Clean Energy, 2023, Vol. 7, No. 6, 1268–1281
https://doi.org/10.1093/ce/zkad054
Advance access publication 20 November 2023
Review Article

Electric vehicle battery capacity degradation and health estimation using machine-learning techniques: a review

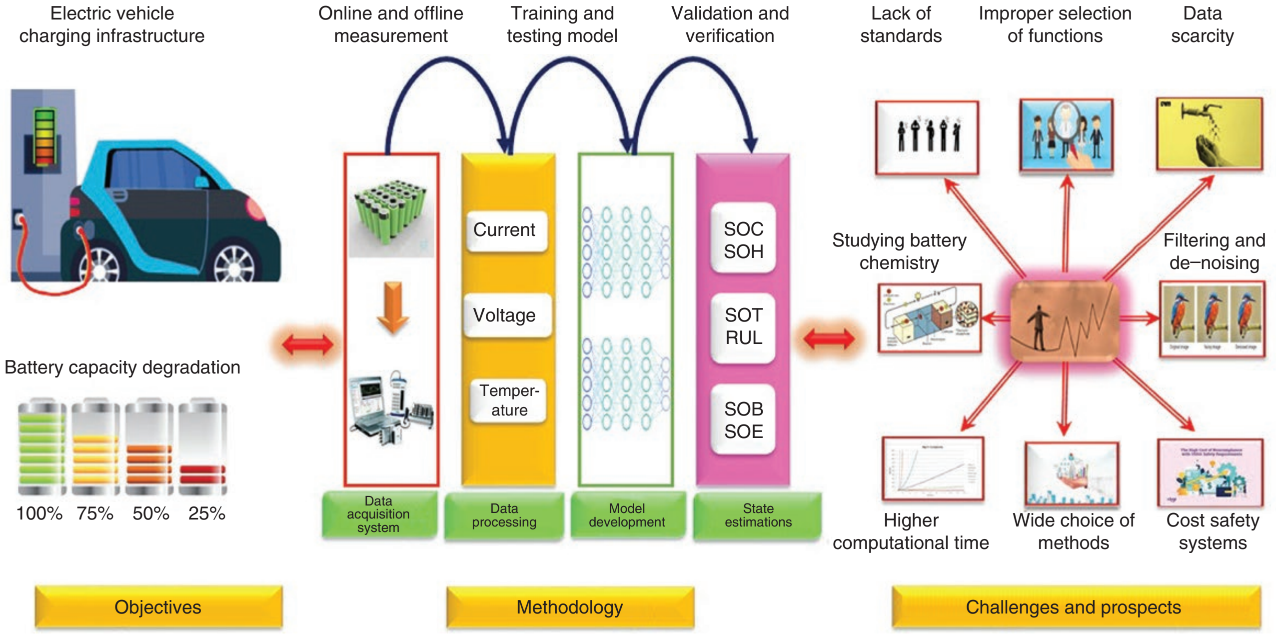
Kaushik Das and Roushan Kumar*

Department of Mechanical Engineering, School of Engineering, University of Petroleum and Energy Studies, Dehradun, India
*Corresponding author. E-mail: rkumar@ddn.upes.ac.in; automotive.roushan@gmail.com

Abstract

Lithium-ion batteries have an essential characteristic in consumer electronics applications and electric mobility. However, predicting their lifetime performance is a difficult task due to the impact of operating and environmental conditions. Additionally, state-of-health (SOH) and remaining-useful-life (RUL) predictions have developed into crucial components of the energy management system for lifetime prediction to guarantee the best possible performance. Due to the non-linear behaviour of the health prediction of electric vehicle batteries, the assessment of SOH and RUL has therefore become a core research challenge for both business and academics. This paper introduces a comprehensive analysis of the application of machine learning in the domain of electric vehicle battery management, emphasizing state prediction and ageing prognostics. The objective is to provide comprehensive information about the evaluation, categorization and multiple machine-learning algorithms for predicting the SOH and RUL. Additionally, lithium-ion battery behaviour, the SOH estimation approach, key findings, advantages, challenges and potential of the battery management system for different state estimations are discussed. The study identifies the common challenges encountered in traditional battery management and provides a summary of how machine learning can be employed to address these challenges.

Graphical Abstract



Keywords: lithium-ion battery; health estimation; machine learning; health degradation; state estimation

Introduction

Development of emission-free electrochemical energy storage systems, along with the monitoring and optimization of their performance, has become a key factor in infrastructure development for electric transportation systems [1]. Centralized and decentralized energy storage and dynamic advancement of new

Received: 26 April 2023. **Accepted:** 17 July 2023

technologies [2, 3] deal with rising carbon emissions and their associated climate change and energy shortages [4]. Lithium-ion batteries (LIBs) [5] excel as a prominent choice among different energy storage options [6] and are seen as a viable option due to their low self-discharge rate, high power densities [7] and longer cycle life, which triggered the new path for the electric vehicle (EV) market and enabled the wide emergence of portable electronic devices [8, 9].

LIBs are rechargeable in nature and can withstand several cycles of charging and discharging, but they are sensitive and may fail if not handled carefully [10, 11]. Ions travel from the cathode [12] terminal to the anode terminal via an electrolyte during charging and vice versa. The lithium ions that have been stored travel back to the cathode via the anode during discharge [13, 14]. The performance and safety of batteries are influenced by every component utilized, so selecting the finest possible combination will aid in producing better batteries. Future development of this technology, which has already made great strides, will be driven by advances in material science and parameter monitoring [15].

LIBs continuously linearly age and nonlinearly degrade from the moment they are manufactured [16] and from the time of first use; this is because of the electrochemistry used, which gives rise to unavoidable internal chemical reactions during storage or runtime [17, 18]. The three stages of degradation are the real processes, the modes that may be seen at the cellular level and the operational impacts of capacity fading. The major factors responsible for LIB health degradation [19, 20] are overcharge with both high current and high voltage regions, overdischarge and cycle frequency, and temperature (both low and high) during storage and in operation. It also covers the state of charge, cycle bandwidth, internal short circuits in a cell, external short circuits in a battery, overheating of a battery and accelerated degradation. However, due to certain inherited properties and limitations, LIBs require a battery management system (BMS) [21] and this includes the following multitask activity: gathering battery data, determining battery status, making predictions, controlling charging and discharging processes, providing safety protection, managing thermal conditions, ensuring balancing, exercising control and facilitating on-board communication [22, 23].

The research gap thorough studies says that the performance of these approaches is not satisfactory for electric mobility applications, even though data-driven algorithms are used in several state-of-health (SOH) estimate procedures. The estimating approaches have not been sufficiently developed and the classification methods of the pertinent study work that has previously been published are frequently fairly crude. Very little research describes different methods to estimate the SOH in EV applications in detail. The research objective is to understand the usage of a reliable battery model and the modelling strategy required to obtain the correct state estimation findings. The SOH estimation techniques for EVs must be dynamic to adapt to the operating conditions as various places have varying environmental conditions and driving habits. The selected capacity fading model still severely restricts the forecast accuracy of a machine-learning (ML) algorithm, which increases the computing cost.

The contribution in the paper covers a comprehensive indication and impact of different states in the BMS. It also covers different deep-learning (DL) methods for health management systems to understand ageing and degradation. Remaining-useful-life (RUL) and SOH prediction work through a data acquisition system, data processing, DL model development and different evaluation methods. This article also discusses various aspects related to faults, prognostics and diagnosis methodologies for different types of faults, specifically focusing on LIBs. It also covers the principles and characteristics of prognostics and diagnosis, as well as the indicators used in health management systems. It concludes the future of health management system trends and a few opinions on the forthcoming progress.

The paper organization is as follows. Section 1 deals with LIB behaviour and covers different influencing factors related to the design, production and application. It also covers degradation mechanisms and electrochemical behaviour. Section 2 explains the SOH estimation approach, key findings, advantages, challenges and the potential of the BMS for different state estimations. Section 3 summarizes the challenges and prospects of using artificial intelligence (AI)/ML as a design and optimization accelerator for the effective estimation of different states for electric mobility applications. Section 4 covers conclusions and future works on ML techniques for SOH prediction in LIBs.

1 Lithium-ion battery behaviour

LIB direct measurable indices are current, voltage, internal impedance and temperature [24]. Indirect indices also show an important role in understanding and monitoring the battery system, which is having a different dynamic state of charge (SOC), power, energy, health, function, temperature and RUL [25]. Among them, the SOC and the SOH are of foremost importance for electric mobility applications [26]. Knowing the SOH accurately is essential to extending battery life and ensuring the system operates safely and reliably. The parameter associated with the SOH covers the general condition of the battery and its capability to deliver the output through a measured impedance and capacity when it is not used conditions [27, 28].

The multiple factors responsible for the final capacity and power fade in the LIB start from the design level until its usage, which gives rise to several main and side reactions at the cell level. Understanding the physics of modes and effects of reactions, degradation modes and their resultant effects is of research interest [29, 30]. Cell influence factors responsible for main and side reactions is presented in Fig. 1 and covers the design, production and application influence factor. It leads to different side and main reactions such as electrode particle cracking, binder decomposition and corrosion that produces degradation and fading effects.

The physical and chemical developments that take place inside the LIB cell are described by electrochemical degradation. While mechanisms offer the most in-depth perspectives on deterioration, they are sometimes the most challenging to detect during cell-level or battery-level operation [31]. Fig. 2 explains the electrochemical degradation mechanisms in LIBs and covers the copper particle cracking mechanism, decomposition, precipitation and dendrite formation; it also explains the copper current collector, an aluminium current collector and degradation mechanisms [32]. It shows the most widely known deterioration processes in LIBs working with a physics-based model only to pay attention to particle cracking and the solid electrolyte interphase.

