IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 6 March 2024, accepted 19 May 2024, date of publication 28 May 2024, date of current version 7 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3406424

SURVEY

Battery Reliability Assessment in Electric Vehicles: A State-of-the-Art

JOSEPH OMAKOR[1], MD SURUZ MIAH[2], AND HICHAM CHAOUI[1], (Senior Member, IEEE)
[1]Department of Electronics, Carleton University, Ottawa, ON K1S 5B6, Canada
[2]Department of Electrical and Computer Engineering, Bradley University, Peoria, IL 61625, USA

Corresponding author: Md Suruz Miah (smiah@bradley.edu)

ABSTRACT Lithium-ion (Li-ion) batteries are used in electric vehicles to reduce reliance on fossil fuels because of their high energy density, design flexibility, and efficiency compared to other battery technologies. However, they undergo complex nonlinear degradation and performance decline when abused, making their reliability crucial for effective electric vehicle performance. This survey paper presents a comprehensive review of state-of-the-art battery reliability assessments for electric vehicles. First, the operating principles of Li-ion batteries, their degradation patterns, and degradation models are briefly discussed. Subsequently, the reliability assessments of Li-ion batteries are detailed using both qualitative and quantitative approaches. The qualitative approach encompasses failure modes mechanisms and effects analysis, X-ray computed tomography, and scanning electron microscopy. In contrast, quantitative approaches involve multiphysics modelling, electrochemical impedance spectroscopy, incremental capacity and differential voltage analysis, machine learning, and transfer learning. Each technique is examined in terms of its principles, advantages, limitations, and applicability in Li-ion batteries for electric vehicles. Comparative analysis reveals that qualitative methods are primarily used in the early design stages to assess potential risks and in post-mortem battery analysis in the laboratory, whereas quantitative techniques such as machine learning and transfer learning offer real-time prognostic health management and anomaly prevention. Additionally, the quantitative techniques tend to be more cost-effective than their counterparts. The potential for consolidating reliability methods through standardization of testing protocols, real-world data integration, controller area network use, and policy regulation is highlighted to guide further research.

INDEX TERMS Capacity fade, causes of failure, data-driven, degradation trajectory, electric vehicle, electrochemical impedance spectroscopy, failure modes mechanisms and effects analysis, incremental capacity and differential voltage analysis, Li-ion batteries, machine learning, model-based, power fade, qualitative analysis, quantitative analysis, remaining useful life, reliability, state of health, state of charge, transfer learning, X-ray computed tomography.

NOMENCLATURE

AI	Artificial Intelligence.
BEV	Battery EV.
BMS	Battery Management System.
BoL	Beginning-of-life.
BSE	Back-scattered Electrons.
CBAM	Convolutional Block Attention Module.
CL	Conductivity Loss.
CNN	Convolutional Neural Network.
CO2	Carbon dioxide.
C-rate	Charging Rate.
CT	Computed Tomography.
DEIS	Dynamic Electrochemical Impedance Spectroscopy.
DNN	Deep Neural Network.
DOD	Depth of Discharge.
DV	Differential Voltage.
DVA	Differential Voltage Analysis.
ECM	Equivalent Circuit Model.
EDX	Energy Dispersive X-ray.
EIS	Electrochemical Impedance Spectroscopy.

The associate editor coordinating the review of this manuscript and approving it for publication was Mouloud Denai.

DM	Degradation Mode.
EoL	End-of-life.
ESS	Energy Storage System.
EVs	Electric Vehicles.
FEG-SEM	Field Emission Gun Electron Microscopy.
FMMEA	Failure Mode Mechanisms and Effects Analysis.
GHG	Greenhouse Gases.
GPR	Gaussian Process Regression.
GRNN	Gated Recurrent Neural Network.
Gt	Gigatonnes.
HEV	Hybrid EV.
HIs	Health Indicators.
HMC	Hamilton Monte Carlo.
ICA	Incremental Capacity Analysis.
ICEs	Internal Combustion Engines.
IR	Internal Resistance.
ISC	Internal Short Circuit.
KPCA	Kernel Principal Component Analysis.
LAM	Loss of Active Materials.
LaB6	Lanthanum hexaboride.
Li-ion	Lithium-ion.
LCO	Lithium Cobalt Oxide.
LFP	Lithium-Iron Phosphate.
LLI	Loss of Li-ions.
LMO	Lithium Manganese Oxide.
LSTM	Long-Short-Term Memory.
LTO	Lithium Titanium Oxide.
MAE	Mean Absolute Error.
ML	Machine Learning.
MMD	Maximum Mean Discrepancy.
Mt	Metric tonnes.
NCA	Nickel-Cobalt-Aluminum-Oxide.
NARX-RNN	Nonlinear Autoregression with exogenous inputs recurrent neural network.
NMC	Nickel-Manganese-Cobalt.
PCA	Principal Component Analysis.
PHEV	Plug-in Hybrid EV.
PHM	Prognostics and Health Management.
PDVF	Poly-vinylidenefluoride.
QC	Quality Control.
RAMS	Reliability, Availability, Maintainability, and Safety.
RC	Resistor-Capacitor.
ROI	Region Of Interest.
RPN	Risk Prioritization Number.
RMSE	Root Mean Square Error.
RUL	Remaining Useful Life.
SE	Secondary Electrons.
SEI	Solid Electrolyte Interface.
SEM	Scanning Electron Microscopy.
SNR	Signal-to-Noise Ratio.
SOC	State of Charge.
SOH	State of Health.
SPM	Single-particle model.
SS-ANN	Spiral self-attention neural network.
P2DM	Pseudo-2D model.
TL	Transfer Learning.
X-ray CT	X-ray Computed Tomography.

I. INTRODUCTION

With the deepening of the global energy crisis, depletion of oil resource, and increased risk of air pollution and global warming, governments and industry players in various countries have proposed solutions to promote alternative energy sources and encourage greenhouse gas (GHG) control policies. Currently, many countries attach great importance to solving GHG problems, particularly those related to carbon dioxide (CO_2) emissions. Fig.1 shows the amount of CO_2 emissions from the four major energy-consuming sectors. The transportation sector accounts for 25% of global energy use [1]. In 2022, CO_2 emissions from energy-related activities experienced a growth of 0.9%, equivalent to 321 metric tons (Mt). This increase led to a record high of more than 36.8 gigatons (Gt) of CO_2 emissions, with the transportation sector accounting for 7.98Gt which is 2.1% or 137Mt higher than the previous year due to the growth in advanced economies [2].

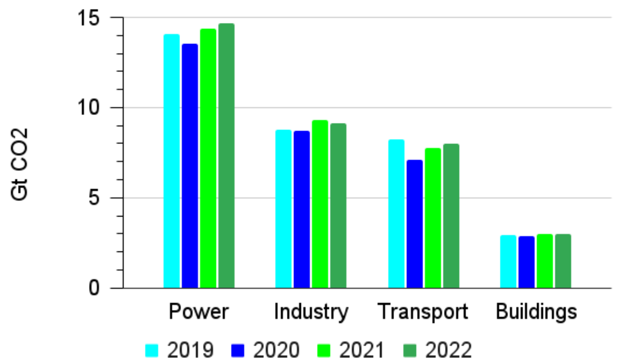

FIGURE 1. Global CO_2 emissions by sector from 2019-2022 [2].

Considering the rising emissions to the atmosphere, transport electrification has been promoted to decarbonize the transport sector, which mainly uses fossil fuel energy, such as petrol and diesel [3]. Substituting conventional internal combustion engine (ICE) vehicles with electric vehicles (EVs) is the best option for reducing CO_2 emissions and their impact. An electric vehicle is a term that describes a vehicle powered by electricity or an electricity-assisted vehicle. Currently, the market offers three types of EVs: pure battery EV (BEV), hybrid EV (HEV), and plug-in hybrid EV (PHEV) [4]. The main components of EVs are the battery pack, converter (inverter), and electric motor, as illustrated by the simplified EV drivetrain in Fig.2. Direct current (DC) power supply from the battery pack is converted into alternating power by the inverter, which is later converted into kinetic energy by the electric motor, producing torque and rotation, which are subsequently transferred to the transmission system that propels the vehicle. The battery is the most sensitive

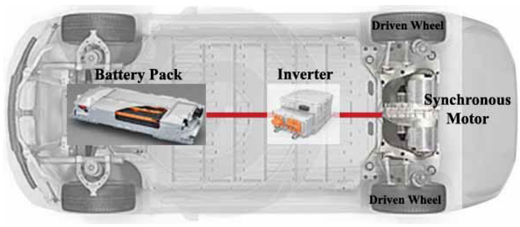

FIGURE 2. Electric vehicle showing key components.

component of an electric vehicle drivetrain because of its cost and weight; therefore, adequate research and development are required. Among all commercially available batteries, lithium-ion (Li-ion) batteries have distinguished themselves by offering exceptional benefits [5], such as light weight, high energy density, low self-discharge, high cycle life, and absence of memory effect [6]. However, Li-ion batteries are characterized by high initial costs. Despite the high initial costs involved, Li-ion batteries are no longer suitable for EVs once they reach 80% [7] of their original capacity owing to various complex phenomena. These phenomena, collectively known as battery aging, include capacity decay and increased cell impedance, which cascade into power fading [8]. Furthermore, for EVs to gain popularity and substitute ICEs, batteries (Li-ion) must maintain high energy capacity and power capability while ensuring safety for a period of over 10 years [9].

A. LI-ION BATTERY AGING AND RISKS

The aging of Li-ion batteries involves various electrochemical and mechanical processes that are heavily influenced by operating conditions [8], battery chemistry, and the environment. The key indicators (capacity and power) of the performance of Li-ion batteries decline over time during cycling, are often known as cycle aging [10], [11], [12], [13], [14] and storage (calendar aging) [15], [16], [17], [18], [19], [20]. Li-ion batteries are intricate systems that are characterized by numerous degradation mechanisms. In recent years, extensive research has been conducted to improve the performance, increase the lifetime, and reduce the safety hazards of Li-ion batteries. A detailed overview of the aging mechanisms, aging stress factors, and degradation modelling approaches for Li-ion batteries is presented in [21]. Han et al. [22] provided a comprehensive review of Li-ion battery degradation during the entire cycle life. Their study analyzed the internal aging mechanisms associated with anode and cathode materials and with their influencing factors that accelerates degradation from design, production, and application perspectives. In [23], a review of the behavior and empirical modelling of Li-ion battery aging is presented, focusing on the effect and interdependence of the operational stress factors. The review concluded that it is difficult to generalize aging behavior based on the effects of the operational conditions. In [24], [25], and [26], the stress factors that cause degradation and aging mechanisms of Li-ion batteries at the component level are discussed. This study is further explored in [22] and [27], where the authors examined the degradation of Li-ion batteries at the cell and pack levels. The stress factors that accelerate calendar and cycling aging of Li-ion batteries have been reviewed in [11], [28], and [29]. The modes of the aging phases were also examined. Two parameters describe the age of batteries: the beginning-of-life (BoL), which marks the initial usage of the battery, and end-of-life (EoL), which is the point in a battery's lifecycle when it reaches a certain capacity threshold, typically 80% or 70% of its nominal capacity, and is no longer considered suitable for its intended use [30]. The aforementioned review papers only addressed the factors influencing the aging and degradation of Li-ion battery packs without curbing the attendant performance decline. Recently, there has been a notable increase in the incidence of EV fires and explosions, with many of these incidents linked to onboard Li-ion battery packs. A series of such incidents has been reported since the introduction of EVs into the market [31], [32], [33], [34], [35], [36]. Typical EV fire accidents are shown in Fig.3. The literature captures various causes of Li-ion battery-induced fires and explosions in EVs, including thermal runaway [40], excessive heat, conductive coolant, external short circuits, high-speed collision deformation, internal short circuits, battery pack piercing and deformation, battery management system (BMS) failure, overcharging, short circuits during charging, and loose contact wires. These accidents, as described in the literature and depicted in Fig.3, not only resulted in economic losses, but also posed a severe risk to the reputation of the EV industry and public confidence in Li-ion battery-related products.

FIGURE 3. EV fire accidents caused or exacerbated by Li-ion battery: (a) and (b) depict a Tesla Model 3 being involved in an explosion. [37]; (c) collision between a conventional car and EV accident resulting in fire exacerbated by Li-ion battery in EV [38]; (d) Tesla SUV crashed into a barrier, leading to explosion and fire of the Li-ion battery [39].

B. IMPORTANCE OF BATTERY RELIABILITY ASSESSMENT

The reliability of Li-ion batteries has become an essential issue for Original Equipment Manufacturers (OEMs) of EVs.

Fig.4 shows the essential aspects of Li-ion batteries, which were considered from 1994 to 2022 in published articles (based on Scopus for Li-ion batteries with reliability as keywords). According to Fig.4, reliability is strongly related to other aspects of Li-ion batteries. It connects with Li-ion components, operating conditions, and predictive methods. Reliability is critical for assessing the overall behavior of Li-ion batteries over their lifespan [41]. Therefore, reliability assessment of Li-ion batteries plays an essential role in EVs' lifetime, design, maintenance, and their service life. According to [42], there are two main perspectives for improving or assessing reliability. One perspective is the development of new Li-ion battery materials and material modifications. In this regard, advances in the development of high-energy, high-power cathode materials for Li-ion batteries have been presented in [43], along with two important aspects of material engineering modification for cathode materials in Li-ion batteries: nanostructure synthesis and surface modification. Cheng et al. [44] provided a comprehensive review of research studies and advancements in the design and synthesis of anode materials such as porous carbon nanostructures, hollow carbon spheres, and nanostructured silicon-based materials. They also highlighted the importance of addressing the volume expansion, mechanical properties, and electrolyte stability in the development of anode materials for Li-ion batteries. A review of recent progress in the development of nonaqueous electrolytes, binders, and separators for Li-ion batteries, as well as their impact on battery performance, is presented in [45]. The development and modification of these Li-ion component materials can improve the reliability of the battery pack system by improving the reliability of the cells; however, this is limited by the reliability of the battery cell, which is at the mercy of current science and technology. The other perspective is to assess the reliability of Li-ion batteries through system design, including thermal management, fault diagnosis and health prognostics. Very few studies have comprehensively reviewed the concept of reliability of Li-ion batteries in EVs in this regard. For instance, [46] provides an extensive examination of the reliability and safety of the major electrical components of EVs, including Li-ion batteries, considering various perspectives related to chemical, thermal, electrical, and mechanical issues. In addition, the concept of reliability of Li-ion battery packs was introduced in [26]. The study investigated the primary failure modes, their mechanisms, and their effects on the power and capacity degradation. To thoroughly explore the reliability assessment of Li-ion batteries, Gandoman et al. [47] considered both practical and technical aspects and examined the reliability of a nickel-manganese-cobalt (NMC) battery as a case study. The aforementioned study did not provide a holistic approach to the reliability assessment of Li-ion batteries in terms of evaluating the probability of faults or degradation occurrences and their effects on the available capacity and power and diagnosing or preventing such occurrences. This paper presents a comprehensive review of state-of-the-art reliability assessments of batteries in EVs, encompassing major areas such as fault diagnostics and prevention, state of health (SOH) estimation, remaining useful life and end-of-life-predictions, state of charge (SOC) estimation, and degradation trajectory predictions. This entails both qualitative and quantitative approaches to reliability assessment. Failure modes mechanisms and effects analysis, X-ray computed tomography, and scanning electron microscopy are subordinates of the qualitative approach. The quantitative approach consists of multiphysics modelling and simulations, electrochemical impedance spectroscopy (EIS), incremental capacity and differential voltage analysis (ICA/DVA), machine learning (ML), and transfer learning (TL).

C. CONTRIBUTION

Owing to the lack of a comprehensive review of the literature on the reliability of Li-ion batteries, this survey paper aims to comprehensively examine and present state-of-the-art techniques and methodologies for reliability assessment of Li-ion batteries. The significant contributions of this study are as follows:

- **Exhaustive literature review:** Through a thorough and methodological literature review encompassing research articles, we comprehensively explored topics such as causes of failure/degradation, degradation mechanisms, degradation modes, and effects and methods for assessing Li-ion battery reliability. By synthesizing insights from diverse sources, we offer a comprehensive understanding of the current research landscape in this domain.
- **Comparison of Techniques:** A notable contribution of this study involves conducting a comparative analysis of diverse reliability assessment techniques. Through this evaluation, we assessed the strengths, limitations, and relevance of each method, in assisting researchers and practitioners in making informed choices tailored to their specific needs and criteria.
- **Emerging trends and innovations:** This survey highlights emerging trends and innovations in the field of Li-ion battery reliability assessments. By identifying novel techniques, such as machine learning-based predictive modelling, and transfer learning, we shed light on the direction of future research and development in the domain.
- **Case studies and real-world applications:** We present a series of case studies and real-world instances that demonstrate the applicability of these reliability assessment techniques. These examples underscore the practical significance of the discussed methodologies and highlight their positive influence on enhancing the safety, performance, and lifetime of Li-ion batteries.

The remainder of this survey paper is organized as follows. Section II discusses the Li-ion battery composition and operation in terms of charge and discharge, as well as its various chemistries. The factors that degrade Li-ion batteries,

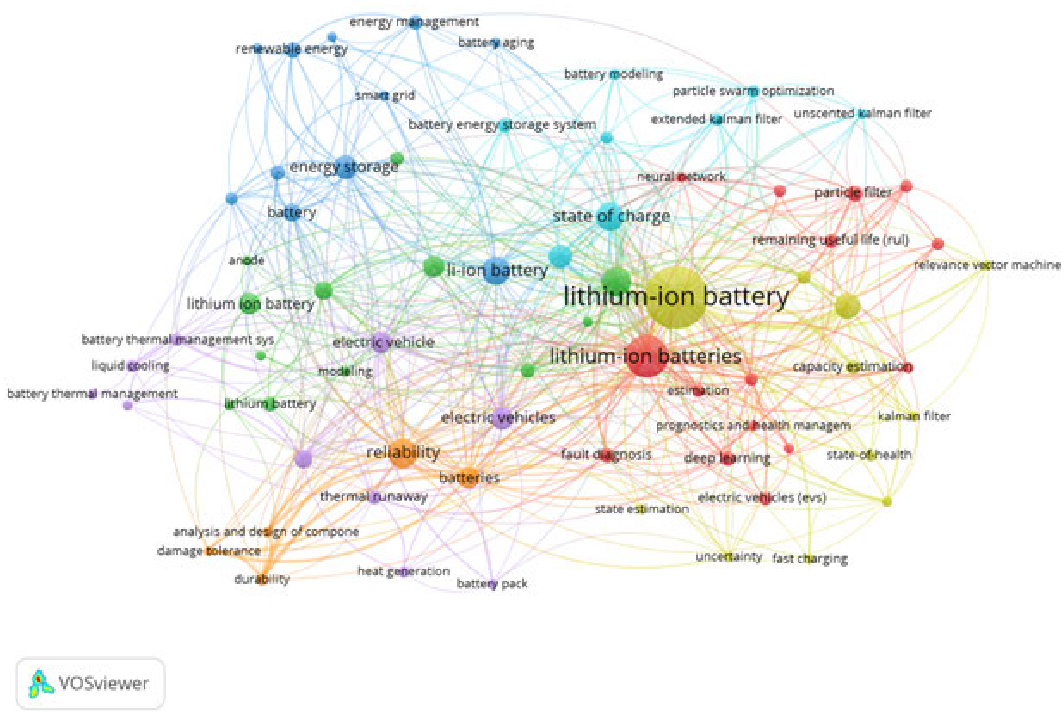

FIGURE 4. Relationship of reliability with various significant aspects of Li-ion batteries.

as well as their modes, mechanisms, and effects, are presented in Section III. A detailed examination of the qualitative and quantitative approaches for evaluating the reliability of Li-ion batteries are presented in Section IV along with their use cases, advantages, and disadvantages. Section V provides recommendations for accurately assessing the reliability of Li-ion batteries. Finally, the conclusion is presented in Section VI.

