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MDPI

Review

Artificial Intelligence Opportunities to Diagnose Degradation Modes for Safety Operation in Lithium Batteries

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Abstract: The degradation and safety study of lithium-ion batteries is becoming increasingly important given that these batteries are widely used not only in electronic devices but also in automotive vehicles. Consequently, the detection of degradation modes that could lead to safety alerts is essential. Existing methodologies are diverse, experimental based, model based, and the new trends of artificial intelligence. This review aims to analyze the existing methodologies and compare them, opening the spectrum to those based on artificial intelligence (AI). AI-based studies are increasing in number and have a wide variety of applications, but no classification, in-depth analysis, or comparison with existing methodologies is yet available.

Keywords: Li-ion battery; safety; degradation mechanism; neural network; modelling

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1. Introduction

The performance of lithium-ion batteries (LIBs) decreases with use due to parasitic reactions occurring at the positive and negative electrodes and even in the electrolyte [1–3]. This degradation is caused by the interaction of chemical and physical mechanisms within the cell, resulting in power and capacity loss.

As summarized in Figure 1, LIBs are degraded by various aging factors or external conditions, ranging from elevated temperature to mechanical stress, among others, leading to performance loss or failure to operate in safe conditions [3,4].

1.1. Degradation Mechanisms for LIBs

The interrelated cause–effect connections or degradation process between the aging factors and the degradation mechanisms are diverse, and many occur simultaneously. The best-known degradation processes are SEI growth, electrode particle cracking, electrolyte decomposition, and delamination [5–9]. Although diverse in origin and nature, they have a limited electrochemical response [10]. It is also common to classify degradation processes into the categories of degradation mechanisms (DMs) listed in Figure 1 [10–12].

The degradation mechanisms are very diverse. Considering thermodynamics as the main degradation axis of a lithium-ion cell, loss of lithium inventory (LLI), loss of active material of the negative electrode (or anode) (LAM_{NE}), loss of the active material of the positive electrode (or cathode) (LAM_{PE}), and kinetic alterations resulting in capacity fade or power fade are considered to be the predominant ones, as mentioned in the previous section [2,8,11].

- LLI: Parasitic reactions such as surface film formation (SEI), decomposition reactions, or lithium plating are the cause of lithium consumption in batteries. This leads to a lack of cycling between the positive and negative electrodes, resulting in a drop in the cell's capacity. In addition, SEI can cause a loss of power [11].
- LAM_{NE}: Due to cracking and the loss of electrical contact or the blocking of active sites by resistive surface layers, the active mass of the NE is no longer available, and hence, lithium insertion ceases. This leads to a reduction in the capacity of the battery power [11].
- LAM_{PE}: Due to structural disorders, particle cracking, or loss of electrical contact, the active mass of the PE is no longer available and insertion ceases, causing the capacity and the power of the battery to decrease [11].

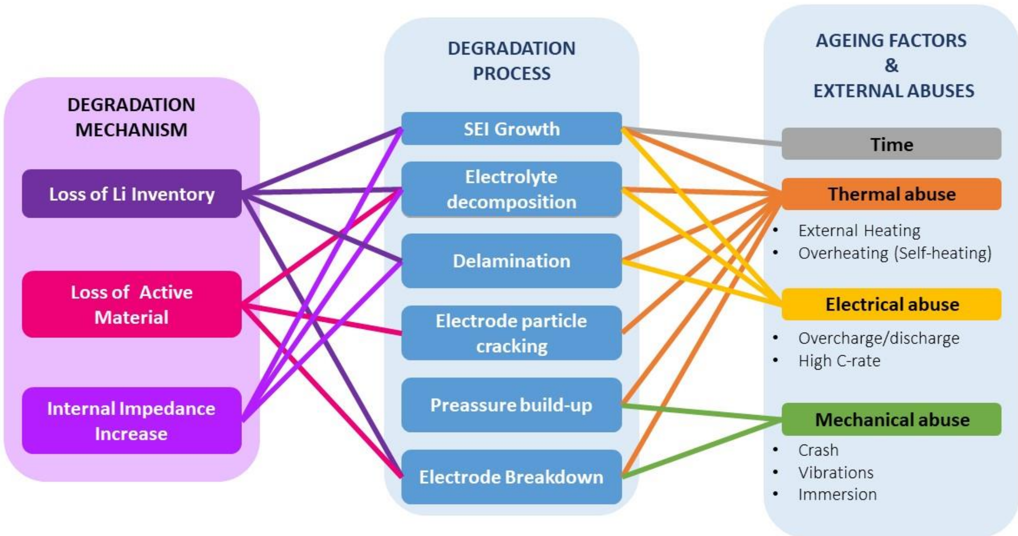

Figure 1. Relation of aging factors and external abuses with their respective degradation processes and mechanisms [13,14].