Fig. 3 illustrates the complex electrochemical behaviour of LIBs that enables their energy storage capabilities. Understanding the electrochemical processes within LIBs is crucial for optimizing their performance and addressing challenges related to capacity fade, degradation and safety concerns. The electrochemical behaviour covers an overview of cell chemistry, lithium intercalation, ion transport, charge/discharge reaction,

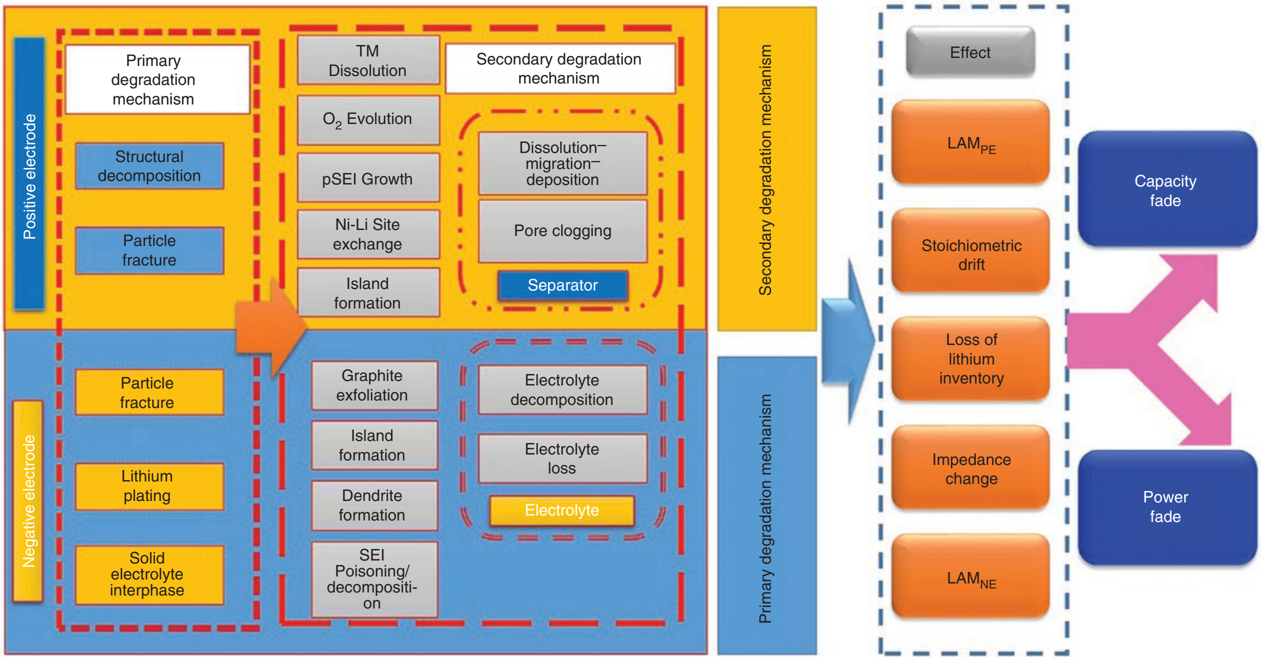


Fig. 1: Lithium cell influence factors responsible for the main and side reactions for capacity and power fade

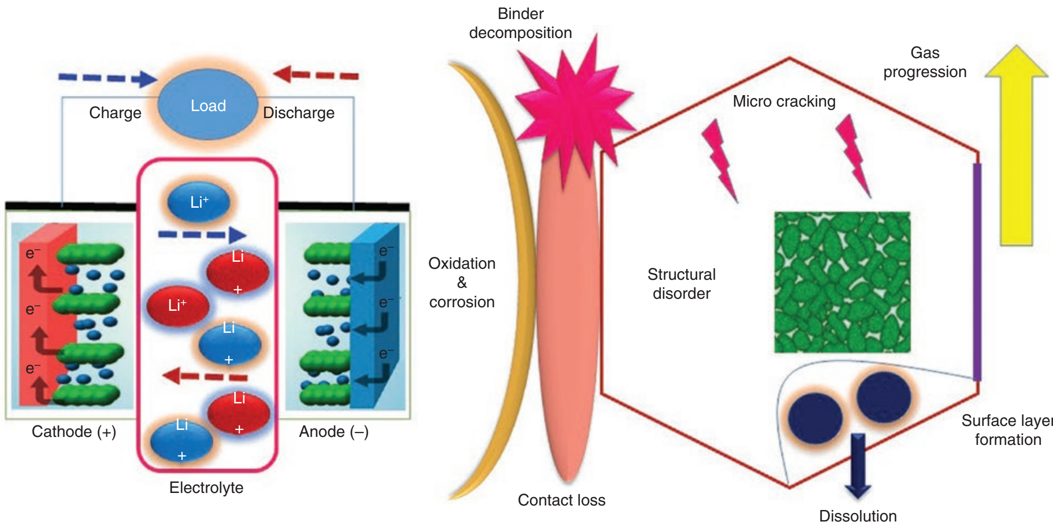


Fig. 2: Electrochemical degradation mechanisms in lithium-ion batteries

solid electrolyte interphase (SEI), side reaction, degradation, capacity and power fade. The process of ageing and degradation is an electrochemical phenomenon that involves the LIB material and its chemical properties. LIB storage, charging and discharging along with external factors are primarily due to the sophistication and complexities of modern mechanical systems, thus SOH estimation is a very difficult and perplexing issue for prognostics and health management [33, 34]. The modelling enables us to predict electrical parameters on terminals and to anticipate temperatures and the SOC considering a wide range of environmental and operating conditions [35]. It is essential to model and analyse the performance of LIBs under various operating conditions.

Therefore, accurate estimation of the SOH under wide environmental and operating factors is an important issue to be talked about. In academics and research, the estimation of the SOH accurately and efficiently improves the estimation and prediction of the RUL, and analytical alterations to the use of the energy storage system can be made in advance so that the system operation is safe and stable, leading to extended service life. However, because of the complicated internal workings and unpredictable operating circumstances of the battery, developing a precise battery model is challenging. ML technologies [36] are becoming more popular because of their adaptability and easily available battery data [37]. The importance of path dependence degradation, or the order in which the different degradation mechanisms are triggered, has also been taken into account. This refers to the various degradation mechanisms triggered by calendar ageing, which takes place while the battery is at rest or being used or charged.

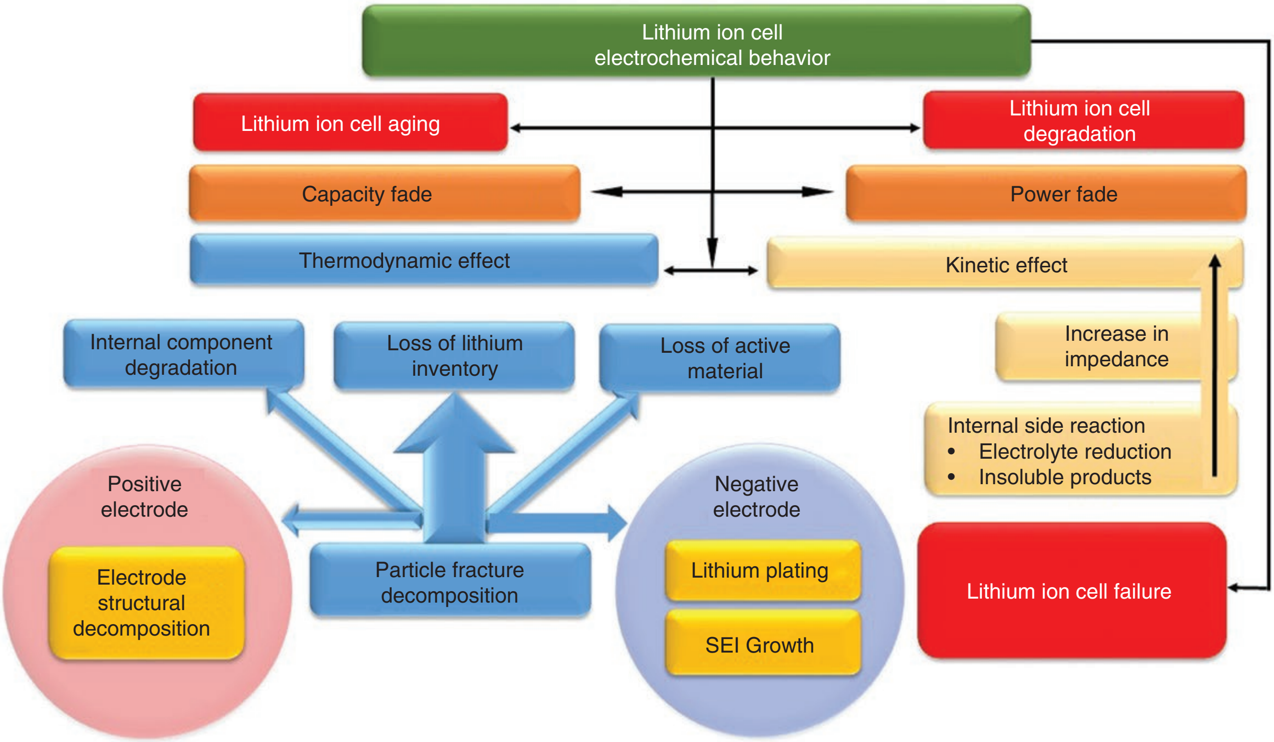


Fig. 3: LIB electrochemical behaviour

2 SOH estimation approach and key findings

The SOH is customarily designated for battery performance and its estimation methods are used with several indirect health indicators. It is divided into different model categories, namely model-based, differential analysis, data-driven and hybrid methods.