II. LI-ION BATTERY AND ITS OPERATION

Similar to other batteries, Li-ion battery cells have four main components: a positive electrode (cathode), negative electrode (anode), electrolyte, and separator [48]. In addition to the active components of Li-ion batteries are the current collectors: copper foil and aluminum foil for anode and cathode respectively, binders, and electronic circuits, tabs, and shells [49]. In most commercial Li-ion battery cells, the anode is composed of a carbonaceous material, typically graphite, which is bonded to a copper current collector using a polyvinylidenefluoride (PVDF) binder. The cathode, on the other hand is typically made of a metal oxide material adhered to an aluminum current collector with a PVDF binder and a carbon additive to enhance electronic conductivity. To prevent electrical short-circuiting, the electrodes are separated using a polymer sheet that allows the transport of ions. Finally, the cell is filled with an electrolyte consisting of a lithium salt dissolved in an organic solvent, facilitating the movement of ions within the cell [50]. Li-ion batteries store electrochemical energy through intercalation of Li-ion (Li^+) in anode and cathode materials. The reactions that occur during the charge and discharge processes of Li-ion batteries are illustrated using models (1)-(2) [49]. The cathode and anode reactions are described as follows:

$$\mathrm{Li}_y\mathrm{MO}_2 \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftharpoons}} \mathrm{Li}_{y-x}\mathrm{MO}_2 + x\mathrm{Li}^+ + xe^- \quad \text{and} \tag{1a}$$

$$x\mathrm{Li}^+ + xe^- + \mathrm{Li}_z\mathrm{C}_n \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftharpoons}} \mathrm{Li}_{z+x}\mathrm{C}_n, \tag{1b}$$

where $_y$, $_x$, and $_z$ represent the atomic numbers, x indicates the number of Li^+ with $0 \leq x \leq y$ and $y \leq 1$, MO is the cathode material, and e^- is the electron, $z \geq 0$, C_n denotes the carbonaceous material with atomic number $_n$, and different carbonaceous materials have different values of $_n$. For graphite, $n_x = 6$, which is the number of Li^+ that can be intercalated into the graphite anode. The overall operating process of Li-ion batteries is given by

$$\mathrm{Li}_y\mathrm{MO}_2 + \mathrm{Li}_z\mathrm{C}_n \underset{\text{discharge}}{\overset{\text{charge}}{\rightleftharpoons}} \mathrm{Li}_{y-x}\mathrm{MO}_2 + \mathrm{Li}_{z+x}\mathrm{C}_n. \tag{2}$$

For brand-new Li-ion batteries, $y = 1$ and $z = 0$.

During the charging process, ions (Li^+) are de-intercalated (extracted) from the cathode material, transverse the electrolyte, and subsequently intercalate (inserted) between the graphite layers in the anode. Meanwhile, electrons flow from the cathode to the anode through the external circuit (as depicted in Fig. 5). This process is reversed during

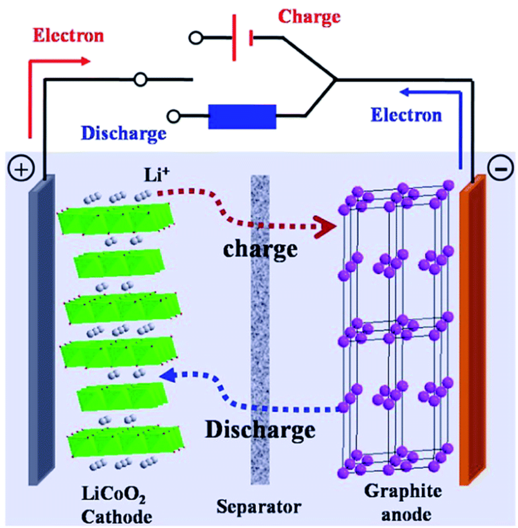

FIGURE 5. Schematic illustration of charge and discharge operation of Li-ion battery [51].

discharge. It is evident these Li-ion batteries function by reversibly shuttling Li^+ between the cathode and anode materials. Consequently, the performance of Li-ion battery is significantly influenced by the inherent characteristics of the electrode materials. Among these materials, the cathode plays a crucial role in determining the overall performance of the battery [51]. Commercial Li-ion batteries are often described based on Li-ion donors in the cathode. Various cathode chemistries are combined with the anode graphite to construct the battery. The cathode chemistries employed in the industries include lithium iron phosphate (LFP), lithium-cobalt oxide, nickel-manganese-cobalt (NMC), nickel-cobalt-aluminum-oxide (NCA), lithium manganese oxide (LMO), and sulfur (S) [48]. Table 1 summarizes the characteristics, advantages, and disadvantages of the different Li-ion battery chemistries.

III. LI-ION BATTERY DEGRADATION

A. DEGRADATION CAUSES AND MECHANISMS

Degradation of the battery at various levels is referred to as aging. The aging process of Li-ion batteries is a complex combination of numerous electrochemical and mechanical processes, that are strongly influenced by several internal and macroscopic factors [55], such as temperature [5], [56], [57], [58], [59], [60], Depth of Discharge (DoD) [61], [62], overcharge [63], [64], [65], overdischarge [66], [67], and time. In addition, degradation is induced in the design and manufacturing stages because of cell inconsistency [27], cell chemistry, and cell and pack design [22]. The electrochemical and mechanical degradation mechanisms (the basic manner in which the battery can degrade) affect different components of the cell, including the electrodes, electrolyte, separator, and current collectors [68]. These degradation mechanisms have been extensively studied and reported in literature. Table 2 presents the various factors that influence the degradation mechanisms of Li-ion batteries as depicted in Fig.6, which illustrates the common degradation mechanisms observed in Li-ion cells. Of all the degradation mechanisms shown in Fig.6, the formation and growth of the solid electrolyte interface (SEI) is the most dominant. These mechanisms and their origins are explained, and diagnostic techniques for identifying these degradation processes are discussed in the next section.

B. DEGRADATION MODES AND EFFECTS

In the aging analysis of Li-ion batteries, different degradation mechanisms have been linked to the degradation modes that contribute to power and capacity fading. Some researchers have identified the loss of lithium inventory (LLI) and loss of active materials (LAM) in the anode and cathode as degradation modes [70], [71], whereas others have extended this further to include an increase in internal resistance (IR) [72], [73], which is inversely referred to as conductivity loss (CL) in [74] and [75]. The most prevalent mode of degradation in cell capacity fading is LLI. It is loss of usable lithium within a cell resulting from side reactions, including the formation and growth of the SEI film, lithium plating, and the loss of lithiated active materials [76]. The loss of active materials refers to the mode in which a portion of the active material in an electrode becomes inaccessible for lithium intercalation during charge/discharge cycles. It is specific to each electrode and is divided into a LAM_{PE} for the positive electrode and a LAM_{NE} for the negative electrode. LAM_{PE} can occur because of structural disorder, dissolution, or loss of electrical contact [77], whereas LAM_{NE} is caused by factors such as particle cracking, loss of electrical contact, or the presence of resistive surface layers that block the active sites of the anode [78]. The degradation associated with the decomposition of the binder or corrosion of the current collector is described by the conductivity loss mode [74]. Finally in the aging trajectory (trajectory of battery degradation) [30], the effects of the degradation mechanisms are manifested in capacity fade (reduction in the usable capacity of the cell) and resistance increase, which cascade to power fade (reduction of the deliverable power of the cell after degradation) [79].

C. DEGRADATION MODELS

Degradation models are mathematical, physics-based, or computational representations used to quantify and analyze the degradation mechanisms and factors that affect the performance and reliability of Li-ion batteries. By developing a degradation model for Li-ion batteries, researchers and engineers can gain insight into the underlying processes, predict future degradation behavior, and devise strategies to mitigate or manage degradation effects. Capacity loss has been identified in the literature as the primary effect of Li-ion battery degradation because it negatively impacts both the remaining useful life and profitability of the battery. Degradation models for capacity loss are usually classified

TABLE 1. Comparison of cathode materials for Li-ion battery cells [26], [52], [53], [54].

Cathode Material	Nominal Voltage (V)	Specific Capacity (mAh/kg)	Energy Density (Wh/kg)	Cycle Life (Cycles)	Advantages	Disadvantages
LCO	3.7	140	110-190	500-1000	Widespread application. High specific energy Good cycle life.	Poor thermal stability. High safety risk.
LMO	3.8	146	100-120	1000	Excellent thermal stability. Inexpensive. Improved safety. Excellent power capability.	Low specific energy density. High capacity loss. Relatively short cycle life.
NCA	3.6	180	100-150	2000-3000	High specific energy. Good specific power. Good lifespan.	High cost. marginal safety.
NMC	3.6	145	100-170	2000-3000	Adaptable to various application. High specific energy. Suitable charging C-rate.	High safety risk.
LFP	3.3	170	90-115	>3000	High current rating. Long cycle life. Good thermal stability. Enhanced safety and tolerance. Low self-discharge.	Low specific energy density.
Sulfur	$\sim$ 2.1V	$\sim$ 1675	$\sim$ 2600	variable	High theoretical capacity. Low cost.	Capacity loss over cycles. Low electrical conductivity. Electrolyte modifications required. newline Polysulfide shuttling. Sulfur volume expansion.

TABLE 2. Degradation mechanisms and causes of Li-ion cell components. [24], [26].

Components	Degradation Mechanism	Causes
Anode	Solid electrolyte interface growth	High state of charge (SOC), Elevated temperatures, frequent charging and discharging processes at high C-rates.
	Lithium plating	Low temperature, low SOC, high charging rates (C-rate)
	Changes of the Active material	Extraction and intercalation of Li-ions, gas evolution within graphite particles
	Anode Contact loss	Inadequate contact between active materials in the anode active material.
Cathode	Structural changes and mechanical stress	Lithiation and delithiation process, phase change in cathode oxides
	Active material dissolution	Dissolution of active materials, particularly in cathodes with managed layered oxide structures.
	Active material isolation	Formation of cracks, fracture of the binder, deterioration of the binder adhesion.
Current collectors	Copper dissolution and Aluminum corrosion	Overdischarge (for copper), overcharge (for aluminum)
Separator	Tearing of separator	Thermal or mechanical damage, presence of metallic particles, dendrite growth causing internal short circuits.
Electrolyte	Electrolyte decomposition and evolution of gases	Flammable and unstable electrolytes, extreme operating conditions (typically temperature above 80°C).

into three categories: electrochemical, empirical, and semi-empirical. Table 3 summarizes the degradation models.

IV. RELIABILITY ASSESSMENT TECHNIQUES OF LI-ION BATTERY

Generally, reliability assessment refers to ensuring the reliability and maintainability of systems by employing tools and techniques to identify, analyze, and prevent potential failures that could adversely affect performance and safety. It covers subfields such as prognostics and health management (PHM), which focus on system health, performance prediction, and advanced diagnostics. It also encompasses reliability, availability, maintainability, and safety (RAMS), which examines the overall group characteristics. Unlike RAMS, PHM uses a detailed approach to monitor the individual components [89]. In particular, a reliability assessment of Li-ion batteries for EVs entails evaluating the probability of the occurrence of faults/degradation and their impact on the available capacity and power [41]. In addition, it incorporates the concepts of the PHM and RAMS to ensure the optimal performance of Li-ion batteries in EV. This section explores the diverse techniques employed to assess the reliability of Li-ion batteries. As shown in Fig. 7, a state-of-the-art reliability assessment method that encompasses qualitative and quantitative approaches is adopted in this study. The application of these reliability techniques in BMS or in

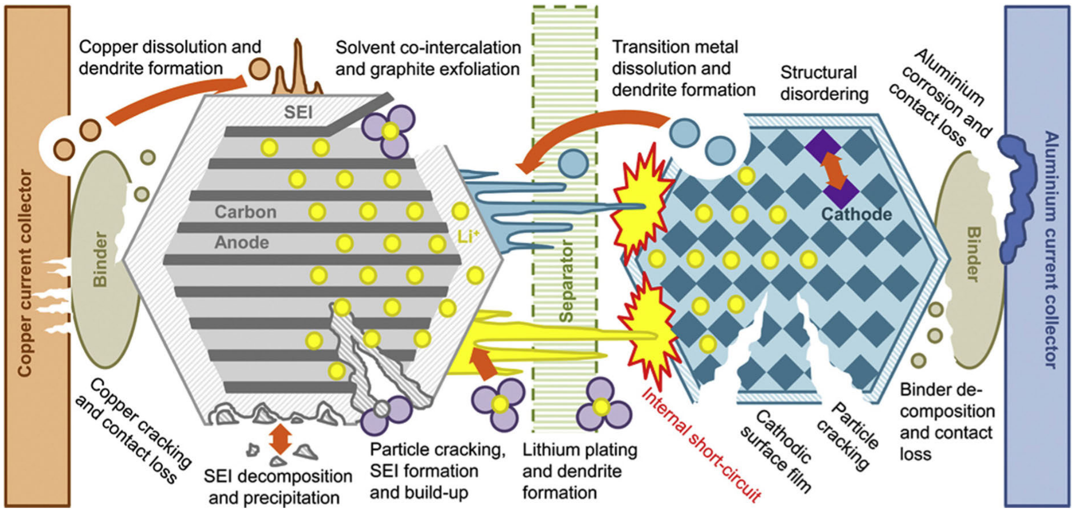

FIGURE 6. Degradation mechanisms in Li-ion batteries [69].

TABLE 3. Comparison of different Li-ion battery degradation models.

Model type	Description	Advantages	Disadvantages
Electrochemical	Electrochemical models simulates the battery's internal chemical parameters such as lithium concentration in the electrodes, kinetic energy, diffusion and charge transfer processes inside a battery cell. [80]–[82].	• Provides high fidelity modelling of the aging phenomena of the battery cell [81]. • Model provides deep insights into degradation mechanisms. • Captures the electrochemical reactions in the battery	• Requires high experimental effort and knowledge of the battery cell. • Long calculation time [81].
Empirical	The empirical model is a statistical model constructed from extensive experimental data. It doesn't require the consideration of the battery's internal physical and chemical processes; rather it focuses solely on processing and analyzing experimental data to create a mathematical model that describes battery performance and behavior. [83], [84].	• Simple model structure [85]. • Few model parameters is required [85]. • Possible to achieve a more optimal solution [86].	• Model parameter mismatch [85]. • Low generalization ability [84]. • Extensive aging test needed to parameterize the model [86]. • Low robustness at -20°C [84]. • The internal aging mechanism and microstructure evolution process of the batteries cannot be considered [87].
Semi-empirical	A semi-empirical model falls between theoretical and empirical models. It's created by fitting or tuning certain parameters using both known experimental data and theoretical models. Typically developing a semi-empirical model involves integrating experimental data with theoretical principles to enhance its accuracy and practicality. [83], [84], [21], [88].	• High accuracy [87]. • The electrochemical reaction process and side reaction process inside the battery are simplified [87]. • Fast computation time [81]. • Semi-empirical models have the capability to extrapolate data based on their mathematical functions [81]. • Attractive for health conscious energy management systems [81].	• Difficult parameter calibration [85]. • Requires specific operating condition for each battery type [82]. • Requires more laboratory tests [82]. • Aging tests are difficult in the laboratory [82].

the laboratory during cell manufacture will enhance the lifetime, design, maintenance, and service of Li-ion batteries in EVs.

A. QUALITATIVE APPROACH

Qualitative techniques involve assessing the reliability of Li-ion batteries based on descriptive and subjective evaluations. Qualitative methods are useful for identifying the potential risks and failure modes early in the design process. In this section, failure modes mechanisms and effects analysis (FMMEA), X-ray computed tomography, and scanning electron microscopy (SEM) are examined.

1) FAILURE MODES MECHANISMS AND EFFECTS ANALYSIS

Failure Mode Mechanisms and Effects Analysis (FMMEA) is a systematic approach used to identify potential failure

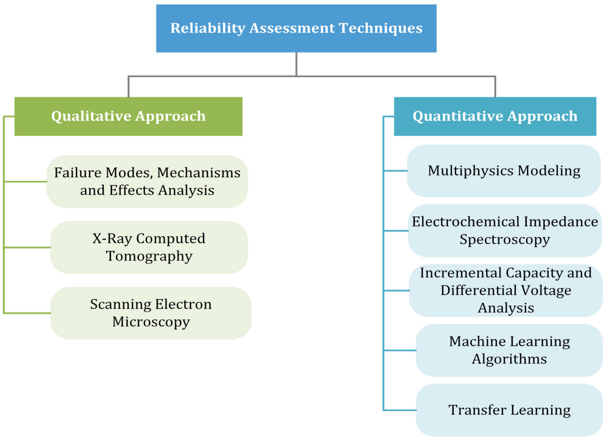

FIGURE 7. Categories of reliability assessment techniques.

mechanisms and their models for all potential failure modes while prioritizing these mechanisms [50]. This is the cornerstone of the physics-of-failure (PoF) approach for evaluating the reliability of systems, subsystems, and components. In comparison to the conventional Failure Mode and Effects Analysis (FMEA) [90], [91], [92], [93], which is developed to identify and categorize failures with a focus on mission success and safety, FMMEA sets itself apart by considering failure mechanisms and their importance in evaluating the potential risks associated with the system. The four key components of the FMMEA principle are described in Fig.8.

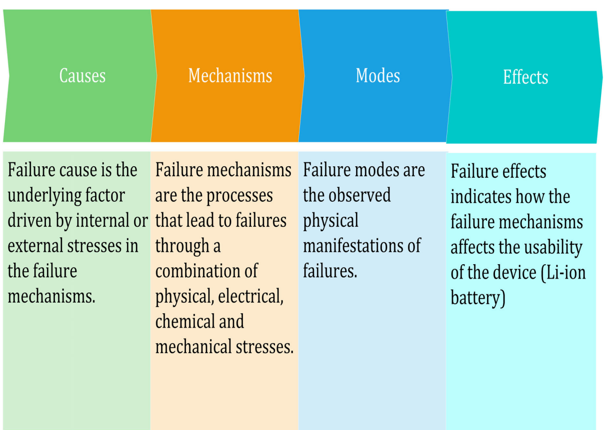

FIGURE 8. Definition of key FMMEA features.

Some failures within systems, such as Li-ion batteries have less impact and are inevitable, such as a gradual capacity decline, whereas other failures are catastrophic, such as thermal runaway, necessitating preventive actions. One way to determine which failures to focus on is to rank failure mechanisms based on their likelihood, severity, and detectability. These mechanisms can be prioritized by assigning scores of severity, occurrence, and detectability and combining them to form an overall risk prioritization number (RPN). The RPN is obtained by multiplying the severity, occurrence, and detectability levels. The final step in prioritization entails categorizing failure mechanisms into risk levels based on their RPNs. For instance, a failure mechanism characterized by a high likelihood of occurrence, high severity, and difficult detection ranks higher than other mechanisms. However, if a failure is easily detectable, its ranking will not be as high as that of other mechanisms. The criteria for classifying the likelihood, severity, and detectability vary based on the expert judgment and experience of the FMMEA team acquired from Li-ion manufacturing, disassembling, reliability tests, and failure studies [94]. The results obtained from FMMEA can offer guidance for determining the parameters of Li-ion batteries that need to be monitored in real-time or during usage. This reliability method has been moderately utilized for Li-ion batteries; however, it has significant potential for assessing their reliability in the future. Hendricks et al. [50] utilized the FMMEA approach to identify potential failure modes, detection methods, and the underlying processes responsible for failures in Li-ion batteries. In [95], FMMEA was used to comprehensively understand battery failures and associated risks. Significant risks include internal short circuits, excessive heat generation, side ruptures, and issues with thermal or battery management systems. These risks play a crucial role in the initiation and propagation of thermal runaways.