1.2. LIB Safety Management

Some of the DMs can generate operating conditions in lithium batteries that generate risky or unsafe situations.

The study of lithium-ion battery degradation and safety is gaining importance due to the widespread use of LIBs in electronic devices and vehicles. Therefore, it is crucial to detect degradation modes that may pose safety risks. Developing new models that help understand the relationships between aging factors, degradation processes, degradation mechanisms, and safety condition estimators is a challenge for manufacturers and operators alike.

For electrochemical and thermal stabilities, lithium-ion batteries need to operate within specific temperature and voltage ranges to ensure safety [15–17]. These ranges can be compromised due to improper usage, such as overcharging, over-discharging, high temperatures, or vibrations [13,15,18]. Once the temperature of the battery exceeds a certain level, self-sustaining exothermic cascade reactions can be triggered and the heat generated can no longer be dissipated efficiently, which could end up causing a thermal runaway (TR) [13,19]. To prevent a hazard, in electric vehicle (EV) applications batteries are positioned centrally, and cooling systems and battery management systems (BMS) are employed [15–18]. When considering safety, the analyzed system has its importance, as the study of an individual cell is different than that of a battery pack. In addition, three different safety-level categories exist: cell design, abuse tolerance, and parts per billion (PPB). Cell design safety level corresponds to materials and process conditions. Cell manufacturers try to automatize the process, making it more efficient together with quality controls based on optical and X-ray inspection techniques. Moreover, these quality control tests search for electrode misalignments, the presence of metal contaminants, and so on [20]. Abuse tolerance also corresponds to cell safety level, and the cell is tested in conditions outside of those estimated by the supplier. Cells that tolerate these abuse conditions without venting or self-destructions are essential. Nevertheless, global safety is not ensured. Finally, PPB-level safety consists of Li-ion cells operating under recommended conditions that failed. In this category the main failure mode is TR [20].

Various methods are being explored to prevent this phenomenon. Some studies focused on adding additives to shield the battery from overcharging [13,21,22]. Others aimed to protect the battery from overheating through strategies like enhancing cathode and anode materials, using thermoprotective separators, or incorporating flame retardants [23–27]. Additionally, modern battery management systems and battery thermal management systems are gaining popularity [28–30].

1.3. Methodologies for Hazard Detection in LIBs

Furthermore, safety tests for batteries can be categorized into three groups based on the type of abuse condition: thermal, electrical, or mechanical [31,32]. Thermal abuse tests subject batteries to high temperatures, either directly or indirectly, to assess their thermal stability and predict the occurrence of thermal runaway (TR) [33,34]. Thermal abuse tests subject batteries to high temperatures, either directly or indirectly, to assess their thermal stability and predict the occurrence of thermal runaway TR [35–38]. Mechanical abuse entails deforming the battery to create a short circuit and initiate TR [39]. It is worth noting that modeling the failure process of one or multiple batteries is complex, and although thermal, electric, and electrochemical models exist, the current trend is to use multi-physics models that combine multiple models, such as electric and thermal, to seek comprehensive answers [40–43].

The internal resistance and electrochemical reactions in lithium-ion batteries generate heat [13,28]. Overcharging the battery during charge and discharge operations can produce additional thermal energy, which must be effectively managed to avoid thermal runaway (TR) or explosions. Battery management systems (BMS) located inside the batteries are responsible for preventing overcharging and over-discharging, thereby extending the battery's lifespan. A BMS also monitors various factors related to degradation mechanisms and safety (DM&S), including the state of charge (SOC), state of health (SOH), operating status, and safety status. Additionally, the BMS ensures energy balance within battery packs, monitors temperature, and provides real-time information to external devices such as electric motors, chargers, and data loggers [28,29,44].