2.1 SOH estimation

The quantitative definition of the SOH is based on the rise in internal impedance of the LIB over a specified period and current capacity decliner. The total beginning-of-life charge capacity, the total maximum charge volume and the total rated capacity are represented by Q_{BOL}, Q_{Max} and Q_{Rated} and represented through Equations (1) and (2):

$$SOC = \frac{Q_{BOL}}{Q_{Rated}} \times 100\% \tag{1}$$

$$SOH = \frac{Q_{Max}}{Q_{Rated}} \times 100\% \tag{2}$$

Several parameters are required for depth of discharge (DOD) estimation: it is the ratio of the released charge capacity rating with a total rated capacity and it is the discharge capacity through discharge current I_d, represented through Equations (3–5):

$$DOD = \frac{Q_{Released\ Rated\ capcity}}{Q_{Rated}} \times 100\% \tag{3}$$

$$\Delta DOD = \frac{\int_{t0}^{t0+\tau} I_d(t)\,dt}{Q_{Rated}} \times 100\% \tag{4}$$

$$DOD(t) = DOD(t_0) + \Delta DOD \tag{5}$$

Without considering battery ageing and operating efficiency, the SOC is represented through Equation (6). Direct measuring techniques measure Q_{Aged} and impedance directly using impedance testing, capacity testing or other testing equipment and then the SOH is computed using Equation (7) [38]:

$$SOC(t) = 100\% - DOD(t) \tag{6}$$

$$SOC(t) = SOH(t) - DOD(t) \tag{7}$$

However, these techniques are not appropriate for actual online applications and may only be used in restricted experimental settings. Indirect analysis methods are of high interest, as these are the most suitable for practical purposes and they are now widely adopted through various methods. The flowchart for the improved coulomb counting method is shown in Fig. 4. The linked memory is first accessed to get the historical battery usage statistics.

2.2 Classification of capacity degradation methods

The SOH is presumed to be in good health and has a value of 100% in the absence of information for a recently used battery; the SOC is first approximated by measuring the loaded voltage based on the starting conditions or open-circuit voltage [39]. The approximating procedure is based on keeping an eye on the I_d and V_d of the LIB voltage. The quantity and direction of the operating current can be used to determine the battery operation mode. Model-based approaches are equivalent circuit models (ECMs) and electrochemical models (EMs). However, due to the complex degradation mechanism and the non-linear behaviour, it is challenging for ECMs or EMs to accurately simulate the static and dynamic characteristics throughout the life of the battery.

It extracts one or more topographies that describe the degradation from the measured battery data, such as current, voltage and temperature, collectively called direct health indicators, whereas environmental and operating parameters are called indirect health indicators (iHIs). It is used to create a connection between health indicators and the SOH using different ML methods. Fig. 5 illustrates the classification of capacity degradation estimation methods, which cover direct measurement; indirect measurement; data-driven and knowledge-based estimation; and co-estimation techniques. Fuzzy logic, AI, signal processing and linear and non-linear models are used in the estimation approach. When predicting the SOH of EV batteries, it is often useful to consider indirect health indicators in addition to key health indicators. Internal resistance, voltage response, capacity fade, cycling efficiency, self-discharge rate, temperature sensitivity and charge acceptance are indirect indicators that provide comprehensive summarizations of the overall health of the battery [40].

The impedance of the LIB increases as it ages or degrades, so measuring the internal resistance of the battery can serve as an indirect health indicator. Higher internal resistance values

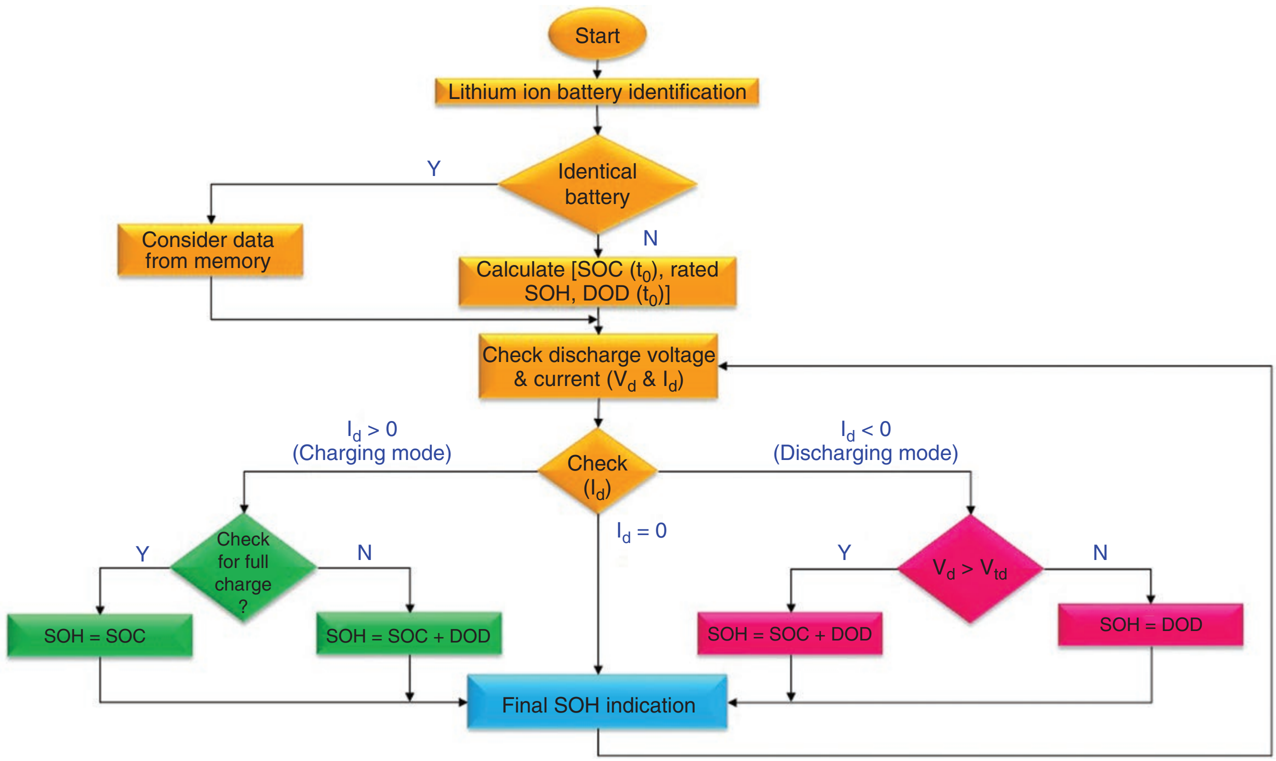


Fig. 4: SOH estimation flowchart through SOC and DOD data and a coulomb counting algorithm

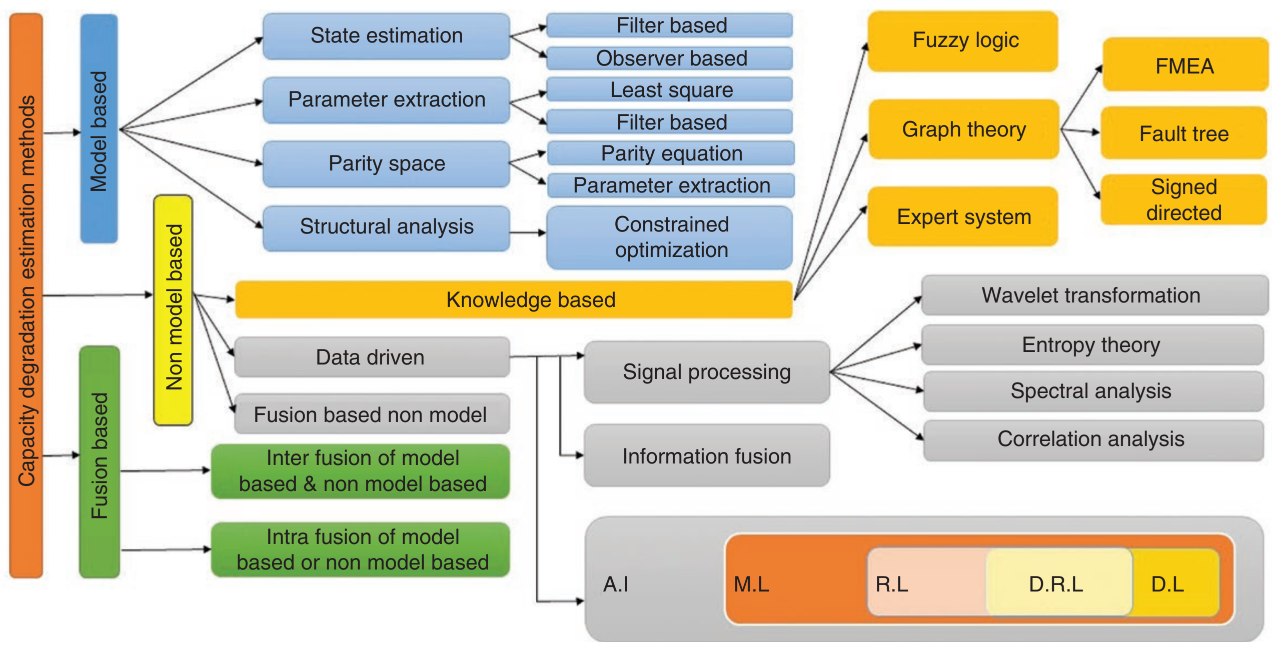


Fig. 5: Classification of capacity degradation estimation methods

Table 1: Different indirect health indicators for the SOH estimation approach with key health indicators