2) X-RAY COMPUTED TOMOGRAPHY

X-ray computed tomography (CT) is a non-invasive technique employed for the visual examination and qualitative assessment of material structures and compositions, playing a crucial role in both performance monitoring and quality control during the manufacturing of Li-ion batteries [96]. It employs X-rays and a computer-aided tomographic process to generate three-dimensional (3D) representations of the scanned battery.

Fig.9 shows an X-ray CT scan applied for the detection of Li-ion battery capacity. X-ray CT consists of two principal components: X-ray Source and X-ray detector. After the battery was charged and discharged by the electrochemical performance system, it was projected onto a detector from the X-ray source. When X-rays pass through a battery, they undergo attenuation due to absorption and scattering. The extent of attenuation is measured by a detector that captures the remaining X-rays and forms a gray-scale two-dimensional (2D) image [97]. However, this 2D image offers limited information regarding the internal structure of the battery due to the overlapping details of its various components. A computer imaging system for X-ray CT enables reconstruction of a comprehensive 3D model by collecting a series of 2D projections acquired from different angles. This reconstruction process is similar to assembling a puzzle by analyzing X-ray information collected from various perspectives.

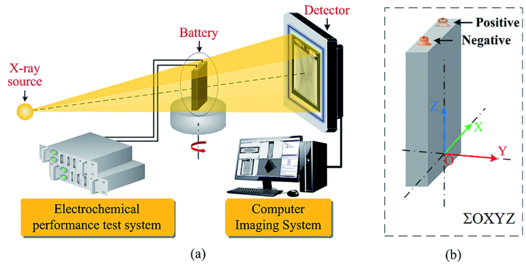

FIGURE 9. **(a) Schematic representation of the X-ray Computed Tomography method for the Li-ion battery capacity. (b) Coordinate of the system for batteries. [96].**

Several studies have utilized X-ray CT to gain insight into various aspects of Li-ion batteries. For example, Rahe et al. [98] utilized nano X-ray CT to reveal particle cracks and current-collector corrosion on the cathode side of a Li-ion battery. In [99], the assessment of the internal gas evolution relied on X-ray CT and was applied to diagnose degradation in conjunction with internal resistance analysis. The study focused on the tomogram Region Of Interest (ROI) volume to assess electrolyte decomposition, which triggers internal gas evolution. The author's implementation involved accelerated aging experiments on two LFP batteries at different C-rates. For the first battery, degradation is primarily attributed to SEI formation and growth, whereas the degradation of the second battery is linked to increased charge transfer resistance and loss of lithium inventory. This investigative approach provides insights into the impact of rest time during the degradation diagnosis. However, it may not be universally applicable to batteries with different shapes, such as cylindrical and prismatic cells. To ensure the safety of EV users who unintentionally utilize Li-ion batteries outside the recommended temperature ranges, Zhao et al. [100] employed external compression to Nickel Cobalt Manganese at high temperatures for 10h and conducted X-ray CT scans to analyze the electrode stack structures. The X-ray CT revealed that the cell tested at 100^{o}C without compression experienced delamination at various points and had deposits on the electrode surface. However, localized delamination was not observed in compressed cells. As shown in Fig.10, Vanpeene et al. [101] employed the X-ray CT technology to scan silicon-based electrodes. This allowed them to examine morphological characteristics such as volume expansion, cracks, and changes in porosity. Analyzing how these electrode traits transform throughout cycling provides insights into the impact of various cycling conditions on battery performance.

3) SCANNING ELECTRON MICROSCOPY

Scanning electron microscopy (SEM) is a microscopic technique that allows the direct observation of the structural evolution of active materials in Li-ion batteries. SEM provides real-time insights into battery performance and degradation mechanism identification, and assists in the rational design of electrode materials [102] and invariably in reliability assessment. SEM operates by focusing a beam of electrons generated by thermionic emission from a tungsten filament, solid-state crystals, such as lanthanum hexaboride (LaB6), or generated by a field emission gun made from tungsten onto the Li-ion battery sample surface [103]. Elastic or inelastic interactions occur when an electron beam hits the sample surface. In inelastic interactions, secondary electrons (SE) are emitted with energies that are different from those of the incident electrons. Conversely, in elastic interactions, electrons are deflected, which causes scattering. Electrons deflected at angles greater than 90^o are referred to as back-scattered electrons (BSE). Subsequently, a specialized detector captures the SE emitted by the sample and the BSE. These collected signals are then employed to construct an image of the sample's surface or other information. The SE has a relatively low energy (50eV), and can only escape from the top few nanometers (nm) of the sample surface. Consequently, the SE signals provide an accurate representation of the sample surface topography. Image contrast is achieved using surface features that obstruct the emitted SE. BSE has a higher energy than SE and deflects differently depending on the atomic number of surface elements. Elements with higher atomic numbers deflect a greater proportion of the incident electrons toward the detector. Consequently, the BSE image reflects the elemental composition of the sample. When the incident electrons interact with the sample surface, they can emit X-ray photons. Detecting these X-ray signals provides valuable information regarding the elemental composition of the surface using energy-dispersive X-ray (EDX) spectroscopy. This complements the surface imaging obtained using SE and BSE [104].

Operando and in-situ characterizations are two approaches to SEM for real-time investigation of Li-ion batteries. Both in-situ and operando characterization methods involve the study of reactions under real-time conditions. However, in situ characterization focuses on controlled experiments to comprehend dynamic changes, whereas operando characterization specifically aims to analyze reactions during active operation, particularly when matching charge and discharge profiles. The use of SEM techniques in these approaches is highly effective for understanding the interfacial reactions in Li-ion batteries and devising strategies to improve battery performance and reliability.

In recent years, researchers have investigated the microstructure and morphology of Li-ion batteries using SEM. For example, to fully understand the micro-scale deformation and failure mechanisms of discharged battery cell components, Zhu et al. [106], carried out nanoindentation tests and in-situ tensile tests under SEM to determine the elastic modules of the coating materials and the elastic-plastic and fracture behavior of electrodes. Interrupted tests were conducted on a polypropylene separator and its deformation was investigated under SEM. The results revealed that the cathode experienced surface micro-cracks before failure, whereas the anode remained intact until later in the

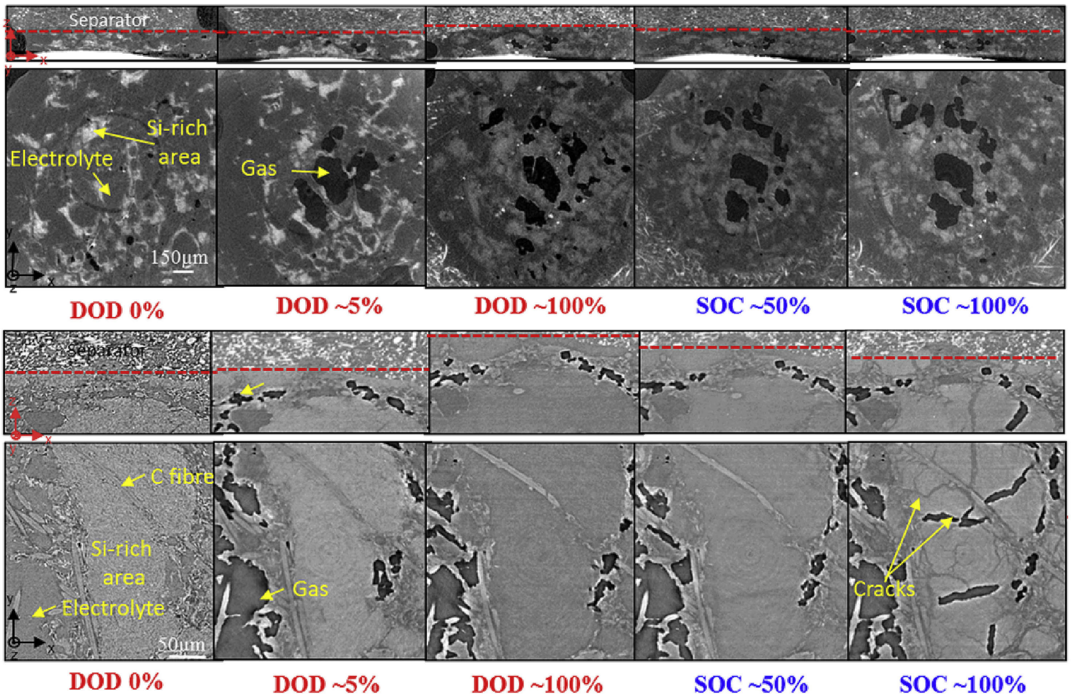

FIGURE 10. Investigation of Silicon-Based Electrode Thickness Changes during Cycling via X-Ray CT [101].

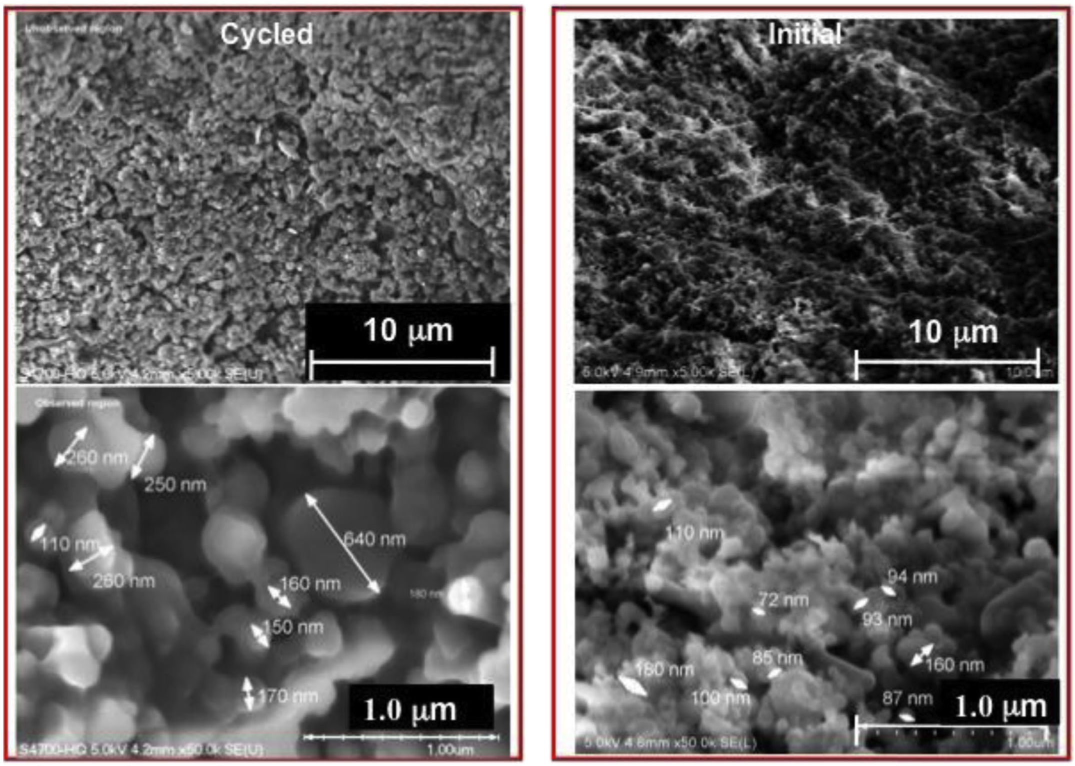

FIGURE 11. Right side: SEM images of the Silicon anode with an average particle size of 100nm before cycling at 10μm and 1.0μm magnifications. Left side: Same electrode after two cycles at 10μm and 1.0μm magnifications [105].

deformation process. The separator underwent distinctive deformation stages, including fibril (the amorphous part of the separator) elongation and pore formation, leading to the eventual onset of failure. For many years, silicon (Si) has been regarded as a favorable element for enhancing the energy capacity of Li-ion batteries. However, the use of Si as an anode for Li-ion batteries is predisposed to large volume expansion/contraction during cycling which is responsible for the cracking of the Si particles. The size dependence of the Si properties of Si-based anode materials has been identified as a potential approach for mitigating the volume change. To investigate the effect of particle size on volume change in Si-based anode batteries, authors in [105] examined a 100nm particle size of Si and 2-10μm of Silicon oxide (SiO) based anode in in-situ SEM during electrochemical cycling to provide new insight into the microstructural evolution of the respective particles. The electrodes using a nano-sized Si anode were observed in-situ using a field emission gun electron microscopy (FEG-SEM) whereas the larger SiO anode particles were examined using a variable-pressure SEM. The SEM image in Fig.11 reveals that the nano Si electrode contained Si particles with sizes ranging from 70 to 200nm, and with an average particle size of approximately 100nm. As anticipated, the in-situ SEM depicting the evolution of the electrode revealed a significant change in the electrode volume throughout the cycling process. Another notable observation from the SEM is the electrochemical sintering (a phenomenon where dispersed particles come together and merge, forming a flocculation structure) of the particles occurring during the cycling process. Because of this phenomenon, the electrode exhibits increased rigidity, reaching a stage where it cannot accommodate volume changes during cycling. This leads to electrode fracture in the next cycle after the sintering, eventually resulting in electrode failure. The SiO Was used to limit the volume change of the active component. Surprisingly, the results show that the volume change did not originate from the particles themselves but rather from the expansion of pre-existing voids between the particles when carbon is present. These voids expand and contract during cycling. Consequently, the study concluded that Si cannot rival graphite unless cost-effective methods for synthesizing clamped hollow nanostructures that can circumvent these issues are developed for commercial use.

Lithium metal plating on graphite anodes in Li-ion batteries causes capacity degradation and eventual battery failure. In [107], an overcharge experiment was conducted on a graphite anode, and the morphology and structure of the graphite were analyzed using SEM. The study revealed that the failure mechanism of graphite during overcharging is similar to that of a lithium metal electrode. Specifically, the deposited lithium reacts with the electrolyte, forming a new SEI layer, which further inhibits accessibility in subsequent cycles. Reference [108] provided a novel in-situ SEM technique. This technique utilizes an ionic liquid as the electrolyte within the SEM vacuum chamber, allowing real-time monitoring of the morphological changes of the tin dioxide (SnO_2) anode, including both the active and passive materials. The results showed that various active degradation mechanisms, such as the formation of interface layers, volume expansion, growth of protrusions, and mechanically induced cracks in the electrode particles during cycling, were evident in the SnO_2 material. Additionally, the electrochemical performance of the anode material is significantly influenced by the particle size. The effect of short-term discharge cycling on the performance of 21,700 Li-ion cells with NCA cathodes was examined in [109]. The study aimed to identify the specific modes of performance degradation. The study also systematically analyzed the mechanisms responsible for capacity loss in six Li-ion cells using SEM.

B. QUANTITATIVE APPROACH

Quantitative techniques involve the use of numerical data and mathematical models to assess the reliability of Li-ion batteries. It essentially entails knowledge-based and model-based techniques, including multiphysics modelling, Electrochemical Impedance Spectroscopy (EIS), Incremental Capacity and Different Voltage analysis (ICA/DVA) machine learning algorithms, and transfer learning. The techniques are discussed in this section.

1) MULTIPHYSICS MODELLING

A Li-ion battery is an intricate electrochemical energy system that encompasses various electrochemical reactions, mass transfer, charge transfer, heat transfer, fluid dynamics and interrelated processes. It is sometimes challenging to find an effective solution for investigating the performance of Li-ion batteries by using a simplistic single-field model. When viewed through the lens of systems engineering, Li-ion batteries emerges as complex dynamic systems that span multiple scales and multiphysics. To effectively model and analyze Li-ion battery systems, a multidisciplinary approach involving fields such as materials science, electrochemistry, heat transfer, and fluid dynamics is indispensable. A multiphysics model employs fundamental principles and equations drawn from the aforementioned fields to forecast the performance of a Li-ion battery system. These equations are concurrently solved to account for the interactions between various physical and chemical properties. Multiphysics modelling also entails the coupling of two or more of the following main models or other relevant features, as required by the modeller to accurately represent the physical and chemical properties of a Li-ion battery.

- **Electrochemical models:** Electrochemical models are designed to represent the internal battery process, particularly the charge transfer process, electrochemical reactions, ion transport, and diffusion within electrodes and electrolytes [110], [111]. They are formulated as nonlinear partial differential equations, incorporating fundamental laws such as Ohm's law, Faraday's first law, the Butler-Volmer equation, and Fick's law of diffusion to depict the underlying electrochemical reactions of batteries. Despite their accuracy and adaptability, their complexity and lack of readily available parameters limit their practical applications in BMSs. These models primarily come in two forms: the single-particle model (SPM) and pseudo-2D model (P2DM) [112].

- **Equivalent circuit models:** The equivalent circuit model (ECM) utilizes a combination of analog electrical circuit elements to emulate battery dynamics, providing noticeable flexibility and simplicity [113]. Based on the level of simplification, representation of internal dynamics, accuracy, and fidelity, ECM can be classified into Thevenin, Norton, Single-RC network, multiple-RC network, integer-order models, and fractional-order models. ECM has been used in several varieties to investigate the reliability of Li-ion batteries. For example, Hu et al. [113] established a Li-ion battery using a fractional-order model based on fractional-order calculus. They devised a co-estimation method for SOC and SOH with maximum steady-state errors within 1%, even in the presence of noise and disturbances.
- **Thermal model:** Electrochemical reactions and charge transport within batteries generate heat during charging and discharging [114], [115]. Excessive heat can be unsafe and can reduce the battery performance. The thermal model determines heat generation and propagation, predicts thermal runaway, and is used to provide thermal management functions to the battery [110].
- **Fluid dynamics models:** Fluid dynamics models of Li-ion batteries focus on simulating and understanding the movement of liquids such as the electrolyte within a battery cell [42], [116]. These models are essential for studying the heat transfer, ion transport, and distribution of reactants within the battery, which affect their performance, efficiency, and safety.

The limitations of experimental approaches have been overcome by multiphysics modelling. Multiphysics modelling is cost-effective because it simulates the battery behavior in a virtual environment. Furthermore, it naturally yields insights into the evolution of the physical and chemical properties of battery systems over time. Typically, these models depict the battery from a microscopic to macroscopic level, utilizing variables such as concentration, voltage, current density, and heat generation to describe its properties [117]. Multiphysics simulations of Li-ion batteries are commonly conducted using COMSOL Multiphysics [118], [119]. Typically, there is a close match between the experimental and simulated voltage results [120], [121]. Some authors have also introduced computational frameworks for modelling Li-ion batteries. Newman, a contributor to the P2D electrochemical model, devised the Dualfoil framework for Li-ion battery simulation [122], another noteworthy framework is LIONSIMBA, developed by Torchio et al. in MATLAB [123], which offers faster computation times than COMSOL Multiphysics [124]. Kosch et al. introduced their framework, which employs orthogonal collocation and the Lobatto IIIA method to reduce the computational expenses [125]. Allu et al. introduced their framework and demonstrated its suitability for various cell geometries [126].