In contrast, a BTMS (battery thermal management system) regulates the temperature inside the battery pack for both high and low temperatures to avoid overheating and achieve an improvement in electrochemical performance. In addition to ensuring cooling, it guarantees temperature homogeneity and optimum operating temperature [30,45,46]. This system can decrease the internal resistance but cannot cope with the heat generated by the internal electrochemical reactions. Nowadays, BTMS has been applied as a key and integral part to maintain the temperature in an optimum range [46].

Reliability and safety concerns arise from DMs [1,5]. Estimating the battery's state of health (SOH) and state of charge (SOC) enables the study, diagnosis, and prediction of DMs [47,48]. Various methodologies exist, including experimental testing, physical modeling, data-driven approaches, and hybrid methods, each of which have strengths and challenges [49–51]. Experimental methods require time and scientific knowledge for data interpretation, whereas physical models rely on extensive experimental databases [52]. Data-driven methods have gained importance and consistency, with initial models being constructed and refined using abundant data to align with the collected information [53,54].

Feinauer et al. proposed combining data from various sensors (temperature, voltage, resistance, audio, ultrasound transmission, and reflection) to estimate the safety level of the cell [55]. Data-driven approaches are valuable for studying battery health due to the correlation between the state of health (SOH) and electrical, thermal, and mechanical behaviors. Lifetime estimation models have gained popularity due to their ability to fit extensive data collected under controlled experimental conditions. These models exhibit high computational efficiency and acceptable accuracy under similar operating conditions [53,54].

Data-driven methods are gaining prominence in real-world applications for battery health estimation and prediction. These methods provide advantages over complex physical models and are increasingly preferred.

According to data-driven methodologies, one of the approaches that is gaining popularity is the use of artificial intelligence (AI) and machine learning (ML) together with neural networks (NNs) and deep learning (DL) [56–59]. Machine learning methods, known for their flexibility and nonlinear matching capabilities, are highly favored for health estimation and prediction. Specialized aging tests considering multiple factors that impact battery health are conducted to generate a suitable training dataset. Intelligent techniques are then used to map these factors to the battery's health state, synthesizing an underlying relation. The advances in capacity processors, communications, and AI are increasingly being used to predict and diagnose the SOH and the SOC along with battery DMs. DL algorithms are the most widely used. The database that feeds these algorithms at their core includes images, text, or time series, which, translated to the battery field, would correspond to current, voltage, temperature, temperature maps, time series, charge/discharge cycles, or calendar aging [60–62]. On top of the growing sophistication of the algorithms required, the quantity of data needed for training and validation is also critical, as battery data generation is challenging and time-consuming [63–65]. The existing datasets, despite providing invaluable information, are sparse and only provide data from a few cells under limited test conditions [66,67]. Hence, this is a major obstacle to the application of DL algorithms, as large amounts of data are needed for the training process. Nonetheless, initiatives such as battery archives and battery data genomes are facilitating future work [67].

This review aims, on the one hand, to analyze the conventional methodologies used in the determination of the SOH and the SOC as well as the diagnosis of DM&S in lithium-ion batteries. On the other hand, it analyzes the new emerging methodologies such as the use of artificial intelligence, the use of neural networks, and new algorithms for the same purpose. It intends to compare both currents to analyze the advantages and disadvantages associated with the use of neural networks and the growth of their implementation in the battery field.

2. Conventional DM&S Estimation Methods

DM&S diagnosis is important to ensuring the safe functioning of LIBs. Existing conventional methodologies are classified into two main groups, experiment based and model based.

2.1. Experiment-Based Methods

Experimental methods are of considerable importance in the assessment of the SOH and the DM&S of batteries. They are usually laboratory based due to the need for specific equipment and often are time-consuming, involving many procedures [7,68]. During the process there may be systematic errors and external factors that affect the results obtained. The battery behavior is obtained by the voltage, current, and temperature applied directly, like capacity measurements or impedance measurements. Other indirect measurements [12] are the optimization and processing of data to locate parameters, the load curve method, ICA (Incremental Capacity Analysis) and DVA(Differential Voltage Analysis), and ultrasonic inspection [12,51]. This section describes some of the most relevant methods, such as internal resistance, electrochemical impedance spectroscopy, battery capacity measurement, and incremental capacity analysis and differential voltage analysis.