Studies	Indirect health indicators	State	Type	State estimation
[10]	Anticipated charge storage and internal resistance for k-th cycle Total cycle count for k-th cycle	SOH	Cell	Particle filter
[42]	Variability coefficients of voltage and current curves observed during the partial charging phase	SOH	Cell	Multi-kernel Gaussian process regression model
[25]	iHI1 is the time needed to get to the lowest discharge point iHI2 is the battery temperature rise at the highest point iHI3 is a time decrement from 3.8 to 3.5 V iHI4 is the first maximum slope of the voltage characteristic curve during the discharge operation iHI5 is the point at which the temperature of the battery peaks iHI6 is the first maximum curve of the current curve when charging at a constant voltage iHI7 is the charging time iHI8 is the area under the current characteristics	SOH and RUL	Cell	Gaussian process regression model
[43]	Ohmic internal resistance Polarized internal resistance	SOH	Cell	Extreme learning machine (ELM)-based feedforward neural networks
[44]	Initial discharge voltage drop Time interval to equal discharging voltage difference	SOH	Cell	Long short-term memory neural network
[45]	Required time for a consistent voltage disparity during charging	SOH and RUL	Cell	ELM and random vector functional link network
[46]	Time-domain and frequency-domain condition indicators	SOH	Cell	Incremental support vector regression model

typically indicate reduced battery performance and capacity [41]. The voltage profile of a battery during charging and discharging can provide insights into its health. As batteries degrade, their voltage response may deviate from the expected behaviour. Monitoring voltage patterns and comparing them with a healthy reference can help in estimating the SOH indirectly. Capacity fade refers to the reduction in the energy storage capacity of a battery over time. By periodically measuring the available capacity and comparing it to the initial capacity, one can estimate the SOH of the battery indirectly. Capacity fades can be a comprehensive summarization of overall battery health. Cycling efficiency represents the ratio of the energy discharged during a cycle to the energy required to recharge the battery [36]. As batteries degrade, their cycling efficiency tends to decrease due to increased internal losses. Monitoring the changes in cycling efficiency can provide an indirect measure of battery health. A healthy battery should exhibit low self-discharge rates when not in use. Higher self-discharge rates can indicate internal issues or degradation. Monitoring the self-discharge rate over time can provide an indirect assessment of battery health.

Battery health is often affected by temperature, humidity, dust and vibration. Monitoring how the performance and capacity of a battery change with temperature and other parameter variations can serve as an indirect health indicator. Higher temperature sensitivity and larger deviations from the expected behaviour may indicate a reduced SOH. The ability of the battery to accept charge and to discharge efficiently can be an indirect indicator of health. If the charge and discharge acceptance of a battery deteriorate over time, it suggests a reduced SOH. Monitoring the charge acceptance rate during charging sessions can help in estimating battery health indirectly. By considering these indirect health indicators alongside direct health indicators such as capacity and internal resistance, a more comprehensive assessment of battery health and an SOH estimation can be achieved. ML techniques can leverage these health indicators along with historical data to develop accurate models for estimating battery health and predicting the SOH. Table 1 lists the different iHIs for SOH estimation indicators and covers different state estimations using model-based or data-driven approaches. Most indirect iHIs are available in the literature and are based on discharging data and much less on charging data.

2.2.1 *Advantages and disadvantages of different ML methods*

Discharging data are affected widely by operating and environmental conditions; the data are widely varied with a low level of accuracy. The charging and discharging data are normally defined as a pattern with a low level of variance widely explored for indirect health indicator parameters for the estimation and co-estimation of the SOH and RUL. Fig. 6 illustrates the advantages and disadvantages of ML techniques for SOH prediction. Advantages deal with easily identifying trends and patterns, less human involvement and handling multi-dimensional data whereas disadvantages cover data acquisition complexity, high error susceptibility and interpretation of results.

From material science to engineering application, the lithium-ion battery poses a complex multivariable challenge with a variety of properties including cost, environmental effects, life-cycle analyses, safety, performance and abundant resource issues [47]. These properties generate a large set of data that has been growing exponentially in recent times [15, 48]. AI methods that are learning from training experience and applied to any system have come up exponentially with the advent of associated hardware and software development over the period and are ubiquitous in our modern world.

2.2.2 *Different ML methods for SOH estimation*

The massive data generated for LIB to manage, monitor, understand and assimilate are a huge challenge, where AI and its subset, ML, is handy to assist researchers in efficiently solving the parameterization and data challenges on the user and manufacturing side. A strong collaboration between experimentalists, modelling specialists and AI/ ML experts is needed. Fig. 7 explains different ML methods for SOH estimation. It covers regression, classification, clustering, association and control methods. The primary data-driven approaches at this level are classified into four categories: unsupervised, supervised, semi-supervised and reinforced learning, which is further categorized according to the differences in data-mining methods as the support vector machine (SVM), relevance vector machine (RVM), long short-term memory (LSTM), Gaussian process regression (GPR) and DL [5]. In supervised learning, we have a labelled data set in which each example is associated with a corresponding target label. In unsupervised learning, we have an unlabelled data set and identify patterns or structures within the data. Semi-supervised learning is a ML paradigm that lies between supervised learning and unsupervised learning. Approaches for data-driven methods are further classified into four domains: statistical data, artificial neural networks (ANNs), filtration and vector machines [49].

Semi-supervised learning [36] combines the elements of supervised and unsupervised approaches by utilizing a small amount of labelled data along with a larger amount of unlabelled data. The functionality of the labelled data provides valuable information for training a model, while the functionality of unlabelled data helps in leveraging the underlying structure of the data. In EVs, lithium-ion battery ML and its algorithms depend on the quantity, quality and reliability of multidimensional data sets, and uncover patterns in data and open applications that are challenging to deal with using other methods. This has high relevance for material discoveries, manufacturing, performance optimization, diagnostics, and prognostics and health management (PHM) in which multitudes of input parameters are to be considered simultaneously.

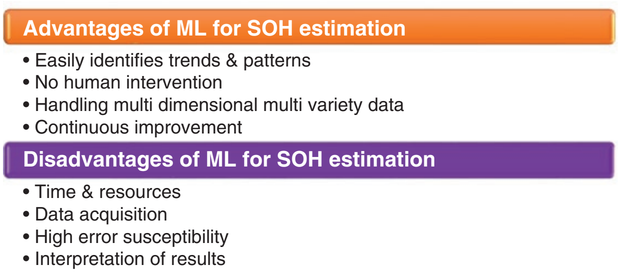


Fig. 6: Advantages and disadvantages of ML methods for SOH estimation

2.2.3 *Assessment of SOH estimation approach*

Table 2 lists different assessments of the SOH estimation approach through ML and key observations, scope, content and limitations. In its traditional form, ML relies on data and its physics agnostic. This implies that instead of providing a physical explanation for a link, ML might seek to find it through interpolation of training data [11, 50, 51].

The research community unanimously agreed that ML-based SOH is one of the best among all other types of SOH estimation methodologies with specific advantages and limitations. Online estimation of SOH and RUL is not a trivial assignment due to its non-linear behaviour and the computing exhaustive processes it requires [64, 65]. Table 3 lists different algorithms and methods

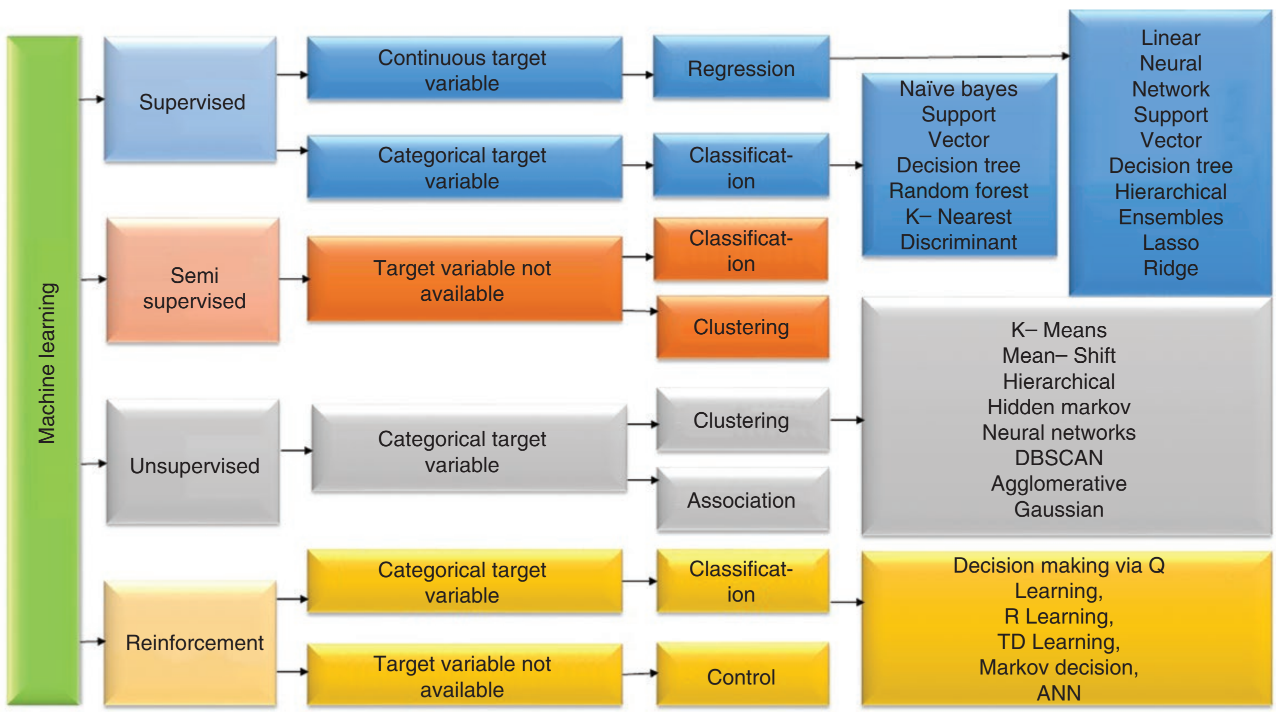


Fig. 7: Different ML methods for SOH estimation

Table 2: Assessment of SOH estimation approach through ML and key observations and findings