Recently, owing to advancements in multiphysics simulation technology, numerous scholars have conducted reliability analyses and optimization studies on Li-ion battery packs using these simulation tools. Xia et al. [127] proposed an innovative reliability optimization approach for a Li-ion battery pack that utilizes response surface methodology and multiphysics coupling simulation consisting of an electrochemical-thermal model for cells and a fluid dynamics model for the battery pack to analyze the physical characteristics during operation. In the study, a temperature-dependent degradation model was used to represent cell capacity fading, and randomness in the capacity fading was modeled using stochastic distributions. Xia et al. [128] established a reliability and lifespan assessment method for Li-ion battery packs based on Multiphysics coupling models. The proposed model, which couples the electrochemical, thermal, SEI formation model of cells, fluid dynamics, and the series-parallel circuit model, describes the coupling relationships of temperature and current between cells while also considering the effects of the geometric structure and heat dissipation method on the cell inconsistencies. Fig.12 depicts the sub-models and their coupling relationships, with detailed explanations provided in [128]. They also presented a lifespan model that considers capacity degradation and percentile life. Experiments were conducted on a test bench to validate the proposed method. The outcomes are highly encouraging, indicating that the battery degradation rate initially decreases and then accelerates throughout its lifespan, and the thermal management strategy, which involves periodically altering the airflow direction, prolongs the lifespan of Li-ion battery packs by 5.1%. Although the verification of the model was limited to charge and discharge cycles without reflecting complex real-world operational conditions, it still holds the potential to conduct a thorough analysis of the processes occurring inside the battery.

An electrochemical-thermal model was utilized to optimize the design parameters of Li-ion batteries. This optimization process considered factors such as the particle radius, electrode thickness, volume fraction of active material, and C-rate in [129]. In [130], a coupled Multiphysics model comprising mechanical, electrochemical, Internal Short Circuit (ISC), thermal, and thermal runaway models was developed to describe how Li-ion batteries deform, respond to ISC, and experience temperature changes during drop-weight tests. The model can effectively predict the reaction of Li-ion batteries to dynamic loads at different impact energies and SOCs. In [131], a pseudo-two-dimensional mathematical model for Li-ion batteries was developed, incorporating multiphysics transport processes and a model for SEI growth. The model was validated using experimental data. The simulation results reveal that the battery operating conditions significantly affect the SEI layer formation. Higher charging/discharging rates accelerate battery capacity fading; however, effective surface cooling may mitigate capacity fading. Simulations of different electrolyte salt concentrations in the study show that increasing the salt concentration improves Li-ion diffusion and stabilizes cell performance when facing resistance due to ion consumption. To diagnose the capacity fading of a Li-ion battery, Wang et al. [132] utilized

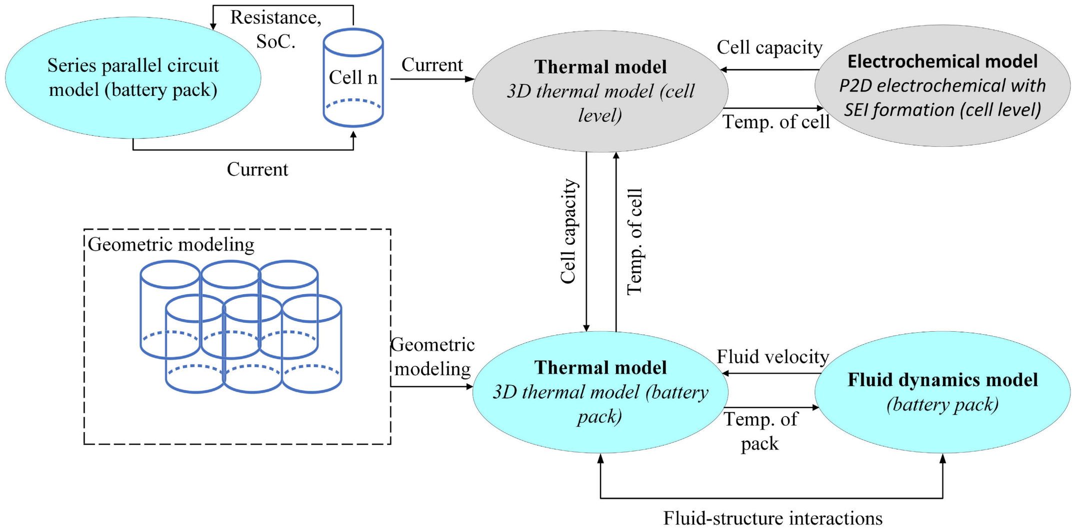

FIGURE 12. The multiscale Multiphysics model of Li-ion battery pack and their coupling relationship developed by Xia et al. [128].

a heterogeneous electrochemical-diffusion-induced stress-coupled Multiphysics aging model established in [133]. The Multiphysics aging model relies on the establishment of parameter limits for battery near failure, as determined by the battery model. The aging model also assesses the impact of crack propagation owing to diffusion-induced stress and the formation and growth of the SEI. The parameters are determined using identification techniques, and the model is validated against the measured data. Notably, using parameters from a new battery to predict the terminal voltage after 400 cycles resulted in a mean absolute error (MAE) of just 14.8mV. This investigation is particularly relevant in real-world battery applications because the continuous monitoring of the identified parameters enables the online diagnosis of battery failures. This allows for timely issuance of an early warning signal as the battery approaches the end of its operational life. Such practice holds significant importance in ensuring that the battery maintains its required performance and safety standards. In a previous study, Yiding et al. [134], developed a comprehensive Multiphysics model that combined mechanical, electrochemical, and thermal factors to investigate the failure mechanisms of Li-ion batteries. This model, rooted in structural damage, is utilized to analyze the behavior of Li-ion batteries when subjected to mechanical abuse during the severe short-circuit phase, considering both the real 3D structure and the entire battery level. Given the intricate nature of battery modelling and the temperature inconsistencies during operation, a reliability design method for Li-ion battery packs was developed in [42]. The method considers the thermal disequilibrium and relies on cell redundancy. The method involves a comprehensive Multiphysics model that integrates electric, thermal, and fluid dynamics in a 3D structure. Additionally, it incorporates a stochastic degradation model for batteries under real-world dynamic conditions and a multi-state system reliability model for battery packs. The relationships between the Multiphysics, degradation, and system reliability models were used to assess the reliability of battery packs and provide examples of various redundancy strategies. By comparing the reliability of battery packs with different cell numbers and configurations, several conclusions were obtained for the redundancy strategy. More notably, reliability did not monotonically increase with the number of redundant cells for thermal disequilibrium effects. More use cases of the Multiphysics model for reliability assessment can be found in [128] and [135].

2) ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY

EIS is a vital tool for assessing battery dynamics, particularly for Li-ion batteries. This is an accurate technique for simulating such batteries. It involves applying a small-amplitude sinusoidal current (galvanostatic) or voltage (potentiostatic) signal to the battery at various frequencies and measuring the impedance of the battery. This allows characterization of the response of the battery to the applied signal. The impedance spectrum of the battery can be obtained by performing the process at different frequencies in the kilohertz (kHz) to megahertz (MHz) range. This allows for the determination of the impedance expression as well as the real and imaginary components of the battery system, which are related by the following equations [136]:

$$\bar{Z} = \frac{Y}{X} = \frac{u(t)}{i(t)} = \frac{U\sin(\omega t)}{I\cos(\omega t - \phi)} \tag{3}$$

$$Z' = |\bar{Z}|\cos(\phi) \tag{4}$$

$$Z'' = |\bar{Z}|\sin(\phi) \tag{5}$$

$$\bar{Z} = \sqrt{Z' + Z''} \tag{6}$$

where U represents the magnitude of the voltage signal, I represents the magnitude of the current signal, $\bar{Z}$ represents the absolute value of the measured impedance, Z' represents the real part of the cell impedance at frequency ω, Z'' is the imaginary part of the cell impedance at frequency ω, and ϕ is the phase angle of the impedance. Fig.13 illustrates a standard EIS plot for a Li-ion battery, with the real impedance part on the horizontal axis and the imaginary impedance part on the vertical axis, which is segmented into high, mid, and low-frequency regions. This typical EIS graph depicts the impedance, with the intersection of the curve with the real axis signifying the ohmic resistance of the battery. The mid-frequency curve, resembling a semi-circle, is linked to the double electric layer between the electrode and electrolyte of the battery. In the low-frequency range, the EIS curve becomes a straight line, indicating a solid diffusion process within the Li-ion active material particles [137].

Remarkable progress has been made in the use of EIS to investigate the performance of Li-ion batteries. Zhang et al. [60] developed an equivalent circuit model (ECM) using EIS by integrating the charge transfer resistance and solid electrolyte interface to map their relationships with SOH (ratio of a battery's current capacity to its nominal capacity) [30] at different SOCs and temperatures. Model parameters were established using the Hamilton Monte Carlo (HMC) sampling technique. The charge transfer resistance obtained via EIS and influenced by the temperature and SOC was chosen as the impedance characteristic for estimating the SOH using a probabilistic model. Fig.14 shows the correlation between SOH and charge-transfer resistance. This empirical study reveals that the EIS-based SOH estimation method has a mere 4% error when simultaneously accounting for both the temperature and SOC effects. However, specific conditions such as 80% SOC at 30°C, yielded an even lower error of 1.29%. This model enables a more precise evaluation of the battery's SOH, accommodating the changes in these dynamic factors.

Temperature significantly influences the electrochemical kinetics and substance transfer in Li-ion batteries. The electrochemical impedance spectra of Li-ion batteries were examined in [137] using fractional-order theory to estimate the SOC. The effectiveness of this approach, which estimates the SOC through EIS, was compared with the widely used integral-order and electrochemical impedance models with polarization resistance. The results demonstrate that the proposed model yields a smaller root mean square error (RMSE) at both −20°C and +25°C when compared to the other two models. This distinction is particularly evident at lower temperatures. Nevertheless, it is important to note that this evaluation did not account for potential measurement noise and random disturbances [138]. A single weak cell within a module can negatively affect the output power and overall performance of the entire module. To ensure safety and cost-effectiveness, it is crucial to perform quality control (QC) tests on individual cells before assembling them into battery modules. Lambert et al. [139] demonstrated the use of an EIS-based technique for QC testing at the end of a Li-ion battery production line. This technique successfully distinguished between viable and non-viable cells. The findings of the study indicate that EIS is a suitable measurement method for determining cell state and overall quality during various stages of cell manufacturing. Koseoglou et al. [140] used dynamic EIS (DEIS) to identify lithium plating in Li-ion batteries during charging. They discovered that the impedance around 1Hz, associated with the charge transfer in the EIS curve notably drops during lithium plating. This technique allows the detection of lithium plating onset without the need for specialized sensors or intricate models, thus simplifying the process.

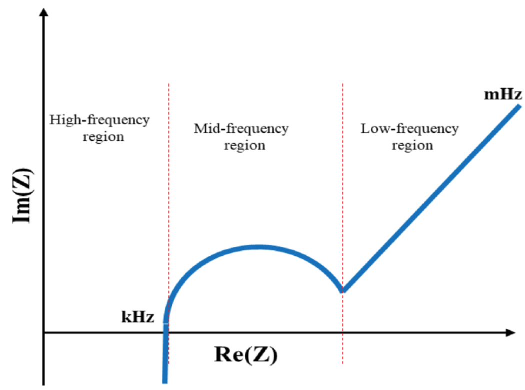

FIGURE 13. Standard EIS pattern for a Li-ion battery [137].

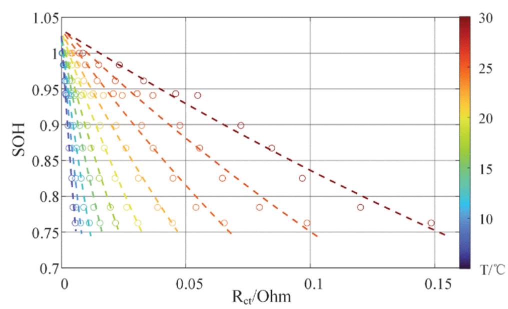

FIGURE 14. Relationship between SOH and charge transfer resistance under temperature variations [60].

3) INCREMENTAL CAPACITY AND DIFFERENTIAL VOLTAGE ANALYSIS

Accurate estimation of the states of the battery (SOC, SOH) can contribute to the reliable and safe operation of the battery, as well as extend its lifespan. Incremental capacity (IC) and differential voltage (DV) methods are valuable and non-destructive techniques used to identify degradation modes, estimate the states of Li-ion batteries, and determine their capacity. It can be implemented within a BMS for effective diagnosis, monitoring, and analysis [73]. In IC and DV analyses, the cell voltage plateaus are transformed into clearly identifiable $\frac{dQ}{dV}$ (derivative of capacity with respect to voltage) and $\frac{dV}{dQ}$ (derivative of voltage with respect to capacity) peaks and valleys on the IC and DV curves, respectively [141] and [142]. The IC curve is derived by calculating the derivative of the battery discharge/charge capacity with respect to the terminal voltage (V) for both positively and negatively polarized electrodes, mathematically represented by Equation (7) [143]. The inverse of the IC gives the DQ curve, as expressed by Equation (8) [144].

$$\frac{dQ}{dV} \approx \frac{\Delta Q}{\Delta V} \tag{7}$$

$$\frac{dV}{dQ} \approx \frac{\Delta V}{\Delta Q} \tag{8}$$

The peaks and valleys in the IC and DV curves represent the intercalation and de-intercalation processes respectively. The characteristics of the extracted peaks, such as positions, heights, areas [145] for the IC curve, as well as valley decrease and capacity shift for the DV curve could serve as indicators directly connected to the degradation process of Li-ion batteries. Furthermore, the extracted features can be utilized to monitor the health of the battery and its states [146].

IC and DV analyses are commonly employed techniques for identifying battery aging mechanisms and estimating key important Li-ion battery parameters. Weng et al. [141] estimated the battery SOH based on ICA by relating the peak intensity of the IC curve to capacity loss. The results indicated that the ICA technique can predict the SOH with an error margin of 1%. Authors in [147] employed an interpolation-based IC curve acquisition method to approximate IC values within a 3.8-4.0V voltage range. This technique uses charging profiles to train a partial least square regression algorithm, estimating the capacity of three commercial 18650-sized Li-ion cells in real-time. Sun et al. [148] proposed a battery capacity estimation approach employing a back-propagation neural network with ICA features. Their work also integrated a data-driven model with the Arrhenius model to enhance accuracy. It is important to note that the IC curve is influenced by the charging conditions used in the experiment to estimate the capacity of the battery. Whereas the above IC-based capacity estimation approaches rely on standard charging conditions (typically charging from 0% SOC with a 1/2C current at 25°C), they do not capture the complex and varying conditions of EV operation in which the batteries are seldomly discharged fully. To address this scenario, in addition to the standard charging experiments conducted to establish the relationship between the capacity and characteristics of IC curves, an additional non-standard charging experiment was conducted in [149]. The non-standard experiment involved charging the battery under varying initial SOCs and at different temperatures. The purpose of the experiments was to examine the impact of the initial SOC and temperature on the IC curves. Finally, in this study, the authors developed an adaptive capacity estimation method based on the ICA. Zheng et al. [142] transferred the traditional voltage-based IC/DV curves to SOC-based IC/DV curves, which were unaffected by changes in battery resistance and polarization during aging. They introduced a joint estimation technique for battery SOC and capacity by utilizing three feature points on IC and DV curves. This proposed approach stands out from the others owing to its simplicity and easy implementation without compromising accuracy. In addition, it possesses the capability of extending the SOC and capacity estimation technique from a single-cell level to a pack level, thereby increasing its practical applicability. For more cases of IC/DV analysis for reliability assessment, readers are encouraged to peruse [73], [141], [143], [144], [145], [150], [150], [151], [152], [153], and [154], [155].

Despite the promising results obtained from the above literature, one prominent limitation of IC/DV analysis is its high sensitivity to data noise, making it challenging to accurately identify the peaks in the IC/DV curves owing to measurement noise in the battery system [147], [156], [157]. Prefiltering is typically required to address this issue. Researchers have utilized Gaussian/Lorentzian filters [158], [159], Kalman filters [149], moving average filters [160], [161], the improved center least square method [162], and the Butterworth filter [144] to attenuate the noise signal. As an example, Fig.15 depicts the noise of the original IC curve suppressed or smoothed with the application of a first-order low-pass filter.

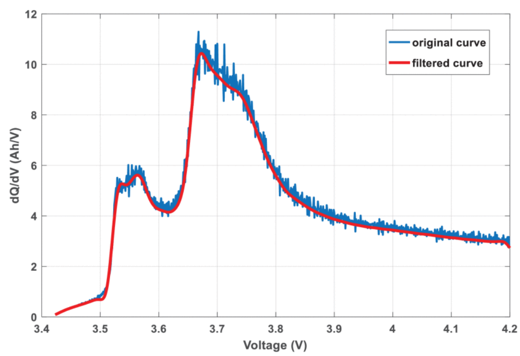

FIGURE 15. Original IC curve and filtered IC curve [163].

4) MACHINE LEARNING TECHNIQUES

a: PRELIMINARIES

Machine Learning (ML) is a subset of artificial intelligence (AI) and refers to a specific approach where computers can learn and improve their performance on a task without being explicitly programmed for the task. Instead of following a fixed set of rules, machine learning algorithms learn patterns and insights from data, enabling them to make predictions, classify objects, or make decisions based on past experiences [89]. It is a branch of computer science that focuses on creating algorithms to derive valuable insights from the data. Over the past two decades, it has been a prominent and extensively researched field with diverse applications in both industrial and academic sectors. ML algorithms have been widely employed in various disciplines, including reliability assessment, for which this study provides a comprehensive overview. Machine learning algorithms typically partition a dataset into three main subsets: training, validation, and testing datasets. The training dataset is utilized to optimize the trainable parameters of the model (developed from machine learning), whereas the validation dataset helps determine the best hyperparameter settings and selects the final model during the iterative process. The testing data is used to assess the training quality of the model [164]. Generally, ML is categorized into supervised, unsupervised, and reinforcement learning [165]. Supervised learning is employed for two main tasks: the classification problem, which predicts labels (discrete values such as success or failure), and regression, which predicts quantities (such as resistance or capacity values) [166]. Unsupervised learning is mostly applied to exploratory analysis, dimensionality reduction techniques, and feature extraction [166]. Reinforcement learning (RL) sets itself apart from supervised and unsupervised learning, as it operates within a dynamic environment. Unlike other methods that involve clustering or labeling data, RL seeks to identify the optimal sequence of actions to achieve a favorable outcome. This is accomplished by employing an agent, which is a software entity, to explore, interact with, and learn from the environment. An agent must balance exploration and exploitation to make informed decisions. It uses a single function to map state observations to actions, replacing the need to separately control system sub-components [166].

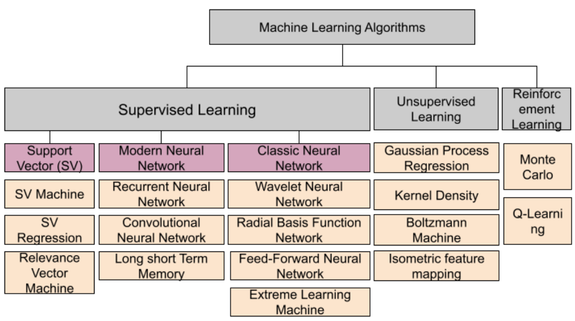

FIGURE 16. **Machine learning techniques for reliability assessment of Li-ion battery.**

b: ML TECHNIQUES FOR BATTERY RELIABILITY ASSESSMENT

A complete family of ML techniques that have been utilized for reliability assessment and implemented in the BMS of Li-ion batteries is shown in Fig. 16. Each of these techniques is briefly explained in [82], [167], [168], [169], [170], and [171] to aid readers. ML has recently garnered considerable interest in reliability assessment using diverse approaches in Li-ion batteries for EVs. Selected studies on different machine learning algorithms for the reliability assessment of Li-ion batteries are presented in Table 4.