2.1.1. Internal Resistance

One of the methodologies that plays a significant role is internal resistance measurement, which provides substantial information about the end of life of a battery [12,50,69]. It consists of the resistance of a substance when an electric current passes through. There are several factors affecting the internal resistance of a battery, such as the constituent materials and their structure, state of charge (SOC), electrolyte internal temperature, load current, battery capacity, and rate of discharge of the battery [70,71]. Furthermore, polarization resistance (PR) and ohmic resistance (OR) are the two main contributions of internal resistance. In addition, OR contributes to the contact resistance of the separator, electrolyte, and electrode material cell components [50,72]. However, PR consists of the conversion state between the electrodes and the electrolyte during the correspondent electrochemical reactions. Therefore, it could be said that the increase in internal capacity is directly related to battery capacity and discharge time. It is important to remark that even if it is a time-consuming and non-suitable technique for online assessment, it is reliable, noninvasive, direct, and widely used as an indicator for charge evaluation [50,68,73,74]. One of the most common methods is the current pulse method, based on Ohm's law. It consists of measuring the voltage drop of a battery for a given current, then calculating the internal resistance with the following equation [68]:

$$R_b(SOC,T) = \frac{OCV(SOC,T) - V_{bat}(SOC,T)}{I_{pulse}} \tag{1}$$

R_b represents the internal resistance of the battery, OCV is its open circuit voltage, V_{bat} is its voltage, and I_{pulse} is the applied current [68]. This method is widely used in laboratories to define the behavior of the internal resistance of a battery under different operating conditions with very good accuracy. However, it is more suitable for stationary and laboratory applications due to its slow process.

2.1.2. Electrochemical Impedance Spectroscopy

Another non-destructive or non-invasive technique is electrochemical impedance spectroscopy (EIS) [12,50]. Impedance is the total resistance of a device or circuit to the flow of an alternating current at a certain given frequency. It is commonly used to predict the aging state of a battery by providing information about the tested coin cell, reaction kinetics, local corrosion rate, electrochemical mechanisms, and remaining useful life (RUL) of a lithium-ion battery [51,75,76]. This methodology offers the opportunity to study both solid and liquid materials, i.e., insulators, semiconductors, and mixed and ionic materials. EIS enables the study of charge transfer in heterogeneous systems with the possibility of chemical sensors, fuel cells, and corrosion processes [12,50,52,77,78]. Furthermore, it can be applied in diverse ways depending on the purpose of the experiment. This choice would depend on the specific conditions and the range of measurement requirements, the accuracy of the measurement, and the ease of experimentation [51,79].

Depending on the test, it is applied in various ways, although always dependent on the specific conditions, the range requirements, the accuracy of the measurement, and the experimental facility. Finally, as it is a non-destructive methodology, battery cell disassembly is not needed. In this way, cells are protected from moisture and oxygen [12,80,81]. In addition, it is a technique that could be applied in operando conditions. It is time-consuming and only applicable for stable environments. Nevertheless, it provides an accurate estimation of the RUL and predicts battery degradation [50].

2.1.3. Battery Capacity Measurement

Battery capacity measurement corresponds to the amount of energy contained in a battery, which deteriorates over time [50,82,83]. It reflects the amount of energy that is storable in that battery. Energetic capacity corresponds to the energy that can be removed or retained in a LIB [7,84]. Battery capacity measurement is the fastest method. Nonetheless, it is not suitable for online assessment, but in this case, it is necessary for the battery to be fully charged [85].

2.1.4. Incremental Capacity Analysis and Differential Voltage Analysis

Incremental capacity analysis (ICA) and differential voltage analysis (DVA) are parameters that change during the operation of batteries, providing the possibility to track their aging by experimental testing [75,86,87]. They are time-consuming techniques, as the curves are obtained at low currents, such as C/20. According to the ICA method, it is considered a valuable method, as accurate battery characteristics are obtained by integrating changes in capacitance and battery voltage. Nevertheless, high-quality research data are required, as are long input preprocessing hours. This methodology is only suitable for LIBs, and it is efficient for analyzing the capacity loss of batteries and is robust and reliable, providing high accuracy [50,68,88]. Figure 2 shows the process of combining both methodologies. It consists of four steps. First, the load tests are performed, and then the voltage-based combination is generated, after which the data are transformed and passed to the SOC-based ones. Finally, by means of fusion algorithms such as Kalman filters or artificial neural network combinations, the desired features are obtained, as described by Zheng et al. [88].