Studies	Scope and contents	Observations	Limitations
[27]	The principle of each algorithm is rigorously derived followed by flow charts with a unified form	SVM, ANN and DL have high potential and are hotspots for research	SOH features from short-term measurement data for facilitating practical applications are not explored
[30]	Data-driven methods with real-world EV battery data for performance evaluation, advantages and limitations	SVM, RVM and LSTM are medium to high in accuracy, robustness and generalization	A comprehensive study on ML methods is not evaluated on various parameters
[49]	Summarizes advantages and disadvantages of mainstream SOH estimation and prediction methods	The fusion method, having high accuracy but also high algorithm complexity and algorithm compatibility, remains to be proven	Methodologies were not elaborated on nor reviewed for errors in estimation
[52]	Available cell technologies, various methods and models, their advantages and disadvantages and quantitative analysis of various methods for SOH	A general review of SOH estimation methods is conducted	Measurement errors are not notified. Non-destructive methods for battery condition monitoring are proposed but no details of methods or methodologies were presented
[53]	Charging–discharging mode, discharging mode and charging mode as three parallel experiment methods	Different methods are not extensively explained in the literature	Defined only based on certain available data sets and any validation of the results not carried out
[54]	Battery models such as electrochemical models, mathematical models, circuit-oriented models and combination models and ML and metaheuristic methods for SOx estimation	The necessity for different state estimations and modelling for LIB is established	Detailed descriptions of methods and methodologies were not carried out for different chemistry, form factors and operating and environmental conditions
[55]	Various models for SOH, publicly available battery data sets and estimation methods	ML is dependent on data characteristics and is computationally complex. Estimation methods are ideal for an experimental environment but are not suitable for practical engineering applications	Error in measurements such as MAF, root mean square error, etc. is not reported or reviewed. Comparative analysis of different chemistries of LIBs is not discussed
[56]	Performance prognostics and characteristics on physics-based, data-driven and hybrid classes	PHM based on SOH and RUL is very important for the application	Comparative analysis of different ML algorithms for SOH is not reviewed or introduced comprehensively
[57]	Compared feature-based classification of SOH estimation methods and issues and challenges in predicting SOH for LIBs with possible solutions. Also explained internal and external challenges in SOH estimation	Efficient filtering is required in ML whereas model-based features are efficient for laboratory analysis and take care of dynamic performance	Comparative analysis of different ML algorithms for SOH is not reviewed or not fully involved
[58]	Discussed challenges of real-time PHM, feasibility and cost-effective ML-based SOH with different stress factors	SOH is often used as an input for ageing model predictors and is heavily correlated and co-estimation is required	The health feature generation process is neglected
[59]	ML-based SOH and health feature extraction methods with accuracy and execution process	Multi-kernel relevance vector machine (MK–RVM) method has higher SOH prediction accuracy than other relevant methods such as support vector regression and GPR models	
[60]	Different data-driven approaches to SOH modelling	Comparative review of a different approach with advantages and disadvantages	Algorithms for SOH were not reviewed
[61]	SOC and SOH joint estimation methods	Effective feature selection and prediction methods based on less sample data should be discovered to improve prediction accuracy and efficiency	ML-based algorithms for SOC–SOH co-estimation were not explored in depth
[62]	SOH estimation with iHI, its advantages and restrictions in terms of real-time automotive applications	Real-time estimation of battery SOH is important regarding battery fault diagnosis	ML-based SOH was not elaborated on and explained
[63]	SOH estimation methods according to signals that are used to extract iHIs	Thorough comparison among the existing methods to provide a comprehensive understanding of SOH estimation	ML-based SOH was not elaborated on and explained

used for SOH estimation with different data sets such as own experimental data, National Aeronautics and Space Administration (NASA), Oxford Battery Degradation Dataset (OBDD), Center for Advanced Life Cycle Engineering (CALCE) and Massachusetts Institute of Technology (MIT). While mathematical models suffer from significant estimation errors when attempting to precisely estimate internal battery dynamics, the combination of mathematical and EMs yields improved results, albeit at the cost of increased complexity and a higher demand for computational resources. In contrast, data-driven methods aim to address the

Table 3: Different methods and algorithms used for SOH estimation with different categories of data sets

Studies	Algorithms/methods used	Category
[17]	Random forest regressor (RFR)	Own experiment
[37]	Gaussian process regression (GPR)	Own experiment
[66]	Support vector regression (SVR)	Own experiment
[67]	Cross D-Markov Machine and Fast Wavelet Transform	Own experiment
[68]	Temporal convolution network (TCN) and long short-term memory (LSTM) network	Experimental and NASA—Prognostics Center of Excellence (PCOE)
[69]	Convolutional neural network (CNN)	Experimental and NASA–PCOE
[70]	Metabolic extreme learning machine (MELM)	Own experiment
[23]	Secondary structural ensemble learning (SSEL)	OBDD
[71]	Second-order central difference particle filter (SCDPF)	CALCE and NASA–PCOE
[72]	Support vector machine (SVM) with radial basis function as kernel function	NASA–PCOE
[73]	LSTM recurrent neural network	MIT data set
[74]	Fusion of Autoregressive Moving Average Model and Elman Neural Network	Own experiment
[75]	Gated Recurrent (GR)	OBDD
	Unit Neural Network (UNN)	
[76]	Backpropagation long short-term memory (B-LSTM) neural network (NN)	CALCE
[28]	Attention depth-wise temporal convolutional network	NASA–PCOE
[77]	Least squares support vector machine (LSSVM)	NASA–PCOE
[78]	GPR	Sandia National Lab
[3]	Multiple linear regression (MLR), sparse Gaussian process regression (SGPR), Deep convolutional neural network (DCNN) method	Own experiment
[21]	Artificial neural network (ANN)	Own experiment
[79]	Parallel layer ELM	NASA–PCOE
[80]	Gate recurrent unit CNN	NASA–PCOE and OBDD
[81]	SVM	MIT data set
[82]	SVM	Own experiment
[83]	SVM	MIT data set
[84]	bat algorithm- Extreme learning machine (BA- ELM)	NASA–PCOE
[85]	SVR	CALCE
[38]	LSTM	Own experiment
[86]	LSTM	SMC–EV, China
[87]	SVR	NASA–PCOE
[17]	Gradient boosting ELM	NASA–PCOE
[88]	Deep extreme learning machine (DELM)	NASA–PCOE
[89]	ELM–LSTM	NASA–PCOE
[33]	CNN–LSTM	NASA–PCOE
[90]	Feedforward Neural Network (FNN)–CNN–LSTM	Own experiment
[91]	Recurrent neural networks (RNN)	Own experiment
[92]	Bidirectional LSTM (BiLSTM)	NASA–PCOE
[93]	Deep Neural Network (DNN)	NASA–PCOE
[2]	NN–LSTM	NASA–PCOE
[94]	LSTM	NASA–PCOE
[95]	Improved ant lion optimization algorithm (IALO)–SVR	NASA–PCOE

limitations of both mathematical and EMs, each of which has its respective drawbacks.

The necessity for battery ageing data is an integral part of the data-driven ML method, although fetching authentic data is a time-consuming and cost-intensive process. Table 4 explains the SOH estimation findings with different algorithms/methods used with feature source, index and precision. A big share of researchers had adopted raw and processed data from internationally acclaimed labs and companies for the development of their ML-based algorithm and their findings are well adopted. NASA–PCOE is very popular among several data repositories. Table 5 lists the advantages and disadvantages of the multiple mainstream ML approach used for SOH estimation.

To get the appropriate state estimate results, a trustworthy battery model and modelling approach must be used. The classification methods of the applicable research work published are often rather rudimentary and there has not been sufficient work done on the estimation techniques. Very little effective research describes different methods to estimate the SOH in EV applications in detail. For EVs operating in different locations with diverse environmental conditions and driving patterns, the SOH estimate methods must be dynamic to adopt the operating conditions [57].

ML amplifies the computational demands, while the effectiveness of its predictions remains significantly constrained by the employed capacity fading model [58].

3 Challenges and prospects

The current research discusses the ideas, methods, tools, results and difficulties of applying AI/ML as a design and optimization accelerator for the effective estimation of SOH, which is the latest research issue in current LIBs for electric mobility application. Despite all the expectations and promises around AI and ML, there is still a long way to go before data-driven techniques are widely used in the SOH estimation area. Table 6 lists the different challenges in the implementation of ML in the SOH. The thorough explanation of the SOH, its estimate and the application still present some significant challenges in the BMS.

Since exterior behaviours are a composite of many interconnected internal responses, it is challenging to monitor and simulate the internal condition and ageing mechanism of LIBs since they are still poorly understood and cannot be directly monitored. In the minor ageing conditions (C-rate@1C, T@25 °C), the major ageing cause is believed to be the development of the SEI layer. But even in moderate cases of ageing, 'abnormal' phenomena such as abrupt capacity decline have been noted, suggesting an ageing process distinct from SEI growth.

The heterogeneity of ageing processes makes SOH and RUL prediction difficult. Diverse ageing circumstances exhibit the same capacity/resistance at one stage but differ dramatically at the next, validating the need for a multi-parameter SOH model. Periods of fast discharging may be alternated with slower discharging or periods of inactivity in real-world usage patterns; consequently, further research into this component is required for more precise health evaluation and lifetime prediction. Voltage, current and temperature are frequent measures that are effects of the interaction of several internal electrochemical processes. It is still difficult to extract and estimate the right characteristics to fully define the SOH using the working data that are currently available. EV battery capacity degradation and health estimation pose several challenges, and ML methods can help to address these challenges, as shown in Fig. 8. The challenges include lack of standards, improper selection of functions, battery ageing and degradation, battery chemistry, variability and uncertainty, lack of real-time monitoring, limited training data, cost safety system and model interpretability.