These techniques are valuable tools for assessing the reliability of Li-ion batteries in EVs to ensure safety and efficiency throughout their lifespan. Whereas each technique has specific uses, using a combination of these offers a more complete insight into Li-ion battery performance in EV applications. The merits, limitations, and dominant application areas of each reliability assessment technique are highlighted in Table 5 to guide researchers and industrial personnel in which methods to adopt.

5) TRANSFER LEARNING

Typically, ML algorithms are trained and tested using the training and testing datasets from the same distribution. However, this assumption often does not hold true in practical scenarios. If there is a shift in the test dataset, retraining the ML algorithm requires considerable fresh training data, incurring significant expense and time to sustain the accuracy [182]. To circumvent the potential malfunction of ML algorithms when faced with a new distribution in the test dataset, transfer learning (TL) has emerged. TL involves transferring acquired knowledge from a prior source dataset to facilitate the construction of models for a new target dataset. A minimal amount of freshly generated training data is sufficient to reconstruct the ML algorithm, even if the data does not stem from a similar test data distribution [183]. Transfer learning can be categorized into three types based on the changes that occur when moving from a source problem to a new target problem: inductive, transductive and unsupervised [184].

Recently, TL has been applied to Li-ion batteries. For example, Lu et al. [78] proposed a novel approach for transferring degradation mode (DM) knowledge from synthetic LFP battery datasets to real-world LFP batteries using a deep-domain adaptation approach. The study used a deep CNN architecture composed of a series of residual blocks, called ResNet-50, to classify the DM for the LFP. However, the classification accuracy was insufficient, and the DM results were not utilized to further investigate SOH. Che et al. [185] combined TL and Gated Recurrent NN (GRNN) to predict the RUL of a Li-ion battery. In their approach, GPR was used to optimize the threshold of the health indicator (peak voltage at the change point between the first two charging stages) to determine the EOL of the battery. After optimizing these health indicators, they applied TL and GRNN to predict the RUL. TL was used to transfer relevant information from a source to a test battery, thereby improving prediction accuracy. Although the results demonstrated that the method could predict RUL with an error of fewer than five cycles after fine-tuning, it highly depended on the chosen health indicator, leading to inaccurate RUL predictions. In [186], a semi-supervised self-learning approach for predicting the lifetime of Li-ion batteries was proposed. As shown in Fig.17, the method adopted by the authors involves two main components: capacity estimation and degradation prediction. In the capacity estimation component, three health indicators (HIs) were extracted from the partial capacity-voltage curve of the battery. These HIs capture important information regarding the degradation pattern of the battery. A capacity estimation model based on

TABLE 4. Machine learning algorithms application in reliability assessment of Li-ion batteries.

Machine Learning algorithm	Application	Remarks	Ref.
Migrated Gaussian Process Regression (GPR)	Predicting battery nonlinear two-stage aging trajectory considering the effect of the knee point.	• Introduction of a data-driven model, migrated Gaussian Process Regression for accurate prediction and uncertainty quantification. • Demonstrated outperformance of migrated-GPR over zero-mean GPR for training before and after the knee point. • Effective prediction with just 30% initial data, significantly decreasing experimental effort. • Supports early maintenance and analysis for second-life battery suitability.	[172]
K-means clustering and Gaussian Naive Bayes	Assessment of the impacts manufacturing conditions (active material percentage, liquid to solid ratio, and coating gap between electrode and current collectors) on electrode and prediction of electrode heterogeneity.	• The proposed method has high throughput sample prediction. • It can be applied to varieties of Li-ion battery chemistries. • Electrode heterogeneity can be predicted with high precision.	[173]
Linear Principal Component Analysis (PCA) and nonlinear Kernel PCA	Early detection of soft internal short circuit of Li-ion battery.	• Although the linear PCA approach offers computational advantages, the nonlinear kernel PCA method's high sensitivity and specificity allow for earlier detection of internal short circuits. • The method has the potential to early detect abnormal temperature changes in jelly roll battery structure without the need for temperature sensors.	[174]
Hybrid of modified Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN)	Thermal runaway prognosis based on abnormal heat generation.	• Thermal runaway predictive variable is limited to temperature. • The CNN-LSTM model accurately predicted battery temperature 8 minutes in advance, demonstrating a mean relative error of only 0.28%. • Thermal runaway prediction was effectively achieved with a 27-minute advance, enhancing the method's practicality.	[175]
eXtreme Gradient Boosting algorithm	Detection of previous over-discharge and prevention of fault alarms from being broken by subsequent charging operation of Li-ion battery in electric vehicles.	• High accuracy is achieved. • Sensitivity to sample data.	[66]

a neural network with LSTM layers was trained using HIs and a limited number of labelled checkpoints. The model reconstructs the historical capacity of the battery using the HIs and available checkpoints. In the degradation prediction component, a degradation prediction model based on a neural network with LSTM layers is trained using the reconstructed capacities from the capacity estimation model. The model was self-trained using the pseudo-values of the estimated

TABLE 4. ***(Continued.)*** **Machine learning algorithms application in reliability assessment of Li-ion batteries.**

Machine Learning algorithm	Application	Remarks	Ref.
Nonlinear autoregressive with exogenous inputs recurrent neural network (NARX-RNN)	SOH estimation of Li-ion batteries under sensor measurements unavailability.	• The proposed SOH estimation approach holds promise for industrial applications prone to random data unavailability.	[176]
NARX-RNN	Long-horizon SOH and RUL prediction of Li-ion battery.	• The algorithm achieved an RMSE within 3% and MAE within 2% for unseen data. This high level of accuracy is crucial for reliable SOH estimation and RUL prediction. • Low computational complexity.	[177]
Hybrid of Monte Carlo tree search and deep neural network.	Preventive maintenance considering reliability.	• The algorithm is responsible for determining when and which battery cells should be replaced. • It is 10 times faster and offering superior decision-making performance than the game theoretical approach.	[178]
Feed-forward migration neural network	Prediction of aging trajectories of Li-ion batteries.	• It's able to predict the aging trajectories without covering the knee point. • Stable results with random initialization. • It is applicable to various battery types without needing electrochemical data.	[179]
Back-propagation neural network (BPNN)	SOH estimation of Li-ion batteries under different dynamic operating conditions based on feature extraction.	• The SOH estimation method relies on the accuracy of equivalent circuit model and the fused features. Inaccuracies or limitations in these components, could affect the accuracy of the SOH estimation. • SOH estimation method is independent of the accuracy of the SOC of the battery. • Lacks robustness and adaptability to extreme or unfamiliar operating conditions.	[180]
The ternary hybrid of CNN, convolutional block attention module (CBAM) and LSTM.	SOH estimation of Li-ion batteries without manual feature extraction.	• The CBAM helps reduce noise in the raw data and improves CNN's ability to extract health features. • Achieved high accuracy in SOH estimation.	[181]
Spiral self-attention neural network (SS-ANN)	Real-time temperature prediction for thermal fault prognosis	• Adaptable to various climates and operational conditions. • Excellent temperature prediction aids in the early detection of thermal anomalies.	[40]

capacity. This self-training process improves the accuracy of future degradation predictions. The model also incorporated a probabilistic dense layer to estimate uncertainty using probabilistic predictions of future capacity. The proposed method was evaluated for different application scenarios, including batteries with different profiles and types. The

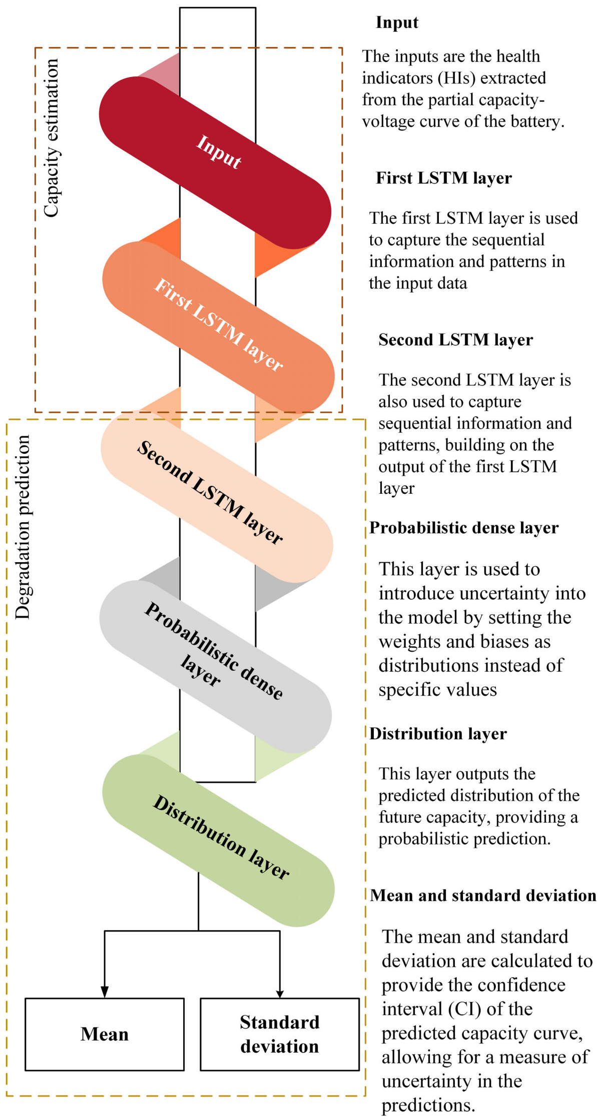

FIGURE 17. Framework and training process of the lifetime model.

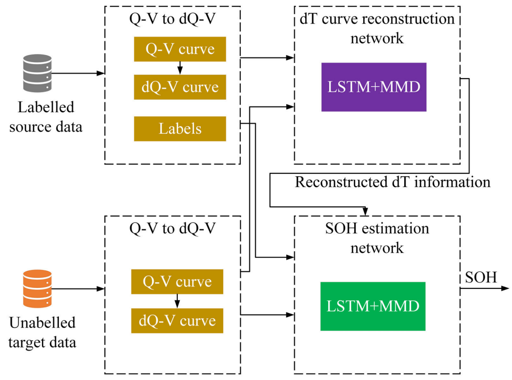

FIGURE 18. Framework for domain adaptative battery health prognostics with dT curve reconstruction and SoH estimation.

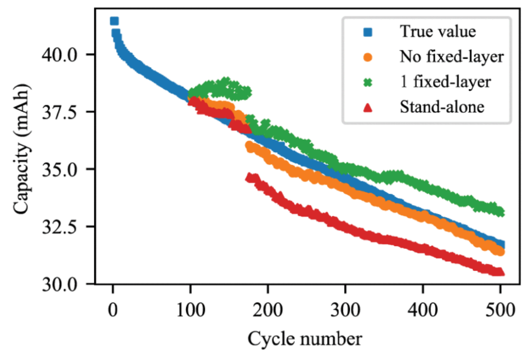

FIGURE 19. DNN-TL with no fixed-layer and 1 fixed-layer compared with the stand-alone DNN model [183].

results showed that the method achieved an accurate lifetime prediction with limited known labelled data. The mean lifetime prediction error was less than 23 cycles, with only three known checkpoints for battery aging under different profiles. For different battery types, the errors were less than 50 cycles with less than 4.1% relative errors for long-lifespan batteries and less than 20 cycles with less than 5.21% relative errors for short-lifespan batteries. However, this method demonstrated good accuracy with a small amount of checkpoint data, obtaining these checkpoints in real-world applications remains challenging. The limited availability of labelled data can hinder the effectiveness of this method. Feature-based SOH estimation has recently received considerable attention, with researchers using different HIs, such as voltage, current and time. To consider the rarely utilized variable temperature of a battery as a health indicator, the authors of [187] proposed a novel method for battery health prognosis using sensor-free differential temperature (dT) voltammetry reconstruction and SOH estimation. The proposed method uses a multi-domain adaptation approach to improve the dT curve reconstruction and SOH estimation accuracy. The framework presented in Fig.18 illustrates an approach using a domain-adaptive end-to-end framework. The capacity-voltage (Q-V) curve is transformed into a dQ-V curve (forming the dQ sequence) and inputted into a neural network. An LSTM layer extracted the hidden information owing to the strong temporal relationships in the data. This was followed by a fully connected layer that predicted the dT sequence. The maximum mean discrepancy (MMD) loss minimizes the domain differences between the source and target batteries. The estimated dT and dQ sequences were then used for SOH estimation, incorporating MMD loss to reduce domain discrepancies before the final output. The results revealed that under different scenarios, the mean errors were less than 0.067^{o}C/V for dT curves and 1.78% for SOH. Compared with the conventional data-driven method without TL, the proposed method reduces the error for the dT curve reconstruction by more than 20% and the SOH estimation error by more than 47%. In another study [183], TL in conjunction with a Deep Neural Network (DNN) was proposed for capacity estimation of Li-ion batteries using EIS measurements as the input features to the base model. In the

TABLE 5. Advantages and disadvantages of the different reliability evaluation techniques [97], [189], [190], [191], [192], [192], [193], [194], [195].

Techniques	Main area of Application	Advantages	Disadvantages
FMMEA	Comprehensive risk assessment and failure prevention for battery systems.	• Assesses risks and criticality of failure modes. • Helps prioritize and allocate resources for mitigation. • Enhances understanding of battery failure behavior. • Facilitates design improvements and risk reduction. • Supports early detection and prevention of failures.	• Requires domain knowledge and expertise. • Time-consuming process. • Subjective assessment may potentially lead to bias. • Limited to known failure mechanisms. • Can be resource-intensive for detailed analysis. • Lack of data support.
X-ray computed tomography	Internal structure analysis, defect detection, and quality control of battery cells and packs.	• Provides detailed 3D internal structure. • Non-destructive technique. • Detects internal defects and anomalies. • Identifies thermal management issues. • Aids in diagnosing degradation mechanisms. • Suitable for in-situ and post-mortem analysis.	• Radiation exposure can be a concern. • Equipment and setup costs can be expensive. • Complex data interpretation. • Requires large amount of data storage and data analysis. • Often requires the service of an expert to operate scan equipment. • Subject to artifacts and noise.
Scanning electron microscopy	Identifying contaminants or impurities in battery materials, investigating particle size and distribution, analyzing the morphology of electrodes and SEI, characterizing electrode materials.	• High-resolution imaging. • Ability to conduct chemical analysis using energy dispersive x-ray spectroscopy. • Crystallographic analysis using electron backscatter diffraction. • Minimal sample manipulation [196].	• High cost and complexity: SEM equipment is expensive and requires skilled operators. • Sample preparation can be time-consuming and may introduce artifacts [196].
Multiphysics modelling	Capacity fade prognosis, State of Health estimation, internal short circuit and thermal runaway investigation.	• It considers various multi-faceted nonlinear paths that decrease the performance of Li-ion battery. • Facilitates the optimization of Li-ion battery designs. • Enables realistic simulations that mimic real world conditions and behaviors [42].	• Creating and solving Multiphysics models can be complex requiring advanced mathematical skills. • Simulation setup, execution, and post-processing can be time-consuming due to the complexity of models. • Demands significant computational resources, including high-performance computing clusters [42].

TABLE 5. ***(Continued.)*** **Advantages and disadvantages of the different reliability evaluation techniques [97], [189], [190], [191], [192], [192], [193], [194], [195].**

Techniques	Main area of Application	Advantages	Disadvantages
EIS	Battery performance monitoring, state-of-health estimation, and degradation analysis.	• Non-destructive technique. • Measures internal resistance and impedance. • Possibility for on-board implementation subject to SNR and time invariance. • Enables measurement at frequencies and SOC. • Good measurement accuracy.	• Complex computation (requires fitting a model). • Not universal (model dependent). • Accuracy dependent on different sources: measurements and model. • Complex hardware design and time-intensive signal injection processes.
IC-DV analysis	Detection of capacity fade, electrode degradation, and performance issues.	• Accuracy dependent mostly on the measurement. • Possibility for on-board implementation subject to C-rate. • Simple calculation. • Universal (model independent).	• Long test duration (10h/cell). • Some degradation modes may not be captured. • Sensitivity to measurement noise. • Complex data analysis and interpretation. • Limited to specific testing conditions.
Machine learning algorithms	Data-driven predictive maintenance, remaining useful life estimation, and anomaly detection.	• Automates complex data analysis. • Handles large and complex datasets. • Identifies failure patterns not obvious to humans. • Enables real-time monitoring and prediction. • Supports decision-making for maintenance. • Provides insights into degradation mechanisms.	• Requires significant data for training. • Data quality and availability affect performance. • Black-box nature limits interpretability. • High computational requirements for complex models. • Model selection and parameter tuning complexity. • Vulnerable to bias if training data is not diverse.
Transfer Learning	Battery health monitoring, fault diagnosis, and performance optimization.	• Improved model performance. • Requires less data for training new models. • Shortens development time by utilizing existing knowledge. • Enhanced generalization: Can adapt well to new or useen data.	• Transferring knowledge might lead to overfitting if not adjusted properly. • Dependency on source data quality.

study, the base DNN model was trained and validated using a source dataset comprising EIS measurements and battery capacity at 25°C and 35°C. Then, followed by retraining and validation of the base model using the first 50% and first 20% of the target dataset at 45°C. This created a new DNN-TL model that carried the knowledge from the base model. The DNN-TL model was then used to predict the remaining portion of the target dataset (50% and 80%), which were considered as missing data. The effect of the number of fixed layers on the DNN retention was also investigated. Finally, the efficacy and comprehensiveness of the method were evaluated by comparing it with a benchmark standalone DNN base model without TL. Fig.19 depicts the performance of the predicted capacity based on DNN-TL with no fixed layer and one fixed layer compared with the standalone DNN model and the true value of the capacity based on the validation dataset. Evidently, the DNN-TL model followed the true capacity value and outperformed the standalone DNN model. In addition, the DNN-TL model with no fixed layer demonstrated outstanding performance compared with other models, specifically the standalone base model. Generally, the results showed that the DNN-TL model achieved high accuracy in the estimation of the battery capacity, with an MAPE of 0.605% and an average coefficient of determination (R-squared) of 0.9683. However, only EIS measurements at SOC 0% and 100% were tested in their approach, limiting the effectiveness of the method across a wider range of SOC values. Moreover, EIS measurements are noise-related and hence require signal-processing techniques such as filtering. TL has also been applied to health assessment in PHM in [188]. The proposed framework integrates probabilistic multi-task learning (2D convolutional neural network-Long Short-Term Memory-Bayesian neural network and Kneedle method) to predict battery knee, lifetime, SOH degradation, and aging rate variations early. The health assessment strategy involves the detection of different working condition stages such as "green" health region, "yellow" accelerating aging region, and "red" fast aging region. This assessment was based on the predictions of the knee slope, future degradation curve, and variation rates of the degradation curve. The framework also includes onboard prediction, cloud-edge collaboration for model improvement, and TL for model adjustment in onboard applications. The proposed method combined different prediction tasks to improve integrity. Simultaneously, it maintains accuracy, is flexible for adjustment to additional practical requirements, and can be extrapolated to other batteries aged under various operating conditions. The results indicated that the proposed method improves early predictions, sequence prediction reliability, and detection of accelerated battery aging, thus providing a suitable solution to facilitate practical applications and economizing resources by minimizing the need for separate model construction. It also shows impressive accuracy and provides advantages for integrating distinct, yet interrelated prognostic tasks into future battery management systems.