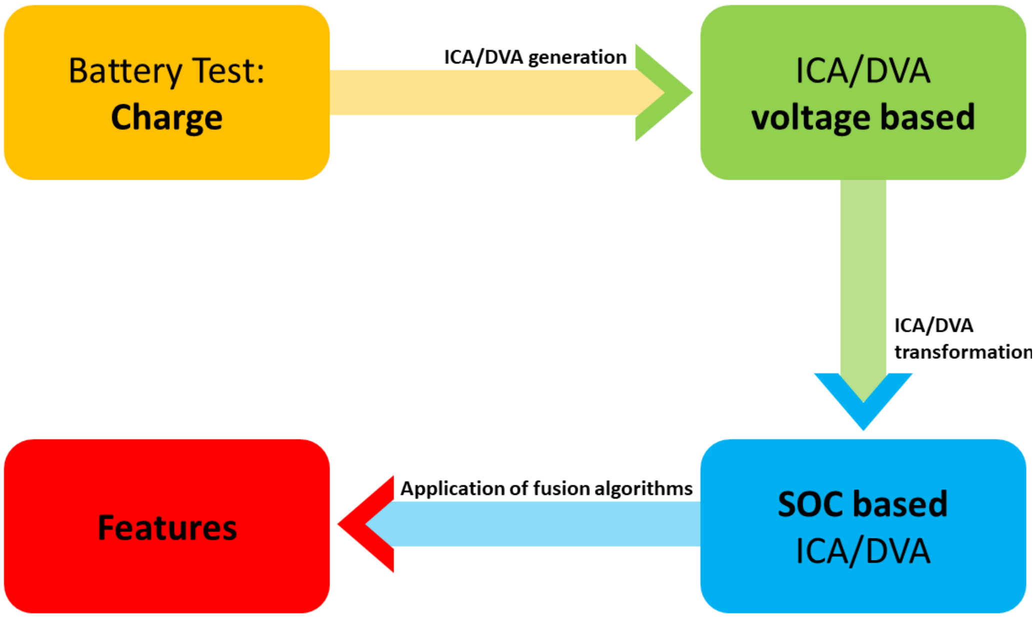

Figure 2. ICA/DVA combination methodology process [88].

2.2. Model-Based Methods

For model-based fault diagnosis, a residual signal is usually obtained by comparing the measurable signal with the signal generated by the model. The residual is then evaluated to determine the diagnostic results [89]. The development of high-fidelity battery models, which include electrical models, thermal models, and multi-physics models, provides the basis for model-based fault diagnosis. Because of their deep understanding of battery system dynamics, these methods can not only detect faults but also locate them and estimate their magnitude [48,90]. Therefore, they are becoming the primary method for LIB fault diagnosis. It should be noted that these methods can be affected by model uncertainty, interferences, and noise.

As previously mentioned, model-based methods are also applied for DM&S estimation, the equivalent circuit model, the electrochemical model, and mathematical fitting.

2.2.1. Equivalent Circuit Model

In the equivalent circuit model, a battery is considered an electric circuit in which different elements are considered, such as resistances, capacitors, or inductors, that are connected in series or in parallel [50]. In addition, the model also considers different conditions (temperature, storage time, C-rate, overcharging, and over-discharging) affecting battery aging. As an experimental methodology, this is also a non-destructive method that only requires temperature, voltage, and current for its estimation. In addition, the kinetic process of the battery system can be investigated [84,91]. Unfortunately, there is no definition for chemical and physical processes, as the model considers the system an electric circuit, which could be a problem for the understanding of degradation mechanisms [92].