Table 4: Key findings with different algorithms/methods used for SOH estimation with feature source, index and precision

Studies	Method	Feature sources	Index	Precision
[7]	Classification and regression trees	Charging and discharging profile	MSE	0.03
[67]	FC–FNN	Impedance measurements	MAE	0.9%
[68]	LSTM–TCN	Charging and discharging profile	RMSE	0.0273% (Ah) 0.0547% (IR)
[96]	genetic algorithms - wavelet neural networks (GA-WNN)	Charging and discharging profile	MAE	1.53–1.81%
[69]	CNN	Charging profile	MAE	1.6%
[23]	Secondary structural ensemble learning (SSEL)	Charging profile	RMSE	0.3556–0.5718%
[73]	LSTM–RNN model	Impedance measurements	RMSE	0.25–0.50%
[28]	AD–TCN	Charging and discharging profile	RMSE	0.014–0.083%
[85]	SVR	Charging profile	MAE	0.0039
[97]	Single hidden layer feedforward neural network	Charging and discharging profile	MAE	1.87–2.65%
[98]	SVM	Current pulse test	MAE	0.89%
[99]	ANN	Charging profile	R^2	0.9943
[34]	Online sequential ELM	Charging and discharging	R^2	0.99
[91]	RNN	Charging profile	R^2	0.994–0.997

MSE, mean squared error; MAE, mean absolute error; RMSE, root mean square error.

Table 5: Advantages and disadvantages of the multiple mainstream ML approach used for SOH estimation

Methods	Advantages	Disadvantages
Supervised	Allows collecting ageing data or producing a SOH data output and helps in optimizing performance criteria from the previous experience	Computation time is vast, unwanted data down efficiency, preprocessing of data is a big challenge and always-in need for updates
Semi-supervised	Easy to understand and has a simple, stable and highly efficient algorithm. Also reduces the amount of annotated data used	Iteration results are not stable and not applicable to network-level data. It has low accuracy
Unsupervised	High costs and time are involved in selecting training data. Varying consistency in classes may not match spectral classes	Opportunity for human error is minimized and is relatively easy and fast to carry out
Reinforced	High capability to solve complex problems and is capable of achieving long-term results for SOH. It is very useful for achieving perfection, especially in non-linear health profiles	Only useful for complex situations such as SOH affected by environmental and operational circumstances. The algorithm needs a lot of ageing data and a lot of computation work

The precise threshold for end-of-life (EOL) parameters based on the ageing mechanism is presently undisclosed and, unlike capacity or impedance, they have clear EOL values; substantial trials are required to corroborate the EOL parameters based on the ageing mechanism. The SOH mapping from the cell level to the battery pack level is complicated and the disparity in the number of cells in the LIB pack design and industrial and laboratory scales make it difficult to accurately and practically monitor the SOH at the pack level. For battery packs, SOH estimates are challenging to reconcile due to structural complications and computing demands. Due to its sluggish variations, the SOH does not always need to be updated immediately like the SOC, but this does not imply that the computing cost is negligible.

Table 6: The challenge with the implementation of ML in the SOH

Studies	Challenges
[15]	Descriptors, user-friendly tools, lack of standards, immature presentations, data scarcity, error determination and bridging scales
[37]	Inadequate selection of functions can result in limited knowledge generalization and the emergence of overfitting
[52]	Studying battery chemistry is necessary to associate it with the SOH
[100]	Filtering and denoising, further research on the SOH estimation of EVs
[93]	Higher computational time
[101]	Wide choice of methods and standards
[102]	Data scarcity and cost safety concern

The authentication of the suggested SOH prediction techniques is currently inadequate and only a small number of ageing tests are conducted under wide environmental and operating conditions dealing at the battery pack level with varying degrees of uncertainty. The majority of the work is verified at the cell level, charged or discharged under distinct current profiles with set ambient temperatures. The majority of research methods are created utilizing laboratory data, leading to a substantial shortfall between laboratory test results and real-world applications. To increase the prediction accuracy and effectiveness using data-driven methodologies, it is recommended to investigate effective feature selection and estimation techniques based on small sample data. Ideally, a SOH estimation model should start estimating the SOH right after the first charge–discharge cycle.

4 Conclusions

AI/ML techniques provide promising results for improving lithium-ion battery SOH and RUL estimation by leveraging vast amounts of battery data and capturing complex relationships. However, challenges such as data availability, interpretability and model generalization must be carefully addressed to ensure the effective and reliable application of AI/ML in the electric mobility domain. Continued research and collaboration are required to overcome limitations and completely unlock the potential of AI/ML in lithium-ion battery management for EVs. Different kinds of EVs employ LIBs and, in related fields, these applications call for a safe, dependable and thermally suitable selection of batteries. Battery prognostics techniques are commonly misused and their usefulness is underappreciated due to a lack of adequate communication tools between material scientists

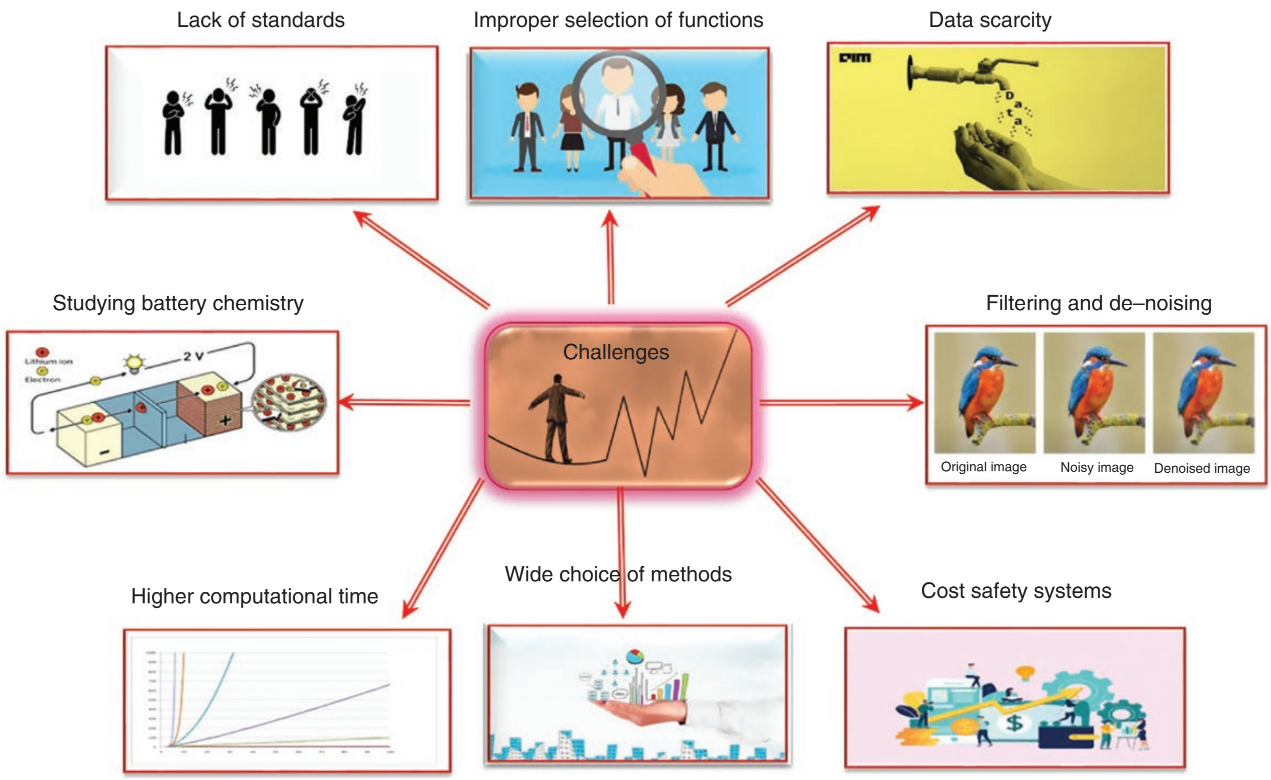


Fig. 8: General challenges of electric vehicle battery capacity degradation and health estimation using ML methods

possessing a comprehensive understanding of LIB internals and engineers responsible for guaranteeing optimal battery management for EVs.

The cycle life of a lithium-ion battery is increasing from a few hundred to thousands of cycles and all state computations that previously required a smaller data set must now accommodate more data. The selection of an efficient DL strategy must handle a sample of data with numerous dimensions. Currently, the majority of research is based on laboratory data, although certain public data sets, such as NASA, MIT, Oxford, Panasonic and CALCE, were captured under different dynamic operating conditions. To increase the prediction accuracy and effectiveness using data-driven methodologies, it is recommended to investigate effective feature selection and estimation techniques based on small sample data. The SOH estimation of LIBs has been published and addresses how to apply the technique in real time in EV applications. A SOH estimate model should ideally begin estimating the SOH immediately following the initial charge–discharge cycle. DL technique interpretability in the LIB for SOH and RUL estimation uses a supervised and unsupervised learning approach and it is a type of black box. Investigating the underlying significance of computed findings can provide more insightful information and can indicate the SOH of a battery and improve performance in health prediction and evaluation.

Acknowledgements

The authors were able to develop, implement and assess the performance of the system in a cutting-edge electric and hybrid vehicle laboratory facility at the University of Petroleum and Energy Studies, Dehradun, India.

Conflict of interest statement

None declared.

Data Availability

In this study data sharing is not applicable as no new data was generated or old data sets are analysed.

References

[1] Kumar R, Pachauri RK, Badoni P, *et al*. Investigation on parallel hybrid electric bicycle along with issuer management system for mountainous region. *J Clean Prod*, 2022, 362:132430.

[2] Li P, Zhang Z, Grosu R, *et al*. An end-to-end neural network framework for state-of-health estimation and remaining useful life prediction of electric vehicle lithium batteries. *Renew Sustain Energy Rev*, 2022, 156:111843.