V. RECOMMENDATION

In light of the comprehensive analysis presented in this survey paper on the reliability assessment of Li-ion batteries for electric vehicles, several key recommendations have emerged.

- **Standardization of Testing Protocols:** The development and implementation of standardized testing protocols for battery reliability assessments are crucial. A unified approach would facilitate accurate comparisons between different studies and ensure a consistent evaluation across the automotive industry. For example, standardized protocols can be used to assess the performance and reliability of Li-ion batteries under various operating conditions such as extreme temperatures, high load demands, and rapid charging. This can help manufacturers and researchers to identify potential weaknesses and optimize battery designs to improve reliability.
- **Integration of Real-World Data:** Incorporating real-world usage data from EVs can provide a more accurate representation of battery performance under various conditions. For instance, by collecting data on driving patterns, charging habits, and environmental factors, researchers can analyze the impact of different usage scenarios on battery reliability. These data can be used to validate reliability assessment techniques and develop predictive models that account for real-world conditions.
- **Integration of Controller Area Network (CAN) for enhanced assessment:** CAN enables the seamless exchange of information between different modules within the EV, such as the battery pack, motor controller, and charging system. This real-time data sharing allows for a holistic understanding of the battery behavior under various conditions, including temperature fluctuations, load changes, and charge/discharge cycles. Utilizing CAN-based communication, researchers can access critical parameters such as voltage, current, temperature, and state of charge with high precision and frequency, enabling them to detect anomalies and deviations in battery performance promptly.
- **Regulatory Considerations:** Policymakers and regulatory bodies should actively engage with researchers and industry experts to establish guidelines that ensure the reliability and safety of Li-ion batteries in EVs. For example, regulations can mandate standardized testing procedures, require the integration of safety features in battery designs, and set performance benchmarks for battery reliability. These regulations should evolve in tandem with technological advancements to ensure the continuous improvement of battery reliability in EVs.

VI. CONCLUSION

The degradation of Li-ion batteries in electric vehicles owing to charging and discharging cycles and their abusive usage highlight the necessity of assessing their reliability. This assessment is crucial for the lifespan, design, maintenance, and service of an electric vehicle. A comprehensive overview of state-of-the-art battery reliability assessment techniques was presented in this survey paper. Based on the synthesized and critically examined nature of techniques, the type of data used, and the way reliability assessments are conducted, this survey paper categorized reliability assessment into two groups: qualitative and quantitative approaches. Qualitative methods such as failure modes mechanisms and effects analysis, X-ray computed tomography, and scanning electron microscopy have focused on understanding the potential failure mechanisms and material structure/composition, respectively. They are primarily used in early battery design, risk identification, and post-mortem analysis; however, they lack real-time applications in battery management systems. Conversely, quantitative approaches, such as multiphysics modelling, electrochemical impedance spectroscopy, incremental capacity analysis/differential voltage analysis, machine learning, and transfer learning provide comprehensive real-time insights into battery performance. Electrochemical impedance spectroscopy, incremental capacity analysis and differential voltage analysis reveal aging-related issues and nonlinear degradation within batteries but require laboratory tests, the data of which can be used to train and validate machine learning models. Machine learning and transfer learning offer adaptable approaches for battery management systems but demand more data and complex computational resources. Quantitative methods are considered more cost-effective than qualitative methods in terms of labor and equipment expenses. Recommendations to enhance the reliability of Li-ion batteries in electric vehicles have been suggested, including standardized testing, real-world data integration, controller area network integration into battery management systems, and regulatory considerations. This survey paper serves as a valuable resource for researchers, engineers, and policymakers in the field, providing insights into the current landscape and guiding future efforts toward achieving higher levels of battery reliability.

REFERENCES

[1] J.-P. Rodrigue, *The Geography of Transport Systems*, 5th ed. Evanston, IL, USA: Routledge, May 2020.

[2] (2022). *CO_2 Emissions in 2022—Analysis IEA*. [Online]. Available: https://www.iea.org/reports/co2-emissions-in-2022

[3] P. Suttakul, W. Wongsapai, T. Fongsamootr, Y. Mona, and K. Poolsawat, ''Total cost of ownership of internal combustion engine and electric vehicles: A real-world comparison for the case of Thailand,'' *Energy Rep.*, vol. 8, pp. 545–553, Nov. 2022.

[4] S. S. G. Acharige, Md. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, ''Review of electric vehicle charging technologies, standards, architectures, and converter configurations,'' *IEEE Access*, vol. 11, pp. 41218–41255, 2023.

[5] A. Senyshyn, M. J. Mühlbauer, O. Dolotko, and H. Ehrenberg, ''Low-temperature performance of Li-ion batteries: The behavior of lithiated graphite,'' *J. Power Sources*, vol. 282, pp. 235–240, May 2015.

[6] D. Shen, T. Xu, L. Wu, and Y. Guan, ''Research on degradation modeling and life prediction method of lithium-ion battery in dynamic environment,'' *IEEE Access*, vol. 7, pp. 130638–130649, 2019.

[7] A. El Mejdoubi, H. Chaoui, H. Gualous, P. Van Den Bossche, N. Omar, and J. Van Mierlo, ''Lithium-ion batteries health prognosis considering aging conditions,'' *IEEE Trans. Power Electron.*, vol. 34, no. 7, pp. 6834–6844, Jul. 2019.

[8] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K. C. Möller, J. O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, ''Ageing mechanisms in lithium-ion batteries,'' *J. Power Sources*, vol. 147, nos. 1–2, pp. 269–281, 2005.

[9] Z. Zhang, W. Fang, and R. Ma, ''Brief review of batteries for XEV applications,'' *eTransportation*, vol. 2, Nov. 2019, Art. no. 100032.

[10] E. Sarasketa-Zabala, I. Gandiaga, E. Martinez-Laserna, L. M. Rodriguez-Martinez, and I. Villarreal, ''Cycle ageing analysis of a $LiFePO_4$/graphite cell with dynamic model validations: Towards realistic lifetime predictions,'' *J. Power Sources*, vol. 275, pp. 573–587, Feb. 2015.

[11] Y. Zhang, C.-Y. Wang, and X. Tang, ''Cycling degradation of an automotive $LiFePO_4$ lithium-ion battery,'' *J. Power Sources*, vol. 196, no. 3, pp. 1513–1520, Feb. 2011.

[12] Y. Zhao, Z. Wang, Z. Sun, P. Liu, D. Cui, and J. Deng, ''Data-driven lithium-ion battery degradation evaluation under overcharge cycling conditions,'' *IEEE Trans. Power Electron.*, vol. 38, no. 8, pp. 10138–10150, Aug. 2023.

[13] S. Xie, L. Ren, X. Yang, H. Wang, Q. Sun, X. Chen, and Y. He, ''Influence of cycling aging and ambient pressure on the thermal safety features of lithium-ion battery,'' *J. Power Sources*, vol. 448, Feb. 2020, Art. no. 227425.

[14] D.-I. Stroe, M. Swierczynski, S. K. Kær, E. M. Laserna, and E. S. Zabala, ''Accelerated aging of lithium-ion batteries based on electric vehicle mission profile,'' in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Oct. 2017, pp. 5631–5637.

[15] D. I. Stroe, M. Swierczynski, S. K. Kær, and R. Teodorescu, ''Degradation behavior of lithium-ion batteries during calendar ageing—The case of the internal resistance increase,'' *Proc. IEEE Trans. Ind. Appl.*, vol. 54, no. 1, pp. 517–525, Sep. 2018.

[16] E. Redondo-Iglesias, P. Venet, and S. Pelissier, ''Efficiency degradation model of lithium-ion batteries for electric vehicles,'' *IEEE Trans. Ind. Appl.*, vol. 55, no. 2, pp. 1932–1940, Mar. 2019.

[17] D. Stroe, M. Świerczyński, A.-I. Stan, R. Teodorescu, and S. J. Andreasen, ''Experimental investigation on the internal resistance of Lithium iron phosphate battery cells during calendar ageing,'' in *Proc. 39th Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2013, pp. 6734–6739.

[18] E. Redondo-Iglesias, P. Venet, and S. Pelissier, ''Eyring acceleration model for predicting calendar ageing of lithium-ion batteries,'' *J. Energy Storage*, vol. 13, pp. 176–183, Oct. 2017.

[19] A. Eddahech, O. Briat, and J.-M. Vinassa, ''Performance comparison of four lithium–ion battery technologies under calendar aging,'' *Energy*, vol. 84, pp. 542–550, May 2015.

[20] E. Redondo-Iglesias, P. Venet, and S. Pelissier, ''Calendar and cycling ageing combination of batteries in electric vehicles,'' *Microelectron. Rel.*, vols. 88–90, pp. 1212–1215, Sep. 2018.

[21] N. Collath, B. Tepe, S. Englberger, A. Jossen, and H. Hesse, ''Aging aware operation of lithium-ion battery energy storage systems: A review,'' *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105634. [Online]. Available: http://creativecommons.org/licenses/by/4.0/

[22] X. Han, L. Lu, Y. Zheng, X. Feng, Z. Li, J. Li, and M. Ouyang, ''A review on the key issues of the lithium ion battery degradation among the whole life cycle,'' *eTransportation*, vol. 1, Aug. 2019, Art. no. 100005.

[23] W. Vermeer, G. R. Chandra Mouli, and P. Bauer, ''A comprehensive review on the characteristics and modeling of lithium-ion battery aging,'' *IEEE Trans. Transport. Electrific.*, vol. 8, no. 2, pp. 2205–2232, Jun. 2022.

[24] M. M. Kabir and D. E. Demirocak, ''Degradation mechanisms in Li-ion batteries: A state-of-the-art review,'' *Int. J. Energy Res.*, vol. 41, no. 14, pp. 1963–1986, Nov. 2017.

[25] M. Broussely, P. Biensan, F. Bonhomme, P. Blanchard, S. Herreyre, K. Nechev, and R. J. Staniewicz, ''Main aging mechanisms in Li ion batteries,'' *J. Power Sources*, vol. 146, nos. 1–2, pp. 90–96, Aug. 2005.

[26] F. H. Gandoman, J. Jaguemont, S. Goutam, R. Gopalakrishnan, Y. Firouz, T. Kalogiannis, N. Omar, and J. Van Mierlo, ''Concept of reliability and safety assessment of lithium-ion batteries in electric vehicles: Basics, progress, and challenges,'' *Appl. Energy*, vol. 251, Oct. 2019, Art. no. 113343.

[27] S. Paul, C. Diegelmann, H. Kabza, and W. Tillmetz, ''Analysis of ageing inhomogeneities in lithium-ion battery systems,'' *J. Power Sources*, vol. 239, pp. 642–650, Oct. 2013.

[28] P. Keil, S. F. Schuster, J. Wilhelm, J. Travi, A. Hauser, R. C. Karl, and A. Jossen, ''Calendar aging of lithium-ion batteries,'' *J. Electrochemical Soc.*, vol. 163, no. 9, pp. A1872–A1880, 2016.

[29] B. Balagopal, C. S. Huang, and M.-Y. Chow, ''Effect of calendar ageing on SEI growth and its impact on electrical circuit model parameters in lithium ion batteries,'' in *Proc. IEEE Int. Conf. Ind. Electron. Sustain. Energy Syst. (IESES)*, Jan. 2018, pp. 32–37.

[30] Y. Che, X. Hu, X. Lin, J. Guo, and R. Teodorescu, ''Health prognostics for lithium-ion batteries: Mechanisms, methods, and prospects,'' *Energy Environ. Sci.*, vol. 16, no. 2, pp. 338–371, 2023.

[31] Q. Wang, P. Ping, X. Zhao, G. Chu, J. Sun, and C. Chen, ''Thermal runaway caused fire and explosion of lithium ion battery,'' *J. Power Sources*, vol. 208, pp. 210–224, Jun. 2012.

[32] X. Feng, M. Ouyang, X. Liu, L. Lu, Y. Xia, and X. He, ''Thermal runaway mechanism of lithium ion battery for electric vehicles: A review,'' *Energy Storage Mater.*, vol. 10, pp. 246–267, Jan. 2018.

[33] B. Ji, X. G. Song, W. P. Cao, and V. Pickert, ''Active temperature control of Li-ion batteries in electric vehicles,'' in *Proc. IET Hybrid Electr. Vehicles Conf. (HEVC)*, Nov. 2013, pp. 1–5.

[34] P. Sun, R. Bisschop, H. Niu, and X. Huang, "A review of battery fires in electric vehicles," *Fire Technol.*, vol. 56, pp. 1361–1410, Jul. 2020, doi: 10.1007/s10694-019-00944-3.

[35] Y. S. Duh, Y. Sun, X. Lin, J. Zheng, M. Wang, Y. Wang, X. Lin, X. Jiang, Z. Zheng, S. Zheng, and G. Yu, "Characterization on thermal runaway of commercial 18650 lithium-ion batteries used in electric vehicles: A review," *J. Energy Storage*, Sep. 2021, doi: 10.1016/j.est.2021.102888.

[36] N. Williard, W. He, C. Hendricks, and M. Pecht, "Lessons learned from the 787 dreamliner issue on lithium-ion battery reliability," *Energies*, vol. 6, no. 9, pp. 4682–4695, Sep. 2013.

[37] Andrew Norsworthy. (Aug. 2023). *EV Fires Require More Water, Firefighters Say*. [Online]. Available: https://dallasexpress.com/national/ev-fires-require-more-water-firefighters-say/

[38] A. Łebkowski, "Electric vehicle fire extinguishing system," *Przeglad Elektrotechniczny*, vol. 93, no. 1, pp. 329–332, Jan. 2017.

[39] Barry Courter. (Jul. 2021). *Electric Cars Introduce New Potential Hazards in an Accident | Chattanooga Times Free Press*. [Online]. Available: https://www.timesfreepress.com/news/2021/jul/18/electric-cars-introduce-new-potential-hazards-acci/

[40] J. Hong, H. Zhang, and X. Xu, "Thermal fault prognosis of lithium-ion batteries in real-world electric vehicles using self-attention mechanism networks," *Appl. Thermal Eng.*, vol. 226, May 2023, Art. no. 120304.

[41] F. H. Gandoman, T. Kalogiannis, M. Berecibar, J. Van Mierlo, and P. Van Den Bossche, "Quantitative analysis techniques for evaluating the reliability of Li-ion battery: Challenges and solutions," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Nov. 2020, pp. 1–5.

[42] Q. Xia, Z. Wang, Y. Ren, B. Sun, D. Yang, and Q. Feng, "A reliability design method for a lithium-ion battery pack considering the thermal disequilibrium in electric vehicles," *J. Power Sources*, vol. 386, pp. 10–20, May 2018.

[43] B. Xu, D. Qian, Z. Wang, and Y. S. Meng, "Recent progress in cathode materials research for advanced lithium ion batteries," *Mater. Sci. Eng., R, Rep.*, vol. 73, nos. 5–6, pp. 51–65, May 2012.

[44] H. Cheng, J. G. Shapter, Y. Li, and G. Gao, "Recent progress of advanced anode materials of lithium-ion batteries," *J. Energy Chem.*, vol. 57, pp. 451–468, Jun. 2021.

[45] J. Xing, S. Bliznakov, L. Bonville, M. Oljaca, and R. Maric, "A review of nonaqueous electrolytes, binders, and separators for lithium-ion batteries," *Electrochem. Energy Rev.*, vol. 5, no. 4, p. 14, Dec. 2022.

[46] F. H. Gandoman, A. Ahmadi, P. V. D. Bossche, J. Van Mierlo, N. Omar, A. E. Nezhad, H. Mavalizadeh, and C. Mayet, "Status and future perspectives of reliability assessment for electric vehicles," *Rel. Eng. Syst. Saf.*, vol. 183, pp. 1–16, Mar. 2019.

[47] F. H. Gandoman, E. M. Ahmed, Z. M. Ali, M. Berecibar, A. F. Zobaa, and S. H. E. Abdel Aleem, "Reliability evaluation of lithium-ion batteries for E-mobility applications from practical and technical perspectives: A case study," *Sustainability*, vol. 13, no. 21, p. 11688, Oct. 2021.

[48] Y. Mekonnen, A. Sundararajan, and A. I. Sarwat, "A review of cathode and anode materials for lithium-ion batteries," in *Proc. SoutheastCon*, Mar. 2016, pp. 1–6.

[49] Y. Qiu and F. Jiang, "A review on passive and active strategies of enhancing the safety of lithium-ion batteries," *Int. J. Heat Mass Transf.*, vol. 184, Mar. 2022, Art. no. 122288.

[50] C. Hendricks, N. Williard, S. Mathew, and M. Pecht, "A failure modes, mechanisms, and effects analysis (FMMEA) of lithium-ion batteries," *J. Power Sources*, vol. 297, pp. 113–120, Nov. 2015.

[51] G.-L. Xu, Q. Wang, J.-C. Fang, Y.-F. Xu, J.-T. Li, L. Huang, and S.-G. Sun, "Tuning the structure and property of nanostructured cathode materials of lithium ion and lithium sulfur batteries," *J. Mater. Chem. A*, vol. 2, no. 47, pp. 19941–19962, 2014.

[52] A. K. M. A. Habib, S. M. A. Motakabber, and M. I. Ibrahimy, "A comparative study of electrochemical battery for electric vehicles applications," in *Proc. IEEE Int. Conf. Power, Electr., Electron. Ind. Appl. (PEEIACON)*, Nov. 2019, pp. 43–47.

[53] A. I. Stan, M. Swierczynski, D. I. Stroe, R. Teodorescu, and S. J. Andreasen, "Lithium ion battery chemistries from renewable energy storage to automotive and back-up power applications—An overview," in *Proc. Int. Conf. Optim. Electr. Electron. Equip.*, Sep. 2014, pp. 713–720.

[54] G. E. Blomgren, "The development and future of lithium ion batteries," *J. Electrochem. Soc.*, vol. 164, no. 1, pp. A5019–A5025, 2017.

[55] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *J. Power Sources*, vol. 241, pp. 680–689, Nov. 2013.

[56] K. Bellache, M. B. Camara, B. Dakyo, and S. Ramasamy, "Aging characterization of lithium iron phosphate batteries considering temperature and direct current undulations as degrading factors," *IEEE Trans. Ind. Electron.*, vol. 68, no. 10, pp. 9696–9706, Oct. 2021.

[57] H. Ge, T. Aoki, N. Ikeda, S. Suga, T. Isobe, Z. Li, Y. Tabuchi, and J. Zhang, "Investigating lithium plating in lithium-ion batteries at low temperatures using electrochemical model with NMR assisted parameterization," *J. Electrochem. Soc.*, vol. 164, no. 6, pp. A1050–A1060, 2017.

[58] Y. Ji, Y. Zhang, and C.-Y. Wang, "Li-ion cell operation at low temperatures," *J. Electrochem. Soc.*, vol. 160, no. 4, pp. A636–A649, 2013.

[59] S. Zhang and J. Zhang, "Optimal state-of-charge value for charge-sustaining mode of plug-in hybrid electric vehicles," *IEEE Access*, vol. 8, pp. 187959–187964, 2020.

[60] Q. Zhang, C.-G. Huang, H. Li, G. Feng, and W. Peng, "Electrochemical impedance spectroscopy based state-of-health estimation for lithium-ion battery considering temperature and state-of-charge effect," *IEEE Trans. Transport. Electrific.*, vol. 8, no. 4, pp. 4633–4645, Dec. 2022.