2.2.2. Mathematical Fitting

The mathematical fitting method consists of fitting a battery's state of health with exponential and polynomial mathematical functions. However, it is impossible to describe the chemical and physical processes that happen inside the battery. The models only have the following variables: C-rate, the depth of discharge, temperature, storage time, number of cycles, and state of charge [50,93]. Two of the most common mathematical models are calendar aging, which reduces the capacity without electrical current, and cycling aging, which reduces the capacity by providing a steady charge–discharge current in a specific voltage range [94]. According to the basis of the methodology there is no mechanism of degradation defined, and the SOH of the battery can only be achieved by mathematical expressions [95]. However, no high computational efficiency as in the electrochemical model is needed due to the development of simple mathematical equations.

2.2.3. Kalman-Based Filters

Kalman-based filter are adaptative filtering methods [96,97]. They consist of identifying the parameters of different battery ECMs (equivalent circuit models) in real time and including battery internal resistance and tracking the SOC and the SOH of the battery. A wide variety of Kalman-based methods exists, such as the Kalman filter, extended Kalman filter, unscented Kalman filter, or dual Kalman filter [97–101]. For that reason, a high-performance controller is vital to its development [102]. These filter methods are commonly used in the literature [68,97,103] due to their accuracy.

2.2.4. Least-Square-Based Filters

Another set of model-based methods is least-square-based filters, which are also adaptative methods [68,104]. The recursive least-square algorithm has achieved increased attention due to its simple implementation and accuracy. The filters are linked to battery parameters such as open circuit voltage or internal resistance [105]. They are considered precise and extremely robust and have a simple structure; however, their accuracy relies on the selected model and requires a high-performance controller, such as Kalman filters.

They have also been applied for SOH estimation. They are accurate and robust, with little modeling error and temperature variations. Nevertheless, they require a higher computational cost than adaptative filters [106].

2.2.5. Electrochemical Models

Finally, simplified electrochemical models accurately represent battery behavior despite being complex models. If they are combined with adaptative filtering they could be simplified [68,107]. As with the other model-based methods, a high-performance controller is needed. They have a complex structure, as they consider different parameters and require a high computational effort. Nonetheless, they describe the degradation phenomena that occur inside a battery [108,109].

3. Emerging Opportunities for AI in DM&S Analysis

The reason why artificial intelligence and machine learning are becoming widely used in battery technology is because they have proven to be supportive in terms of material design and synthesis, manufacturing, and cell characterization, as well as cell diagnosis and prognosis [110].

When looking at cell diagnosis, AI and neural networks open new methods to identify complex nonlinearly dependent degradation paths due to the different operation conditions [111]. The main challenge that the industry is facing is to find new models to determine unsafe operation conditions of Li-ion batteries.

3.1. Artificial Neural Networks Model Learning Opportunities

ANNs are designed to simulate the human brain mathematically through artificial neurons or processing units. These processing units are arranged in input, output, and hidden layers. The input-layer function takes preprocessed data and serves as the conductive pathway to the hidden layers. In this second part (hidden layers), each neuron has a mathematical model that determines its output based on its input. This model can be expressed by weighted linear combinations wrapped in an activation function. The prediction data leave the model through the output layer. In the learning process, the model parameters are adjusted, taking into consideration the number of neurons in each layer, the weights of the interconnections between neurons, and the type of activation function of each neuron [53,112,113].

One of the most important and distinctive features of ANNs is their ability to learn from experience and examples to adapt to changing situations. They can establish themselves automatically by training without identifying the model's parameters and coefficients. ANNs need a large dataset for training and verification to have adequate performance, and the prediction is affected by the selected learning algorithm. Computational cost is a challenge for large-scale applications such as RUL prediction [53,112].

Neural networks have proven to be accurate and feasible tools for in operando diagnosis of SOH of batteries [114], but more recently, valuable contributions have been made to implementing state-of-safety detection methods using impedance spectroscopy and deep learning [114].

ANNs are able to model complex systems, showing several advantages:

- Learning capabilities: Following the appropriate training steps, they can learn complex dynamics. There are several training algorithms with reliable implementations. The main challenge is choosing the structure, the learning algorithm, its parameters, and the inputs and outputs.
- Generalization capabilities: Following the appropriate training steps, if the training examples cover a variety of different states of the system to model, the response of the trained neural network in novel situations (for example, with previously unknown inputs) will probably be acceptable and similar to the correct response. In that case, the model has the name "generalization property."
- Real-time capabilities: After the time-consuming process of training, the response is fast due to the internal parallel structure. It could be complex, but the internal operations are simple and usually fast in most programming languages. This real-time capability is usually independent of the complexity of the learned model.