[3] Driscoll L, de la Torre S, Gomez-Ruiz JA. Feature-based lithium-ion battery state of health estimation with artificial neural networks. *J Storage Mater*, 2022, 50:104584.

[4] Kumar R, Kumar A, Gupta MK, *et al*. Solar tree-based water pumping for assured irrigation in sustainable Indian agriculture environment. *Sustain Prod Consum*, 2022, 33:15–27.

[5] Che Y, Vilsen SB, Meng J, *et al*. Battery health prognostic with sensor-free differential temperature voltammetry reconstruction and capacity estimation based on multi-domain adaptation. *eTransportation*, 2023, 17:100245.

[6] Sloop S, Crandon L, Allen M, *et al*. A direct recycling case study from a lithium-ion battery recall. *Sustainable MaterTechnol*, 2020, 25:e00152.

[7] Akbar K, Zou Y, Awais Q, *et al*. A machine learning-based robust state of health (SOH) prediction model for electric vehicle batteries. *Electronics*, 2022, 11:1216.

[8] Kumar R, Bansal K, Kumar A, *et al*. Renewable energy adoption: design, development, and assessment of solar tree for the mountainous region. *Int J Energy Res*, 2022, 46:743–759.

[9] Kumar R, Ahuja NJ, Saxena M, *et al*. Automotive power window communication with DTC algorithm and hardware-in-the loop testing. *Wirel Pers Commun*, 2020, 114:3351–3366.

[10] Yu J, Mo B, Tang D, *et al*. Indirect state-of-health estimation for lithium-ion batteries under randomized use. *Energies*, 2017, 10:2012.

[11] Zheng X, Deng X. State-of-health prediction for lithium-ion batteries with multiple Gaussian process regression model. *IEEE Access*, 2017, 7:150383–150394.

[12] Che Y, Deng Z, Li P, *et al*. State of health prognostics for series battery packs: a universal deep learning method. *Energy*, 2022, 238:121857.

[13] Gaines L. The future of automotive lithium-ion battery recycling: charting a sustainable course. *Sustain Mater Technol*, 2014, 1–2:2–7.

[14] Kaliaperumal M, Dharanendrakumar MS, Prasanna S, *et al*. Cause and mitigation of lithium-ion battery failure: a review. *Materials*, 2021, 14:5676.

[15] Lombardo T, Duquesnoy M, Bouysidy HE, *et al*. Artificial intelligence applied to battery research: hype or reality? *Chem Rev*, 2021, 12:10899–10969.

[16] Zhan R, Pan L. A cycling-insensitive recycling method for producing lithium transition metal oxide from Li-ion batteries using centrifugal gravity separation. *Sustainable MaterTechnol*, 2022, 32:e00399.

[17] Jafari S, Shahbazi Z, Byun YC, *et al*. Lithium-ion battery estimation in online framework using extreme gradient boosting machine learning approach. *Mathematics*, 2022, 10:888.

[18] Lin CP, Cabrera J, Yang F, *et al*. Battery state of health modeling and remaining useful life prediction through time series model. *Appl Energy*, 2020, 275:115338.

[19] Choi HS, Choi JW, Whangbo TK. Design and development of a battery state of health estimation model for efficient battery monitoring systems. *Sensors*, 2022, 22:4444.

[20] Pan H, Chen C, Gu M. A state of health estimation method for lithium-ion batteries based on improved particle filter considering capacity regeneration. *Energies*, 2021, 14:5000.

[21] Ezemobi E, Silvagni M, Mozaffari A, *et al*. State of health estimation of lithium-ion batteries in electric vehicles under dynamic load conditions. *Energies*, 2022, 15:1234.

[22] Li W, Sengupta N, Dechent P, *et al*. One-shot battery degradation trajectory prediction with deep learning. *J Power Sources*, 2021, 506:230024.

[23] Chen S, Zhang H, Zeng L, *et al*. Secondary structural ensemble learning cluster for estimating the state of health of lithium-ion batteries. *ACS Omega*, 2022, 7:17406–17415.

[24] Kumar R, Gupta N, Bharadwaj D, *et al*. Design and development of electronic clutch control unit for manual transmission. *Mater Today Proc*, 2022, 69:240–245.

[25] Jia J, Liang J, Shi Y, *et al*. SOH and RUL prediction of lithium-ion batteries based on Gaussian process regression with indirect health indicators. *Energies*, 2020, 13:375.

[26] Che Y, Zheng Y, Wu Y, *et al*. Data efficient health prognostic for batteries based on sequential information-driven probabilistic neural network. *Appl Energy*, 2022, 323:119663.

[27] Sui X, He S, Vilsen SB, *et al*. A review of non-probabilistic machine learning-based state of health estimation techniques for lithium-ion battery. *Appl Energy*, 2021, 300:117346.

[28] Kumar R, Gupta MK, Kumar A, *et al*. Analysis of electronic clutch control unit for manual transmission vehicle oriented toward safety. *Mater Today Proc*, 2022, 69:255–260.

[29] Deng Z, Hu X, Xie Y, *et al*. Battery health evaluation using a short random segment of constant current charging. *iScience*, 2022, 25:104260.

[30] Oji T, Zhou Y, Ci S, *et al*. Data-driven methods for battery SOH estimation: survey and a critical analysis. *IEEE Access*, 2021, 9:126903–126916.

[31] Edge JS, Kane SO, Prosser R, *et al*. Lithium-ion battery degradation: what you need to know. *Phys Chem Chem Phys*, 2021, 23:8200–8221.

[32] Gaines L. Lithium-ion battery recycling processes: research towards a sustainable course. *Sustainable MaterTechnol*, 2018, 17:e00068.

[33] Kara A. A data-driven approach based on deep neural networks for lithium-ion battery prognostics. *Neural Comput Appl*, 2021, 33:13525–13538.

[34] Tian H, Qin P. State of health prediction for lithium-ion batteries with a novel online sequential extreme learning machine method. *Int J Energy Res*, 2021, 45:2383–2397.

[35] Che Y, Hu X, Lin X, *et al*. Health prognostics for lithium-ion batteries: mechanisms, methods, and prospects. *Energy Environ Sci*, 2023, 16:338–371.

[36] Che Y, Stroe DI, Hu X, *et al*. Semi-supervised self-learning-based lifetime prediction for batteries. *IEEE Trans Ind Informatics*, 2022, 19:6471–6481.

[37] Burzyński D, Kasprzyk L. A novel method for the modeling of the state of health of lithium-ion cells using machine learning for practical applications. *Knowledge-Based Systems*, 2021, 219:106900.

[38] He Z, Shen X, Sun Y, *et al*. State-of-health estimation based on real data of electric vehicles concerning user behavior. *J Storage Mater*, 2021, 41:102867.

[39] Das K, Kumar R, Krishna A. Supervised learning and data intensive methods for the prediction of capacity fade of lithium-ion batteries under diverse operating and environmental conditions. *Water Energy Int*, 2023, 66:53–59.

[40] Liu K, Peng Q, Che Y, *et al*. Transfer learning for battery smarter state estimation and ageing prognostics: recent progress, challenges, and prospects. *Advances in Applied Energy*, 2022, 9:100117.

[41] Rawat K, Kumar D, Kumar R, *et al*. Structural optimisation of go kart chassis with basic electronic driver assistance systems. In: *2023 2nd International Conference on Paradigm Shifts in Communications Embedded Systems, Machine Learning and Signal Processing (PCEMS)*, Nagpur, India, 5–6 April 2023, 1–6.

[42] Lu D, Chen Z. State of health estimation of lithium-ion batteries based on dual charging state. *Shanghai Jiaotong Daxue Xuebao/Journal Shanghai Jiaotong Univ*, 2022, 56:342–352.

[43] Pan H, Lü Z, Wang H, *et al*. Novel battery state-of-health online estimation method using multiple health indicators and an extreme learning machine. *Energy*, 2018, 160:466–477.

[44] Gupta MK, Kumar R, Verma V, *et al*. Robust control based stability analysis and trajectory tracking of triple link robot manipulator. *J Eur Systèmes Autom*, 2021, 54:641–647.

[45] Gou B, Xu Y, Feng X. State-of-health estimation and remaining-useful-life prediction for lithium-ion battery using a hybrid data-driven method. *IEEE Trans Veh Technol*, 2020, 69:10854–10867.

[46] Khaleghi S, Firouz Y, Van Mierlo J, *et al*. Developing a real-time data-driven battery health diagnosis method, using time and frequency domain condition indicators. *Appl Energy*, 2019, 255:113813.

[47] Kumar R, Ahuja NJ, Saxena M, *et al*. Modelling and simulation of object detection in automotive power window. *Indian J Sci Technol*, 2016, 9:1–6.

[48] Lin Q, Xu Z, Lin CM. State of health estimation and remaining useful life prediction for lithium-ion batteries using FBELNN and RCMNN. *J Intell Fuzzy Syst*, 2021, 40:10919–10933.

[49] Pal A, Kumar R, Sanal Kumar VR. Conceptual design of an automatic fluid level controller for aerospace applications. In: *2015 International Conference on Soft-Computing and Networks Security (ICSNS)*, Coimbatore, India, 25–27 February 2015, 1–8.

[50] Kumar R, Divyanshu, Kumar A. Nature based self-learning mechanism and simulation of automatic control smart hybrid antilock braking system. *Wirel Pers Commun*, 2021, 116:3291–3308.

[51] Tagade P, Hariharan KS, Ramachandran S, *et al*. Deep Gaussian process regression for lithium-ion battery health prognosis and degradation mode diagnosis. *J Power Sources*, 2020, 445:227281.

[52] Sarmah SB, Kalita P, Garg A, *et al*. 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. *J Electrochem Energy Convers Storage*, 2019, 16:040801.