[61] S. Xie, S. Qi, and K. Lang, "A data-driven power management strategy for plug-in hybrid electric vehicles including optimal battery depth of discharging," *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3387–3396, May 2020.

[62] J. D. Dogger, B. Roossien, and F. D. J. Nieuwenhout, "Characterization of Li-ion batteries for intelligent management of distributed grid-connected storage," *IEEE Trans. Energy Convers.*, vol. 26, no. 1, pp. 256–263, Mar. 2011.

[63] N. Lyu, Y. Jin, R. Xiong, S. Miao, and J. Gao, "Real-time overcharge warning and early thermal runaway prediction of Li-ion battery by online impedance measurement," *IEEE Trans. Ind. Electron.*, vol. 69, no. 2, pp. 1929–1936, Feb. 2022.

[64] K. Maher and R. Yazami, "Effect of overcharge on entropy and enthalpy of lithium-ion batteries," *Electrochimica Acta*, vol. 101, pp. 71–78, Jul. 2013.

[65] X. Zhu, Z. Wang, C. Wang, and L. Huang, "Overcharge investigation of large format lithium-ion pouch cells with $Li(Ni_{0.6}Co_{0.2}Mn_{0.2})O_2$ cathode for electric vehicles: Degradation and failure mechanisms," *J. Electrochemical Soc.*, vol. 165, no. 16, pp. A3613–A3629, 2018.

[66] N. Gan, Z. Sun, Z. Zhang, S. Xu, P. Liu, and Z. Qin, "Data-driven fault diagnosis of lithium-ion battery overdischarge in electric vehicles," *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 4575–4588, Apr. 2022.

[67] H. Maleki and J. N. Howard, "Effects of overdischarge on performance and thermal stability of a Li-ion cell," *J. Power Sources*, vol. 160, no. 2, pp. 1395–1402, Oct. 2006.

[68] V. Agubra and J. Fergus, "Lithium ion battery anode aging mechanisms," *Materials*, vol. 6, no. 4, pp. 1310–1325, Mar. 2013.

[69] C. R. Birkl, M. R. Roberts, E. McTurk, P. G. Bruce, and D. A. Howey, "Degradation diagnostics for lithium ion cells," *J. Power Sources*, vol. 341, pp. 373–386, Feb. 2017.

[70] M. Amini, M. H. Nazari, and S. H. Hosseinian, "Optimal scheduling and cost-benefit analysis of lithium-ion batteries based on battery state of health," *IEEE Access*, vol. 11, pp. 1359–1371, 2023.

[71] X. Lu, J. Qiu, G. Lei, and J. Zhu, "State of health estimation of lithium iron phosphate batteries based on degradation knowledge transfer learning," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 3, pp. 4692–4703, Sep. 2023.

[72] F. Yang, D. Wang, Y. Zhao, K. L. Tsui, and S. J. Bae, "A study of the relationship between Coulombic efficiency and capacity degradation of commercial lithium-ion batteries," *Energy*, vol. 145, pp. 486–495, Feb. 2018.

[73] P. Liu, Y. Wu, C. She, Z. Wang, and Z. Zhang, "Comparative study of incremental capacity curve determination methods for lithium-ion batteries considering the real-world situation," *IEEE Trans. Power Electron.*, vol. 37, no. 10, pp. 12563–12576, Oct. 2022.

[74] S. T. Mowri, A. Barai, A. Gupta, and J. Marco, "Modification of degradation mechanism identification technique for cell grading," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Oct. 2021, pp. 1–5.

[75] Z. Jiao, H. Wang, J. Xing, Q. Yang, M. Yang, Y. Zhou, and J. Zhao, "A LightGBM based framework for lithium-ion battery remaining useful life prediction under driving conditions," *IEEE Trans. Ind. Informat.*, vol. 19, no. 11, pp. 11353–11362, Nov. 2023.

[76] D. Anseán, V. M. García, M. González, C. Blanco-Viejo, J. C. Viera, Y. F. Pulido, and L. Sánchez, "Lithium-ion battery degradation indicators via incremental capacity analysis," *IEEE Trans. Ind. Appl.*, vol. 55, no. 3, pp. 2992–3002, May 2019.

[77] S. Lee and Y. Kim, ''Li-ion battery electrode health diagnostics (don't short) using machine learning,'' in *Proc. Amer. Control Conf. (ACC)*, Jul. 2020, pp. 1137–1142.

[78] X. Lu, J. Qiu, G. Lei, and J. Zhu, ''Degradation mode knowledge transfer method for LFP batteries,'' *IEEE Trans. Transport. Electrific.*, vol. 9, no. 1, pp. 1142–1152, Mar. 2023.

[79] J. S. Edge, S. O'Kane, R. Prosser, N. D. Kirkaldy, A. N. Patel, A. Hales, A. Ghosh, W. Ai, J. Chen, J. Yang, S. Li, M. C. Pang, L. B. Diaz, A. Tomaszewska, M. W. Marzook, K. N. Radhakrishnan, H. Wang, Y. Patel, B. Wu, and G. J. Offer, ''Lithium ion battery degradation: What you need to know,'' *Phys. Chem. Chem. Phys.*, vol. 23, no. 14, pp. 8200–8221, 2021.

[80] X. Zhang, Y. Gao, B. Guo, C. Zhu, X. Zhou, L. Wang, and J. Cao, ''A novel quantitative electrochemical aging model considering side reactions for lithium-ion batteries,'' *Electrochimica Acta*, vol. 343, May 2020, Art. no. 136070.

[81] T. Frambach, R. Liedtke, P. Dechent, D. U. Sauer, and E. Figgemeier, ''A review on aging-aware system simulation for plug-in hybrids,'' *IEEE Trans. Transport. Electrific.*, vol. 8, no. 2, pp. 1524–1540, Jun. 2022.

[82] M. Elmahallawy, T. Elfouly, A. Alouani, and A. M. Massoud, ''A comprehensive review of lithium-ion batteries modeling, and state of health and remaining useful lifetime prediction,'' *IEEE Access*, vol. 10, pp. 119040–119070, 2022.

[83] A. Alyakhni, L. Boulon, J.-M. Vinassa, and O. Briat, ''A comprehensive review on energy management strategies for electric vehicles considering degradation using aging models,'' *IEEE Access*, vol. 9, pp. 143922–143940, 2021.

[84] Y. Xiao, J. Wen, L. Yao, J. Zheng, Z. Fang, and Y. Shen, ''A comprehensive review of the lithium-ion battery state of health prognosis methods combining aging mechanism analysis,'' *J. Energy Storage*, Aug. 2023, doi: 10.1016/j.est.2023.107347.

[85] X. Lai, Y. Huang, C. Deng, H. Gu, X. Han, Y. Zheng, and M. Ouyang, ''Sorting, regrouping, and echelon utilization of the large-scale retired lithium batteries: A critical review,'' *Renew. Sustain. Energy Rev.*, vol. 146, Aug. 2021, Art. no. 111162.

[86] H. Ruan, J. V. Barreras, T. Engstrom, Y. Merla, R. Millar, and B. Wu, ''Lithium-ion battery lifetime extension: A review of derating methods,'' *J. Power Sources*, vol. 563, Apr. 2023, Art. no. 232805.

[87] J. Zeng and S. Liu, ''Research on aging mechanism and state of health prediction in lithium batteries,'' *J. Energy Storage*, 2023, doi: 10.1016/j.est.2023.108274.

[88] J. Guo, J. Yang, Z. Lin, C. Serrano, and A. M. Cortes, ''Impact analysis of V2G services on EV battery degradation—A review,'' in *Proc. IEEE Milan PowerTech, PowerTech*, Jun. 2019, pp. 1–6.

[89] M. Payette and G. Abdul-Nour, ''Machine learning applications for reliability engineering: A review,'' *Sustainability*, vol. 15, no. 7, p. 6270, Apr. 2023.

[90] R. Li, J.-F. Wu, H.-Y. Wang, J.-Y. Guo, and G.-C. Li, ''Reliability assessment and failure analysis of lithium iron phosphate batteries,'' *Inf. Sci.*, vol. 259, pp. 359–368, Feb. 2014.

[91] C. Schlasza, P. Ostertag, D. Chrenko, R. Kriesten, and D. Bouquain, ''Review on the aging mechanisms in Li-ion batteries for electric vehicles based on the FMEA method,'' in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Jun. 2014, pp. 1–6.

[92] M. Held and R. Brönnimann, ''Safe cell, safe battery? Battery fire investigation using FMEA, FTA and practical experiments,'' *Microelectron. Rel.*, vol. 64, pp. 705–710, Sep. 2016.

[93] T. L. Fantham and D. T. Gladwin, ''An overview of safety for laboratory testing of lithium-ion batteries,'' *Energy Rep.*, vol. 7, pp. 2–8, May 2021.

[94] M. Kaliaperumal, M. S. Dharanendrakumar, S. Prasanna, K. V. Abhishek, R. K. Chidambaram, S. Adams, K. Zaghib, and M. V. Reddy, ''Cause and mitigation of lithium-ion battery failure—A review,'' *Materials*, vol. 14, no. 19, p. 5676, Sep. 2021.

[95] A. F. Kirkels, J. Bleker, and H. A. Romijn, ''Ready for the road? A socio-technical investigation of fire safety improvement options for lithium-ion traction batteries,'' *Energies*, vol. 15, no. 9, p. 3323, May 2022.

[96] L. Li and J. Hou, ''Capacity detection of electric vehicle lithium-ion batteries based on X-ray computed tomography,'' *RSC Adv.*, vol. 8, no. 45, pp. 25325–25333, 2018.

[97] Y. Wu, S. Saxena, Y. Xing, Y. Wang, C. Li, W. Yung, and M. Pecht, ''Analysis of manufacturing-induced defects and structural deformations in lithium-ion batteries using computed tomography,'' *Energies*, vol. 11, no. 4, p. 925, Apr. 2018.

[98] C. Rahe, S. T. Kelly, M. N. Rad, D. U. Sauer, J. Mayer, and E. Figgemeier, ''Nanoscale X-ray imaging of ageing in automotive lithium ion battery cells,'' *J. Power Sources*, vol. 433, Sep. 2019, Art. no. 126631.

[99] L. Ju, X. Li, G. Geng, and Q. Jiang, ''Degradation diagnosis of lithium-ion batteries considering internal gas evolution,'' *J. Energy Storage*, vol. 71, Nov. 2023, Art. no. 108084.

[100] Y. Zhao, Y. Patel, I. A. Hunt, K. M. Kareh, A. A. Holland, C. Korte, J. P. Dear, Y. Yue, and G. J. Offer, ''Preventing lithium ion battery failure during high temperatures by externally applied compression,'' *J. Energy Storage*, vol. 13, pp. 296–303, Oct. 2017.

[101] V. Vanpeene, J. Villanova, J.-P. Suuronen, A. King, A. Bonnin, J. Adrien, E. Maire, and L. Roué, ''Monitoring the morphological changes of Si-based electrodes by X-ray computed tomography: A 4D-multiscale approach,'' *Nano Energy*, vol. 74, Aug. 2020, Art. no. 104848.

[102] S. Zhou, K. Liu, Y. Ying, L. Chen, G. Meng, Q. Zheng, S. G. Sun, and H. G. Liao, ''Perspective of operando/in situ scanning electron microscope in rechargeable batteries,'' *Current Opinion Electrochem.*, vol. 41, Oct. 2023, Art. no. 101374.

[103] M. J. Jackson and W. Ahmed, *Micro Nanomanufacturing*, vol. 2. Cham, Switzerland: Springer, Oct. 2017.

[104] D. J. Johnson, D. L. Oatley-Radcliffe, and N. Hilal, ''State of the art review on membrane surface characterisation: Visualisation, verification and quantification of membrane properties,'' *Desalination*, vol. 434, pp. 12–36, May 2018.

[105] P. Hovington, M. Dontigny, A. Guerfi, J. Trottier, M. Lagacé, A. Mauger, C. M. Julien, and K. Zaghib, ''In situ scanning electron microscope study and microstructural evolution of nano silicon anode for high energy Li-ion batteries,'' *J. Power Sources*, vol. 248, pp. 457–464, Feb. 2014.

[106] J. Zhu, X. Zhang, H. Luo, and E. Sahraei, ''Investigation of the deformation mechanisms of lithium-ion battery components using in-situ micro tests,'' *Appl. Energy*, vol. 224, pp. 251–266, Aug. 2018.

[107] W. Lu, C. M. López, N. Liu, J. T. Vaughey, A. Jansen, and W. D. Dennis, ''Overcharge effect on morphology and structure of carbon electrodes for lithium-ion batteries,'' *J. Electrochemical Soc.*, vol. 159, no. 5, pp. A566–A570, 2012.

[108] D. Chen, S. Indris, M. Schulz, B. Gamer, and R. Mönig, ''In situ scanning electron microscopy on lithium-ion battery electrodes using an ionic liquid,'' *J. Power Sources*, vol. 196, no. 15, pp. 6382–6387, Aug. 2011.

[109] Z. Wang, S. Xu, X. Zhu, H. Wang, L. Huang, J. Yuan, and W. Yang, ''Effects of short-term over-discharge cycling on the performance of commercial 21,700 lithium-ion cells and the identification of degradation modes,'' *J. Energy Storage*, vol. 35, Mar. 2021, Art. no. 102257.

[110] S. S. Madani, C. Ziebert, and M. Marzband, ''Thermal behavior modeling of lithium-ion batteries: A comprehensive review,'' *Symmetry*, Aug. 2023, doi: 10.3390/sym15081597.

[111] M. Corno, N. Bhatt, S. M. Savaresi, and M. Verhaegen, ''Electrochemical model-based state of charge estimation for Li-ion cells,'' *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 1, pp. 117–127, Jan. 2015.

[112] H. Rezk, A. G. Olabi, T. Wilberforce, and E. T. Sayed, ''A comprehensive review and application of metaheuristics in solving the optimal parameter identification problems,'' *Sustainability*, 2023, doi: 10.3390/su15075732.

[113] X. Hu, H. Yuan, C. Zou, Z. Li, and L. Zhang, ''Co-estimation of state of charge and state of health for lithium-ion batteries based on fractional-order calculus,'' *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10319–10329, Nov. 2018.

[114] J. Hemdani, L. Degaa, M. Soltani, N. Rizoug, A. J. Telmoudi, and A. Chaari, ''Prediction of aging electric vehicle battery by multi-physics modeling and deep learning method,'' in *Proc. 8th Int. Conf. Control, Decis. Inf. Technol.*, 2022, pp. 1641–1645.

[115] Y. Li, B. Xiong, D. M. Vilathgamuwa, Z. Wei, C. Xie, and C. Zou, ''Constrained ensemble Kalman filter for distributed electrochemical state estimation of lithium-ion batteries,'' *IEEE Trans. Ind. Informat.*, vol. 17, no. 1, pp. 240–250, Jan. 2021.

[116] M. K. Tran, M. Mathew, S. Janhunen, S. Panchal, K. Raahemifar, R. Fraser, and M. Fowler, ''A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters,'' *J. Energy Storage*, vol. 43, Nov. 2021, Art. no. 103252.

[117] M. T. Castro, J. A. D. Del Rosario, M. N. Chong, P. Y. A. Chuang, J. Lee, and J. D. Ocon, ''Multiphysics modeling of lithium-ion, lead-acid, and vanadium redox flow batteries,'' *J. Energy Storage*, 2021, doi: 10.1016/j.est.2021.102982.

[118] J. Li, Y. Cheng, L. Ai, M. Jia, S. Du, B. Yin, S. Woo, and H. Zhang, "3D simulation on the internal distributed properties of lithium-ion battery with planar tabbed configuration," *J. Power Sources*, vol. 293, pp. 993–1005, Jun. 2015.

[119] A. Samba, N. Omar, H. Gualous, O. Capron, P. Van Den Bossche, and J. Van Mierlo, "Impact of tab location on large format lithium-ion pouch cell based on fully coupled tree-dimensional electrochemical-thermal modeling," *Electrochimica Acta*, vol. 147, pp. 319–329, Nov. 2014.

[120] A. Nazari and S. Farhad, "Heat generation in lithium-ion batteries with different nominal capacities and chemistries," *Appl. Thermal Eng.*, vol. 125, pp. 1501–1517, Oct. 2017.

[121] E. Hosseinzadeh, J. Marco, and P. Jennings, "The impact of multi-layered porosity distribution on the performance of a lithium ion battery," *Appl. Math. Model.*, vol. 61, pp. 107–123, Sep. 2018.

[122] J. Mao, W. Tiedemann, and J. Newman, "Simulation of Li-ion cells by dualfoil model under constant-resistance load," *ECS Trans.*, vol. 58, no. 48, pp. 71–81, Apr. 2014.

[123] M. Torchio, L. Magni, R. B. Gopaluni, R. D. Braatz, and D. M. Raimondo, "LIONSIMBA: A MATLAB framework based on a finite volume model suitable for Li-ion battery design, simulation, and control," *J. Electrochem. Soc.*, vol. 163, no. 7, pp. A1192–A1205, 2016.

[124] Y. Li, M. Vilathgamuwa, T. Farrell, S. S. Choi, N. T. Tran, and J. Teague, "A physics-based distributed-parameter equivalent circuit model for lithium-ion batteries," *Electrochimica Acta*, vol. 299, pp. 451–469, Mar. 2019.

[125] S. Kosch, Y. Zhao, J. Sturm, J. Schuster, G. Mulder, E. Ayerbe, and A. Jossen, "A computationally efficient multi-scale model for lithium-ion cells," *J. Electrochemical Soc.*, vol. 165, no. 10, pp. A2374–A2388, 2018.

[126] S. Allu, S. Kalnaus, W. Elwasif, S. Simunovic, J. A. Turner, and S. Pannala, "A new open computational framework for highly-resolved coupled three-dimensional multiphysics simulations of Li-ion cells," *J. Power Sources*, vol. 246, pp. 876–886, Jan. 2014.

[127] Q. Xia, Z. Wang, Y. Ren, D. Yang, B. Sun, Q. Feng, and C. Qian, "Performance reliability analysis and optimization of lithium-ion battery packs based on multiphysics simulation and response surface methodology," *J. Power Sources*, vol. 490, Apr. 2021, Art. no. 229567.

[128] Q. Xia, D. Yang, Z. Wang, Y. Ren, B. Sun, Q. Feng, and C. Qian, "Multiphysical modeling for life analysis of lithium-ion battery pack in electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 131, Oct. 2020, Art. no. 109993.

[129] E. Hosseinzadeh, J. Marco, and P. Jennings, "Electrochemical-thermal modelling and optimisation of lithium-ion battery design parameters using analysis of variance," *Energies*, vol. 10, no. 9, p. 1278, 2017.

[130] L. Wang, J. Li, J. Chen, X. Duan, B. Li, and J. Li, "Revealing the internal short circuit mechanisms in lithium-ion batteries upon dynamic loading based on multiphysics simulation," *Appl. Energy*, vol. 351, Dec. 2023, Art. no. 121790.

[131] Y. Xie, J. Li, and C. Yuan, "Multiphysics modeling of lithium ion battery capacity fading process with solid-electrolyte interphase growth by elementary reaction kinetics," *J. Power Sources*, vol. 248, pp. 172–179, Feb. 2014.

[132] Y. Wang, J. Li, S. Guo, M. Zhao, W. Cui, L. Li, L. Zhao, and Z. Wang, "A method of lithium-ion battery failure diagnosis based on parameter boundaries of heterogeneous multi-physics aging model," *J. Power Sources*, vol. 576, Aug. 2023, Art. no. 233235.