3.2. New Model Challenges and Opportunities

Conventional methods based on the first principles are time-consuming. In 2011, the Material Genome Initiative method was proposed, wherein the experimental part, the calculation part, and the data are combined [115]. At that moment, big data was considered a newcomer to materials and, along with it, machine learning (ML). This is a very powerful technique that relies on three main parts: input, model, and output. The model is trained by algorithms that create a relationship between the input and the output without any physical conditions. The main steps of elaboration are the following: data collection, feature engineering, model building, and model application. A suitable model could therefore shorten the calculation time. The learning algorithms are divided into three groups corresponding to the learning process as follows: supervised learning, unsupervised learning, and reinforcement learning.

The previous sections have discussed differential models that correlate the SOH with the electrical, thermal, and mechanical behavior of a battery. Differential analysis is an effective tool that uses voltage, surface temperature, and deformation in different aging states [53]. Subsequently, life estimation models have also become important, since they fit a large number of data collected under defined experimental conditions, with high computational efficiency and high accuracy [53,116]. Finally, data-driven methodologies have become one of the most popular methodologies for battery life estimation and prediction due to their flexibility and non-linear fitting capacity. The interest in the potential of big data and its related statistical and computational tools is increasing for battery health estimation for both academia and industry, as they are flexible and not based on first principal models [117,118]. Their effectiveness depends on the quality and size of the dataset, but in practice it is impossible to test batteries over the full range of possible operating conditions. Overall, data analysis (DA)-based models and ML-based models are widely used data-driven methods for SOH estimation [118].

DA-based models identify characteristics from differential curves of measured data (electrical, thermal, or mechanical signals during the battery cycle) by fitting analytical functions to them. Correlations between the battery's SOH and the electrical, thermal, and mechanical behavior are developed. The most widely applied DA-based models include differential voltage (DV)/incremental capacity (IC) analysis, differential analysis of mechanical parameters, and differential thermal voltammetry (DTV) analysis [53,112].

ML-based models are widely used in data-driven SOH estimation and RUL prediction due to their flexibility or material analysis [119]. ML is a set of methods of data analysis that automates the construction of analytical models. It simulates human mental behavior, so it is understood that the system can learn from the input data, identify patterns, and make decisions or predictions while minimizing human intervention [53]. A procedure must be followed to implement this methodology. Firstly, data are collected, such as temperature, current, or voltage recorded during operation. These are used as input data for the training of the system. Secondly, representative features of the aging process are identified. Thirdly, a machine learning model is trained to learn the relationship between the SOH of the battery and the extracted features. With the model trained, the final step is to implement it in a battery management system (BMS) for online application if needed [53,120].

It is crucial to obtain and adequately represent the dataset in order to obtain a particular model. The variety of techniques is wide and can be classified into supervised and unsupervised learning. In supervised learning, the input and output variables of the training dataset are associated with each other. The algorithm therefore learns a correspondence between the inputs and the outputs with an acceptable degree of fidelity. In contrast, in unsupervised learning the algorithm is fed the given inputs and its goal is to find patterns of interest and identify trends or clusters in the data without additional help [53,112]. So far, in ML studies for battery health diagnosis and prognosis, supervised learning has been the most widely used and considered the most mature and powerful approach. Among the most widely used techniques are artificial neural networks (ANN) [112,113].

The area of identifying safety conditions is where new opportunities open up through the use of neural networks with the combination of data of different natures: thermal images, impedance, voltage, pressure, temperature, sound, etc. Olarte et al. [121] obtained satisfactory results using infrared thermography and modeling for fault detection in lead–acid batteries. In contrast, the use of neural networks could optimize these results.

3.3. Prevalent Neural Networks for Battery SOH Estiamtion

The variety of existing neural networks is wide and diverse. This section aims to collect the main neural networks used for battery analysis. Firstly, RBFN (radial basis function networks) are ANNs with one hidden layer, where the activation functions are only radial basis functions. This makes their training faster and avoids the problem of defining the number of hidden layers. They are used for both classification and regression problems. Wu et al. [122] applied this methodology to the study of SOH estimation in LIBs to ensure the safety and reliability of electric vehicles, providing better estimation of the performance compared to traditional ANNs.