[53] Zhou R, Fu S, Peng W. A review of state-of-health estimation of lithiumion batteries: experiments and data. In: *2020 Asia-Pacific Int. Symp. Adv. Reliab. Maint. Model. APARM 2020*, Vancouver, BC, Canada, 20–23 August 2020, 1–6.

[54] Tamilselvi S, Gunasundari S, Karuppiah N, *et al*. A review on battery modelling techniques. *Sustainability*, 2021, 13:10042.

[55] Ge MF, Liu Y, Jiang X, *et al*. A review on state of health estimations and remaining useful life prognostics of lithium-ion batteries. *Measurement*, 2021, 174:109057.

[56] Meng H, Li YF. A review on prognostics and health management (PHM) methods of lithium-ion batteries. *Renew Sustain Energy Rev*, 2019, 116:109405.

[57] Basia A, Simeu-Abazi Z, Gascard E, *et al*. Review on state of health estimation methodologies for lithium-ion batteries in the context of circular economy. *CIRP J Manuf Sci Technol*, 2021, 32:517–528.

[58] Li Y, Liu K, Foley AM, *et al*. Data-driven health estimation and lifetime prediction of lithium-ion batteries: a review. *Renew Sustain Energy Rev*, 2019, 113:109254.

[59] Shu X, Shen S, Shen J, *et al*. State of health prediction of lithium-ion batteries based on machine learning: advances and perspectives. *iScience*, 2021, 24:103265.

[60] Vanem E, Salucci CB, Bakdi A, *et al*. Data-driven state of health modelling: a review of state of the art and reflections on applications for maritime battery systems. *J Storage Mater*, 2021, 43:103158.

[61] Wang Z, Feng G, Zhen D, *et al*. A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles. *Energy Rep*, 2021, 7:5141–5161.

[62] Noura N, Boulon L, Jemeï S. A review of battery state of health estimation methods: hybrid electric vehicle challenges. *World Electric Vehicle Journal*, 2020, 11:66.

[63] Kumar A, Sharma P, Gupta MK, *et al*. Machine learning based resource utilization and pre-estimation for Network on Chip (NoC) Communication. *Wirel Pers Commun*, 2018, 102:2211–2231.

[64] Ungurean L, Micea MV, Cârstoiu G. Online state of health prediction method for lithium-ion batteries, based on gated recurrent unit neural networks. *Int J Energy Res*, 2020, 44:6767–6777.

[65] Meera CS, Sunny S, Singh R, *et al*. Automated precise liquid transferring system. In: *2014 IEEE 6th India International Conference on Power Electronics (IICPE)*, Kurukshetra, India, 8–10 December 2014, 1–6.

[66] Cai L, Meng J, Stroe DI, *et al*. An evolutionary framework for lithium-ion battery state of health estimation. *J Power Sources*, 2019, 412:615–622.
[67] Jain A, Kumar A, Shukla AP, *et al*. Smart communication using 2D and 3D mesh network-on-chip. *Intell Autom Soft Comput*, 2022, 34:2007–2021.
[68] Bi J, Lee JC, Liu H. Performance comparison of long short-term memory and a temporal convolutional network for state of health estimation of a lithium-ion battery using its charging characteristics. *Energies*, 2022, 15:2448.
[69] Chemali E, Kollmeyer PJ, Preindl M, *et al*. A convolutional neural network approach for estimation of Li-ion battery state of health from charge profiles. *Energies*, 2022, 15:1185.
[70] Chen L, Wang H, Liu B, *et al*. Battery state-of-health estimation based on a metabolic extreme learning machine combining degradation state model and error compensation. *Energy*, 2021, 215:119078.
[71] Chen Y, He Y, Li Z, *et al*. Remaining useful life prediction and state of health diagnosis of lithium-ion battery based on second-order central difference particle filter. *IEEE Access*, 2020, 8:37305–37313.
[72] Chen Z, Sun M, Shu X, *et al*. Online state of health estimation for lithium-ion batteries based on support vector machine. *Applied Sciences*, 2018, 8:925.
[73] Chen Z, Xue Q, Wu Y, *et al*. Capacity prediction and validation of lithium-ion batteries based on long short-term memory recurrent neural network. *IEEE Access*, 2020, 8:172783–172798.
[74] Chen Z, Xue Q, Xiao R, *et al*. State of health estimation for lithium-ion batteries based on fusion of autoregressive moving average model and elman neural network. *IEEE Access*, 2019, 7:102662–102678.
[75] Chen Z, Zhao H, Zhang Y, *et al*. State of health estimation for lithium-ion batteries based on temperature prediction and gated recurrent unit neural network. *J Power Sources*, 2022, 521:230892.
[76] Cheng G, Wang X, He Y. Remaining useful life and state of health prediction for lithium batteries based on empirical mode decomposition and a long and short memory neural network. *Energy*, 2021, 232:121022.
[77] Deng Y, Yinga H, Jiaqiang E, *et al*. Feature parameter extraction and intelligent estimation of the state-of-health of lithium-ion batteries. *Energy*, 2019, 176:91–102.
[78] Deng Z, Hu X, Li P, *et al*. Data-driven battery state of health estimation based on random partial charging data. *IEEE Trans Power Electron*, 2022, 37:5021–5031.
[79] Ezemobi E, Tonoli A, Silvagni M. Battery state of health estimation with improved generalization using parallel layer extreme learning machine. *Energies*, 2021, 14:2243.
[80] Fan Y, Xiao F, Li C, *et al*. A novel deep learning framework for state of health estimation of lithium-ion battery. *J Storage Mater*, 2020, 32:101741.
[81] Fei Z, Yang F, Tsui KL, *et al*. Early prediction of battery lifetime via a machine learning based framework. *Energy*, 2021, 225:120205.
[82] Feng X, Weng C, He X, *et al*. Online state-of-health estimation for Li-ion battery using partial charging segment based on support vector machine. *IEEE Trans Veh Technol*, 2019, 68:8583–8592.
[83] Kumar A, Bansal K, Kumar D, *et al*. FPGA application for wireless monitoring in power plant. *Nucl Eng Technol*, 2020, 53:1167–1175.
[84] Ge D, Zhang Z, Kong X, *et al*. Extreme learning machine using bat optimization algorithm for estimating state of health of lithium-ion batteries. *Applied Sciences*, 2022, 12:1398.
[85] Guo Y, Huang K, Hu X. A state-of-health estimation method of lithium-ion batteries based on multi-feature extracted from constant current charging curve. *J Storage Mater*, 2021, 36:102372.
[86] Hong J, Wang Z, Chen W, *et al*. Online accurate state of health estimation for battery systems on real-world electric vehicles with variable driving conditions considered. *J Clean Prod*, 2021, 294:125814.
[87] Hoque MA, Nurmi P, Kumar A, *et al*. Data driven analysis of lithium-ion battery internal resistance towards reliable state of health prediction. *J Power Sources*, 2021, 513:230519.
[88] Jia J, Yuan S, Shi Y, *et al*. Improved sparrow search algorithm optimization deep extreme learning machine for lithium-ion battery state-of-health prediction. *iScience*, 2022, 25:103988.
[89] Jiang J, Zhao S, Zhang C. State-of-health estimate for the lithium-ion battery using chi-square and ELM-LSTM. *World Electric Vehicle Journal*, 2021, 12:228.
[90] Kaur K, Garg A, Cui X, *et al*. Deep learning networks for capacity estimation for monitoring SOH of Li-ion batteries for electric vehicles. *Int J Energy Res*, 2021, 45:3113–3128.
[91] Khaleghi S, Karimi D, Beheshti SH, *et al*. Online health diagnosis of lithium-ion batteries based on nonlinear autoregressive neural network. *Appl Energy*, 2021, 282:116159.
[92] Khan N, Ullah FUM, Afnan AU, *et al*. Batteries state of health estimation via efficient neural networks with multiple channel charging profiles. *IEEE Access*, 2021, 9:7797–7813.
[93] Khumprom P, Yodo N. A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm. *Energies*, 2019, 12:660.
[94] Li P, Zhang Z, Xiong Q, *et al*. State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network. *J Power Sources*, 2020, 459:228069.
[95] Li Q, Li D, Zhao K, *et al*. State of health estimation of lithium-ion battery based on improved ant lion optimization and support vector regression. *J Storage Mater*, 2022, 50:104215.
[96] Chang C, Wang Q, Jiang J, *et al*. Lithium-ion battery state of health estimation using the incremental capacity and wavelet neural networks with genetic algorithm. *J Storage Mater*, 2021, 38:102570.
[97] Kumar R, Dwivedi PK, Praveen Reddy D, *et al*. Design and implementation of hydraulic motor based elevator system. In: *2014 IEEE 6th India International Conference on Power Electronics (IICPE)*, Kurukshetra, India, 8–10 December 2014, 1–6.
[98] Meng J, Cai L, Luo G, *et al*. Lithium-ion battery state of health estimation with short-term current pulse test and support vector machine. *Microelectron Reliab*, 2018, 88–90:1216–1220.
[99] Siani AG, Mousavi Badjani M, Rismani H, *et al*. State of health estimation of lithium-ion batteries based on the CC-CV charging curve and neural network. *IETE J Res*, 2021, 69:2950–2963. doi:10.1080/03772063.2021.1908853.
[100] Qu S, Kang Y, Gu P, *et al*. A fast online state of health estimation method for lithium-ion batteries based on incremental capacity analysis. *Energies*, 2019, 12:3333.
[101] Saqli K, Bouchareb H, Oudghiri M, *et al*. Critical review of ageing mechanisms and state of health estimation methods for battery performance. *Smart Innov Syst Technol*, 2020, 163:507–518.
[102] Lv C, Zhou X, Zhong L, *et al*. Machine learning: an advanced platform for materials development and state prediction in lithium-ion batteries. *Adv Mater*, 2022, 34:2101474.