[133] Y. Wang, J. Li, S. Ma, M. Zhao, C. Dai, L. Zhao, and Z. Wang, "A multi-scale heterogeneous electrochemical-diffusion-induced stress coupling model for lithium-ion batteries," *J. Electrochemical Soc.*, vol. 169, no. 10, Oct. 2022, Art. no. 100524.

[134] L. Yiding, W. Wenwei, L. Cheng, Y. Xiaoguang, and Z. Fenghao, "Multi-physics safety model based on structure damage for lithium-ion battery under mechanical abuse," *J. Cleaner Prod.*, vol. 277, Dec. 2020, Art. no. 124094.

[135] Z. Chen, R. Xiong, J. Tian, X. Shang, and J. Lu, "Model-based fault diagnosis approach on external short circuit of lithium-ion battery used in electric vehicles," *Appl. Energy*, vol. 184, pp. 365–374, Dec. 2016.

[136] D. Andre, M. Meiler, K. Steiner, C. Wimmer, T. Soczka-Guth, and D. U. Sauer, "Characterization of high-power lithium-ion batteries by electrochemical impedance spectroscopy. I. Experimental investigation," *J. Power Sources*, vol. 196, no. 12, pp. 5334–5341, Jun. 2011.

[137] N. Chen, P. Zhang, J. Dai, and W. Gui, "Estimating the state-of-charge of lithium-ion battery using an H-Infinity observer based on electrochemical impedance model," *IEEE Access*, vol. 8, pp. 26872–26884, 2020.

[138] L. Li, M. Hu, Y. Xu, C. Fu, G. Jin, and Z. Li, "State of charge estimation for lithium-ion power battery based on H-Infinity filter algorithm," *Appl. Sci.*, vol. 10, no. 18, p. 6371, Sep. 2020.

[139] S. M. Lambert, M. Armstrong, P. S. Attidekou, P. A. Christensen, J. D. Widmer, C. Wang, and K. Scott, "Rapid nondestructive-testing technique for in-line quality control of Li-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 64, no. 5, pp. 4017–4026, May 2017.

[140] M. Koseoglou, E. Tsioumas, D. Ferentinou, N. Jabbour, D. Papagiannis, and C. Mademlis, "Lithium plating detection using dynamic electrochemical impedance spectroscopy in lithium-ion batteries," *J. Power Sources*, vol. 512, Nov. 2021, Art. no. 230508.

[141] C. Weng, Y. Cui, J. Sun, and H. Peng, "On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression," *J. Power Sources*, vol. 235, pp. 36–44, Aug. 2013.

[142] L. Zheng, J. Zhu, D. D.-C. Lu, G. Wang, and T. He, "Incremental capacity analysis and differential voltage analysis based state of charge and capacity estimation for lithium-ion batteries," *Energy*, vol. 150, pp. 759–769, May 2018.

[143] C. Pastor-Fernández, W. D. Widanage, G. H. Chouchelamane, and J. Marco, "A SoH diagnosis and prognosis method to identify and quantify degradation modes in Li-ion batteries using the IC/DV technique," in *Proc. HEVC*, 2016, pp. 1–6.

[144] Z. Zhou, B. Duan, Y. Kang, Q. Zhang, Y. Shang, and C. Zhang, "Online state of health estimation for series-connected $LiFePO_4$ battery pack based on differential voltage and inconsistency analysis," *IEEE Trans. Transport. Electrific.*, vol. 10, no. 1, pp. 989–998, Mar. 2024.

[145] Z. Wei, H. Ruan, Y. Li, J. Li, C. Zhang, and H. He, "Multistage state of health estimation of lithium-ion battery with high tolerance to heavily partial charging," *IEEE Trans. Power Electron.*, vol. 37, no. 6, pp. 7432–7442, Jun. 2022.

[146] M. Huang and M. Kumar, "A case study into impacts of usage patterns on lithium-ion battery aging through incremental capacity analysis based health monitoring," in *Proc. Prognostics Syst. Health Manage. Conf. (PHM-Paris)*, May 2019, pp. 309–314.

[147] Y. Wang, J. Zhu, L. Cao, B. Gopaluni, and Y. Cao, "Online capacity estimation of lithium-ion batteries by partial incremental capacity curve," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Nov. 2022, pp. 1–6.

[148] T. Sun, B. Xu, Y. Cui, X. Feng, X. Han, and Y. Zheng, "A sequential capacity estimation for the lithium-ion batteries combining incremental capacity curve and discrete Arrhenius fading model," *J. Power Sources*, vol. 484, Feb. 2021, Art. no. 229248.

[149] B. Jiang, H. Dai, and X. Wei, "Incremental capacity analysis based adaptive capacity estimation for lithium-ion battery considering charging condition," *Appl. Energy*, vol. 269, Jul. 2020, Art. no. 115074.

[150] Z. Xu, J. Wang, P. D. Lund, and Y. Zhang, "Estimation and prediction of state of health of electric vehicle batteries using discrete incremental capacity analysis based on real driving data," *Energy*, vol. 225, Jun. 2021, Art. no. 120160.

[151] X. Li, C. Yuan, X. Li, and Z. Wang, "State of health estimation for Li-ion battery using incremental capacity analysis and Gaussian process regression," *Energy*, vol. 190, Jan. 2020, Art. no. 116467.

[152] D.-I. Stroe and E. Schaltz, "Lithium-ion battery state-of-health estimation using the incremental capacity analysis technique," *IEEE Trans. Ind. Appl.*, vol. 56, no. 1, pp. 678–685, Jan. 2020.

[153] F. Xia, K. Wang, and J. Chen, "State of health and remaining useful life prediction of lithium-ion batteries based on a disturbance-free incremental capacity and differential voltage analysis method," *J. Energy Storage*, vol. 64, Aug. 2023, Art. no. 107161.

[154] S. S. Afshari, S. Cui, X. Xu, and X. Liang, "Remaining useful life early prediction of batteries based on the differential voltage and differential capacity curves," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–9, 2022.

[155] D. Qiao, X. Wang, X. Lai, Y. Zheng, X. Wei, and H. Dai, "Online quantitative diagnosis of internal short circuit for lithium-ion batteries using incremental capacity method," *Energy*, vol. 243, Mar. 2022, Art. no. 123082.

[156] J. Tian, R. Xiong, and W. Shen, "State-of-health estimation based on differential temperature for lithium ion batteries," *IEEE Trans. Power Electron.*, vol. 35, no. 10, pp. 10363–10373, Oct. 2020.

[157] A. Fly and R. Chen, "Rate dependency of incremental capacity analysis (dQ/dV) as a diagnostic tool for lithium-ion batteries," *J. Energy Storage*, vol. 29, Jun. 2020, Art. no. 101329.
[158] Y. Li, M. Abdel-Monem, R. Gopalakrishnan, M. Berecibar, E. Nanini-Maury, N. Omar, P. van den Bossche, and J. Van Mierlo, "A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter," *J. Power Sources*, vol. 373, pp. 40–53, Jan. 2018.
[159] X. Li, J. Jiang, L. Y. Wang, D. Chen, Y. Zhang, and C. Zhang, "A capacity model based on charging process for state of health estimation of lithium ion batteries," *Appl. Energy*, vol. 177, pp. 537–543, Sep. 2016.
[160] X. Li, Z. Wang, and J. Yan, "Prognostic health condition for lithium battery using the partial incremental capacity and Gaussian process regression," *J. Power Sources*, vol. 421, pp. 56–67, May 2019.
[161] X. Bian, Z. Wei, W. Li, J. Pou, D. U. Sauer, and L. Liu, "State-of-health estimation of lithium-ion batteries by fusing an open circuit voltage model and incremental capacity analysis," *IEEE Trans. Power Electron.*, vol. 37, no. 2, pp. 2226–2236, Feb. 2022.
[162] L. Wang, C. Pan, L. Liu, Y. Cheng, and X. Zhao, "On-board state of health estimation of $LiFePO_4$ battery pack through differential voltage analysis," *Appl. Energy*, vol. 168, pp. 465–472, Apr. 2016.
[163] Y. Wu, Q. Xue, J. Shen, Z. Lei, Z. Chen, and Y. Liu, "State of health estimation for lithium-ion batteries based on healthy features and long short-term memory," *IEEE Access*, vol. 8, pp. 28533–28547, 2020.
[164] N. C. Dvornek, P. Ventola, and J. S. Duncan, "Combining phenotypic and resting-state fMRI data for autism classification with recurrent neural networks," in *Proc. Int. Symp. Biomed. Imag.*, May 2018, pp. 725–728.
[165] N. P. Reddy, M. K. Zadeh, C. A. Thieme, R. Skjetne, A. J. Sorensen, S. A. Aanondsen, M. Breivik, and E. Eide, "Zero-emission autonomous ferries for urban water transport: Cheaper, cleaner alternative to bridges and manned vessels," *IEEE Electrific. Mag.*, vol. 7, no. 4, pp. 32–45, Dec. 2019.
[166] H. Khayyam, A. Jamali, A. Bab-Hadiashar, T. Esch, S. Ramakrishna, M. Jalili, and M. Naebe, "A novel hybrid machine learning algorithm for limited and big data modeling with application in Industry 4.0," *IEEE Access*, vol. 8, pp. 111381–111393, 2020.
[167] A. Li, J. Weng, A. C. Y. Yuen, W. Wang, H. Liu, E. W. M. Lee, J. Wang, S. Kook, and G. H. Yeoh, "Machine learning assisted advanced battery thermal management system: A state-of-the-art review," *J. Energy Storage*, vol. 60, Apr. 2023, Art. no. 106688.
[168] W. Q. Tong Poh, Y. Xu, and R. T. Poh Tan, "A review of machine learning applications for Li-ion battery state estimation in electric vehicles," in *Proc. IEEE PES Innov. Smart Grid Technol. Asia (ISGT Asia)*, Nov. 2022, pp. 265–269.
[169] C. Vidal, P. Malysz, P. Kollmeyer, and A. Emadi, "Machine learning applied to electrified vehicle battery state of charge and state of health estimation: State-of-the-art," *IEEE Access*, vol. 8, pp. 52796–52814, 2020.
[170] Y. Huang, W. Yuan, Y. Zhao, and H. Huang, "Machine learning algorithms for new energy vehicles: A brief survey," in *Proc. 9th Int. Conf. Dependable Syst. Their Appl. (DSA)*, Aug. 2022, pp. 1063–1064.
[171] L. Zhang, Z. Shen, S. M. Sajadi, A. S. Prabuwono, M. Z. Mahmoud, G. Cheraghian, and E. S. M. Tag El Din, "The machine learning in lithium-ion batteries: A review," *Eng. Anal. With Boundary Elements*, vol. 141, pp. 1–16, Aug. 2022.
[172] K. Liu, X. Tang, R. Teodorescu, F. Gao, and J. Meng, "Future ageing trajectory prediction for lithium-ion battery considering the knee point effect," *IEEE Trans. Energy Convers.*, vol. 37, no. 2, pp. 1282–1291, Jun. 2022.
[173] M. Duquesnoy, I. Boyano, L. Ganborena, P. Cereijo, E. Ayerbe, and A. A. Franco, "Machine learning-based assessment of the impact of the manufacturing process on battery electrode heterogeneity," *Energy AI*, vol. 5, Sep. 2021, Art. no. 100090.
[174] M. Schmid, B. Liebhart, J. Kleiner, C. Endisch, and R. Kennel, "Online detection of soft internal short circuits in lithium-ion battery packs by data-driven cell voltage monitoring," *Proc. Energy Convers. Congr. Expos. Asia, ECCE Asia*, pp. 1711–1718, May 2021.
[175] D. Li, P. Liu, Z. Zhang, L. Zhang, J. Deng, Z. Wang, D. G. Dorrell, W. Li, and D. U. Sauer, "Battery thermal runaway fault prognosis in electric vehicles based on abnormal heat generation and deep learning algorithms," *IEEE Trans. Power Electron.*, vol. 37, no. 7, pp. 8513–8525, Jul. 2022.
[176] S. Bamati and H. Chaoui, "Developing an online data-driven state of health estimation of lithium-ion batteries under random sensor measurement unavailability," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 1, pp. 1128–1141, Mar. 2023.
[177] S. Bamati and H. Chaoui, "Lithium-ion batteries long horizon health prognostic using machine learning," *IEEE Trans. Energy Convers.*, vol. 37, no. 2, pp. 1176–1186, Jun. 2022.
[178] Q. Wu, Q. Feng, Y. Ren, Q. Xia, Z. Wang, and B. Cai, "An intelligent preventive maintenance method based on reinforcement learning for battery energy storage systems," *IEEE Trans. Ind. Informat.*, vol. 17, no. 12, pp. 8254–8264, Dec. 2021.
[179] X. Tang, K. Liu, X. Wang, F. Gao, J. Macro, and W. D. Widanage, "Model migration neural network for predicting battery aging trajectories," *IEEE Trans. Transport. Electrific.*, vol. 6, no. 2, pp. 363–374, Jun. 2020.
[180] Q. Yu, Y. Nie, S. Liu, J. Li, and A. Tang, "State of health estimation method for lithium-ion batteries based on multiple dynamic operating conditions," *J. Power Sources*, vol. 582, Oct. 2023, Art. no. 233541.
[181] A. Tang, Y. Jiang, Q. Yu, and Z. Zhang, "A hybrid neural network model with attention mechanism for state of health estimation of lithium-ion batteries," *J. Energy Storage*, vol. 68, Sep. 2023, Art. no. 107734.
[182] S. Shen, M. Sadoughi, M. Li, Z. Wang, and C. Hu, "Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries," *Appl. Energy*, vol. 260, Feb. 2020, Art. no. 114296.
[183] I. Babaeiyazdi, A. Rezaei-Zare, and S. Shokrzadeh, "Transfer learning with deep neural network for capacity prediction of Li-ion batteries using EIS measurement," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 1, pp. 886–895, Mar. 2023.
[184] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, 2010.
[185] Y. Che, Z. Deng, X. Lin, L. Hu, and X. Hu, "Predictive battery health management with transfer learning and online model correction," *IEEE Trans. Veh. Technol.*, vol. 70, no. 2, pp. 1269–1277, Feb. 2021.
[186] Y. Che, D.-I. Stroe, X. Hu, and R. Teodorescu, "Semi-supervised self-learning-based lifetime prediction for batteries," *IEEE Trans. Ind. Informat.*, vol. 19, no. 5, pp. 6471–6481, May 2023.
[187] Y. Che, S. B. Vilsen, J. Meng, X. Sui, and R. Teodorescu, "Battery health prognostic with sensor-free differential temperature voltammetry reconstruction and capacity estimation based on multi-domain adaptation," *eTransportation*, vol. 17, Jul. 2023, Art. no. 100245.
[188] Y. Che, Y. Zheng, F. E. Forest, X. Sui, X. Hu, and R. Teodorescu, "Predictive health assessment for lithium-ion batteries with probabilistic degradation prediction and accelerating aging detection," *Rel. Eng. Syst. Saf.*, vol. 241, Jan. 2024, Art. no. 109603.
[189] Y. Zhong, J. Feng, X. Wang, and L. Yan, "The identification method of critical failure mode based on failure information," in *Proc. Int. Conf. Quality, Rel., Risk, Maintenance, Safety Eng.*, vol. 21, 2022, pp. 2186–2192.
[190] D. Xiang, C. Yang, H. Li, Y. Zhou, S. Zhu, and Y. Li, "Online monitoring of lithium-ion battery internal temperature using PWM switching oscillations," *IEEE Trans. Power Electron.*, vol. 38, no. 1, pp. 1166–1177, Jan. 2023.
[191] X. Du, J. Meng, and J. Peng, "Hybrid pseudorandom sequence for broadband impedance measurements of lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 70, no. 7, pp. 6856–6864, Jul. 2023.
[192] C. Pastor-Fernández, K. Uddin, G. H. Chouchelamane, W. D. Widanage, and J. Marco, "A comparison between electrochemical impedance spectroscopy and incremental capacity-differential voltage as Li-ion diagnostic techniques to identify and quantify the effects of degradation modes within battery management systems," *J. Power Sources*, vol. 360, pp. 301–318, Aug. 2017.
[193] S. Zhang, X. Guo, X. Dou, and X. Zhang, "A rapid online calculation method for state of health of lithium-ion battery based on Coulomb counting method and differential voltage analysis," *J. Power Sources*, vol. 479, Dec. 2020, Art. no. 228740.

[194] K. S. R. Mawonou, A. Eddahech, D. Dumur, D. Beauvois, and E. Godoy, ''State-of-health estimators coupled to a random forest approach for lithium-ion battery aging factor ranking,'' *J. Power Sources*, vol. 484, Feb. 2021, Art. no. 229154.

[195] X. Hu, K. Zhang, K. Liu, X. Lin, S. Dey, and S. Onori, ''Advanced fault diagnosis for lithium-ion battery systems: A review of fault mechanisms, fault features, and diagnosis procedures,'' *IEEE Ind. Electron. Mag.*, vol. 14, no. 3, pp. 65–91, Sep. 2020.

[196] M. Golozar, R. Gauvin, and K. Zaghib, ''In situ and in operando techniques to study Li-ion and solid-state batteries: Micro to atomic level,'' *Inorganics*, vol. 9, no. 11, p. 85, Nov. 2021.

JOSEPH OMAKOR received the B.Sc. degree in electrical and electronics engineering from Ambrose Alli University, Nigeria, in 2019, with a focus on control systems and power electronics, and his M.Sc. degree in electrical and computer engineering from Carleton University, Ottawa, Canada, with a focus on energy storage system for electric vehicle precisely on Li-ion battery, hybrid energy storage systems, and the development of algorithm for energy management of Li-ion battery. He did his research with the Intelligent Robotic and Energy System Research Group, Carleton University.

MD SURUZ MIAH received the bachelor's degree from Khulna University of Engineering and Technology (KUET), Bangladesh, and the master's and Ph.D. degrees from the University of Ottawa, Canada. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, Bradley University, Peoria, IL, USA. He is also an Adjunct Professor with the School of Electrical Engineering and Computer Science, University of Ottawa. Before joining Bradley, he spent more than two years conducting research on multi-agent systems and control with the Centre for Operational Research and Analysis (CORA), Defence Research and Development Canada (DRDC), Ottawa, ON, Canada. He served more than a year with the Department of Computer Science and Engineering, KUET, as a Lecturer. He is the author/coauthor of technical papers that are published in leading journals and conferences. His research interests include cyber-physical systems, in particular robot navigation, mechatronics, multi-agent systems, and control. He was a recipient of many prestigious awards, such as the President Gold Medal, Canada's Graduate Scholarship, and the Bradley's Research Excellence Award.

HICHAM CHAOUI (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from the University of Quebec, Trois-Rivi'eres, QC, Canada, in 2011. His career has spanned both academia and industry in the field of control and energy systems. From 2007 to 2014, he held various engineering and management positions in Canadian industry. He is currently an Associate Professor with Carleton University, Ottawa, ON, Canada. His scholarly work has resulted in more than 200 journals and conference publications. He was a recipient of the Best Thesis Award, the Governor General of Canada Gold Medal Award, the Carleton's Research Excellence Award, the Early Researcher Award from the Ministry of Colleges and Universities, and the Top Editor Recognition from IEEE Vehicular Technology Society. He is a Registered Professional Engineer in the Province of Ontario and an associate editor of several IEEE journals.