Secondly, deep learning neural networks (DL) are usually feed-forward neural networks but specifically with more than three layers (including the input and output layers). They are used for massive data processing. Their main use in the battery field is for SOH estimation of various forms. For more information, see the following references [123–126].

Thirdly, convolutional neural networks (CNNs) are a specific type of deep learning neural network that uses the convolution operation instead multiplications in at least one layer. They are typically used for computer vision tasks, but there are also successful applications in time-series processing. In the battery field, they have been used for SOH estimation in the same way as the previous methodologies. In this case, there are studies that use CNNs to estimate the SOH. They perform large data preprocessing, which is subsequently used to feed the CNN-transformer network, offering results of great stability and accuracy [127]. On the other hand, Jiang et al. studied the extraction of qualified health features in conjunction with CNNs [128].

Finally, a long short-term memory (LSTM) network is a kind of recurrent neural network (RNN) specially well suited to dealing with the vanishing gradient problem that sometimes arises in traditional RNN training (when the gradient of the error with respect to the current weights of the network is very small and some traditional training algorithms are used). The typical scope is time-series problems. In the battery field, the estimation of the SOH continues to be the main goal [129]. Teng et al. [130] used this neural network to estimate the SOH of retired batteries, with the aim of reducing pollution and building a battery cycle ecosystem.

4. Conclusions

This review suggests that the complex cause–effect patterns that occur during the degradation processes of Li-ion batteries can be modeled with artificial intelligence techniques by combining data from different sensors or estimators (voltage, temperature, pressure, sound, image, impedance), which opens up new opportunities for the development of production systems or safer battery utilization and management, giving rise to new functions in BMS or BTMS.

Although this new approach is gaining more and more importance, classical methodologies are still vital, Table 1 lists the benefits and challenges of the methodologies discussed in this review. It should be added that experimental methods are the basis for many model-based studies and even more so for artificial intelligence-based ones. Moreover, they are also accurate, some can be used in operando, and most are non-destructive. On the other hand, model-based methodologies analyze not only the system but also its dynamics, search for faults, and identify them, and are the main option for fault diagnosis. However, these methods require great mathematical knowledge, making it difficult to find accurate models that can serve different situations and systems at the same time. In addition, they require significant computational effort.

Table 1. Benefits and challenges of the analyzed methodologies.

	Conventional Methodologies		**New Trends**
	Experimental Based [50,68,97]	**Model Based [68,97]**	**Neural Networks [7,130]**
Benefits	Accurate, robust, reliable, some of them can be used in operando mode, most of them are noninvasive and non-destructive	Analysis of the system and its dynamics, main option in fault diagnosis	Identify nonlinearly dependent degradation paths due to unsafe operating conditions

Table 1. *Cont.*

	Conventional Methodologies		New Trends
	Experimental Based [50,68,97]	**Model Based [68,97]**	**Neural Networks [7,130]**
Challenges	Time-consuming, not all of them are suitable for online assessment	Based on experimental methods, not very accurate in different situations, high mathematical knowledge, high computational effort	Require representative data for the overall search space of battery states and failures

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Nomenclature

Acronym list used in the review.

Acronym	Definition
AI	Artificial intelligence
ANN	Artificial neural network
BMS	Battery management system
BTMS	Battery thermal management system
CNN	Convolutional neural network
DA	Data analysis
DL	Deep learning
DM	Degradation mechanisms
DM&S	Degradation mechanisms and safety
DTV	Differential thermal voltammetry
DVA	Differential voltage analysis
ECM	Equivalent circuit model
EIS	Electrochemical impedance spectroscopy
EV	Electric vehicle
IC	Incremental capacity
ICA	Incremental capacity analysis
LAMNE	Loss of active material from the negative electrode
LAMPE	Loss of active material from the positive electrode
LIB	Lithium-ion battery
LLI	Loss of lithium inventory
LSTM	Long short-term memory
ML	Machine learning
NN	Neural network
OR	Ohmic resistance
PPB	Parts per billion
PR	Polar resistance
RBFN	Radial basis function network
RUL	Remaining useful life
SEI	Solid electrolyte interphase
SOC	State of charge
SOH	State of health
TR	Thermal runaway

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