1
Neural network	82	82.3	<0.5
Support vector machine	60.35	59.19	<2
Kalman filter	84.36	86.57	≤5
Sliding mode observer	90.13	90.261	<2.5
Fuzzy logic	88	91.625	1.4–9.2

designed battery packs can perform well during the operation. During the operation of electric vehicles, the battery packs tend to fail in the nonequilibrium stage. This problem is termed as an equalization of cells in a battery pack [141,142]. After the life span of battery packs, these packs are often lying idle because the recycling and reuse methods are either ignored or the buyers are not aware of. One possibility is to accumulate these battery packs and identify and cluster the cells having life to form a new battery pack. Otherwise, these unused batteries will lead to a serious disposal problem and have bad impact on the environment [143]. Future work for authors could be to work on the proposition of comprehensive design methodology combining the uniformity criterion, equalization criterion, and reuse criterion. This shall be useful for the development of robust battery packs design being able to function synchronically during the operation of vehicles.

4.3 Integration of Mechanical Aspects With Temperature-Related Problems. It is also known that the temperature is the main enemy of the battery. The temperature-related problems such as thermal runaway, rupture, explosion, etc. can be well integrated with the existing research on safety design of the battery/battery pack. For example, the sensors (stress)-based monitoring of the battery is performed at a given temperature. However, in very cold or hot weather conditions, the results may not be applicable. Also, the battery pack enclosure design incorporates only mechanical aspects such as deformation, strength, frequency, etc. which can be well integrated with another objective of uniform temperature distribution (with maximum temperature below the threshold abnormal temperature). This shall result in robust battery pack and its components (enclosure) design, which can withstand impact from both the mechanical and thermal unforeseen shocks/accidents.

4.4 Redesign, Installation, Placement of Battery Pack, and Its Components. An important research direction could be to redesign the battery packs and its components so that it can be easily placed in the vehicle to optimize its space, have minimum impact from crash, and can be easily dismantled, disassembled, and replaced for user friendly and efficient recycling [144,145]. Topology design optimization of the electric vehicle and its integrated components including battery packs could be studied and explored in detail. The other growing aspects are the integration of batteries with photovoltaic systems and super capacitors for improving the efficiency, range of vehicle, and storage in the context of excess energy production from the hybrid systems. For example, combinations of photovoltaic system, wind power, and lithium-ion battery storage into microgrid EV charging station can offer backup power during loss of grid connection and permits exporting power when generation go beyond demand within the microgrid [146].

4.5 Minimization of Safety-Related Problems and Negative Impact on the Environment. Major concern should be taken toward safety-related problems such as cathode breakdown, electrolyte breakdown, over current, over voltage, low current, low voltage, etc. so as to protect the cells from irrecoverable damage. To diminish such problems, integration and improvization of pressure vent controller, circuit interrupter, advance switching techniques, and a reliable thermal management module inside BMS will be helpful.

Also, materials (like cobalt, nickel, etc.) used in the lithium-ion battery are not environmental friendly [112]. Extensive research on it shows that it paves a way toward global warming and environmental toxicity.

4.6 Process-Based Cost Modeling. For common public, price always plays the main decider factor for buying an automobile. Earlier, the price of the lithium-ion batteries, the main component of the battery electric vehicle, was very high. But in the last few years, its price has been dropping gradually. From studies, it is known that its price has been decreasing almost 73% in the last 5–6 years and this percentage will be increasing in upcoming years [112]. In this regard, process-based cost modeling helps in predicting and calculating the cost and sales price of several battery chemistries [147]. This cost is predicted on the basis of battery-related processes. Combination of the learning and dynamic curve model with process-based modeling leads to more precise and efficient production planning and cost forecasting [148]. But for this, exact processes and compositions of the

Table 4 Advantages and disadvantages of various methods for state-of-health estimation of Li-ion battery

Method/model	Advantages	Disadvantages
Coulomb counting	• Less complex • Easy implementation	• Time consuming
Electrochemical impedance spectroscopy	• Lower computational cost	• Applicable for specific charging conditions/current pattern only
Neural network	• Match with other techniques, suitable for different battery applications	• Needs lot of training data as it depends on historic data set
Support vector machine	• This method is suitable in both nonlinear and high dimensional model • Fast and highly accurate method	• It a complex method in terms of computation
Kalman filter	• Accurate estimation can be done • No initial data of SoC/SoH is required • Easy filter of data (noise, etc.)	• Method is complex as it requires large amount of calculations
Thevenin model	• Simple and easy to implement	• Capacity fading cannot be predicted
Fractional order	• Accurate in dynamic load condition	• Weak in self-updating the model parameter
Sliding mode observe	• Simple control structure and robust tracking performance, under uncertain environments • High accuracy can be achieved	• Slow time observer for SoH
Fuzzy logic	• Applicable for complex and nonlinear system	• High amount of computation is required

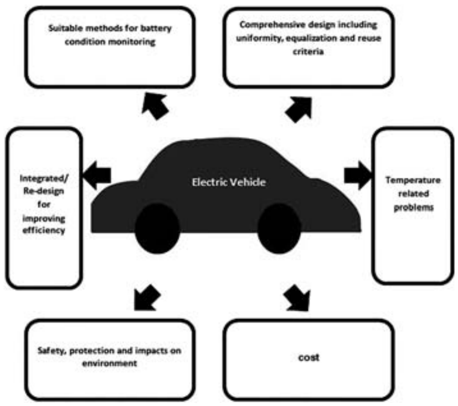

Fig. 5 Scope of research directions in the future

battery chemistries should be known accurately. This can be overcome by recently published patents and through literature survey which describe the processes in detail.

5 Conclusions

This paper reviewed various approaches for SoH estimation of lithium-ion batteries, with a focus on their use in the electric vehicles. From this review, it is evident that among all the models, electrochemical and equivalent circuit models perform well but cannot be directly applied to the other batteries. On the other hand, statistical methods are easily adjustable to the different batteries. However, obtaining the effective and accurate method for the estimation of battery health in the real conditions is a challenging task. In order to investigate the real-time SoH, a few attempts were made by researchers. NDT methods can be considered as the solution for overcoming the difficulties in real-time estimation of SoH of the lithium-ion battery, since it has the capability of changing its parameters according to demand conditions. Furthermore, the commonly used methods which have been reviewed are not favorable for aged battery's SoH estimation and it is found that their chemistry is very difficult to understand; hence, there is a need to study the battery chemistry so that it can correlate with SoH of the lithium-ion battery. From the extensive literature review, it can be concluded that in order to design and develop a new and efficient methodology for estimation of SoH of the lithium-ion battery, major focus should be given in all these issues like accuracy, easy assembling–disassembling of battery packs, end life forecast, suitability for realistic situations, and its effective implementation on BMS simultaneously. Thus, exhaustive research on battery electrochemistry and appropriate research based on realistic situations with its parameters will give a new dimension toward great invention in battery research.

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