Chapter

New Trends and Challenges in Condition Monitoring Strategies for Assessing the State-of-charge in Batteries

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Abstract

Condition monitoring strategies play an important key role to ensure the proper operation and/or working conditions in electrical, mechanical, and electronic systems; in this sense, condition monitoring methods are commonly implemented aiming to avoid undesired breakdowns and are also implemented to extend the useful life of the evaluated elements as much as possible. Therefore, the objective of this work is to report the new trends and challenges related to condition monitoring strategies for assessing the state-of-charge in batteries under the Industry 4.0 framework. Specifically, this work is focused on the analysis of those signal processing and artificial intelligence techniques that are implemented in experimental and model-based assessing approaches. With this work, important aspects may be highlighted as well as the conclusions and prospects may be included for the development trend of condition monitoring strategies to assess and ensure the state-of-charge in batteries.

Keywords: condition monitoring, state-of-charge, battery

1. Introduction

Condition monitoring strategies have been successfully implemented as a part of Condition-Based Maintenance (CMB) programs for several decades with the aim of preventing the occurrence of malfunction problems. Although CBM programs have been effectively implemented, in the last years, Industry 4.0 is changing the landscape in different sectors with the rise of the smart factory and the use of data, such changes have been possible through the digitization of value chains, where the aim is to improve the efficiency, sustainability, and flexibility of operations. These new trends present new tools to further maximize the value of the data that are collected during the equipment operation to coordinate tasks in a predictive environment (before a functional failure occurs). However, it is important to clearly define what information or data to collect will represent a meaningful value to the decision-making process. In this regard, it should be noted that the proper implementation/conversion to the Industry 4.0 may lead to numerous advantages to any process [1, 2]. Thus, **Figure 1** shows the most important benefits that may be reached by the implementation of Industry 4.0, the order of importance may differ according to the process and/or application where Industry 4.0 is implemented.

Thus, the most important profits that are taken into account focused on monitoring strategies applied to assess the condition of a specific system are described below:

- *Productivity improvement*: optimization of the processes carried out in organizations, which refers to the decrease in time and resources allocated to achieve them, as well as the reduction of failures and interruptions in production are eliminated.

- *More security:* it is possible, in some scenarios, to introduce machines or robots in dangerous environments, which increases the safety of the workers who work in these areas.

- *Data management (processing):* allows efficient data management since defined and authorized personnel can access and interact with them from anywhere.

- *Support in decision-making:* factories have large volumes of information, which, when properly treated and classified, improves the decision-making process.

- *Greater traceability:* the traceability of all day-to-day records generated as a result of the business management process is increased.

Under this framework, the term Industry 4.0 can be interpreted as the hyperconnection, where all systems are connected between them and can send,

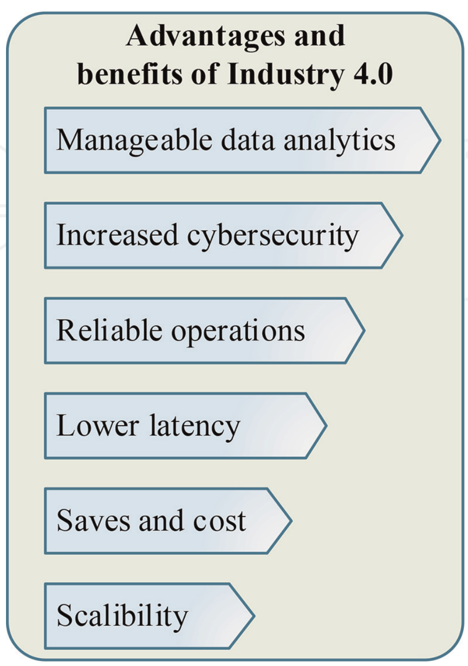

Figure 1.
Most important advantages and benefits reached through the implementation of the Industry 4.0, where such advantages may be found in several research papers focused on the Industry 4.0 [1, 2].

receive, and analyze data and are no longer a novelty. Thus, this new concept is currently used during the collection and monitoring of the control parameters of the equipment to optimize its operation. It is well known that the Industry 4.0 has profoundly changed industrial processes, in fact, in a constant optimization process, also, the Industry 4.0 would reduce energy and resource consumption while improving production. Accordingly, many problems that have been and are still faced by our planet are the product of industrialization, such as climate change, unsafe levels of air pollution, the depletion of resources, or the loss of biodiversity are some examples of the impact of our activity in the world [2, 3]. Also, the implementation of the Industry 4.0 has impacted different subject areas, and it should be noted that engineering and data science applications have been significantly benefited and other areas such as energy have not been widely studied, this statement is supported by the percentage of published papers related to Industry 4.0 for the different subjected areas as **Figure 2** depicts.

As stated, condition monitoring strategies have been extensively applied and its implementation as a CMB program has benefited the industry sector since major of the procedures are accomplished by electronic, electrical, and mechanical elements, where its combination leads to electromechanical systems [4–6]; moreover, it is worth noting that condition monitoring is also a very active area of research in aerospace and civil engineering where the objective also remains to ensure its functionality. In this regard, CBM programs may be implemented with different aims, for example, by analyzing the remaining useful life (RUL), it is possible to predict the occurrence of faults that may affect the functionality of the whole system in a near future, as well as the detection and isolation of faults that have been occurred and are present by analyzing the state-of-health (SOH), and the detection and identification of multiple and combined faults that may occur simultaneously. As stated, despite most of the condition monitoring strategies being developed under a particular framework, i.e., RUL and/or SOH, the principal aim remains to identify abnormal states and/or operations that tend to present deviations from an optimal condition or state of operation; therefore, the most appropriated way of implementing such condition monitoring practices will depend on the application or problem being addressed [7, 8].

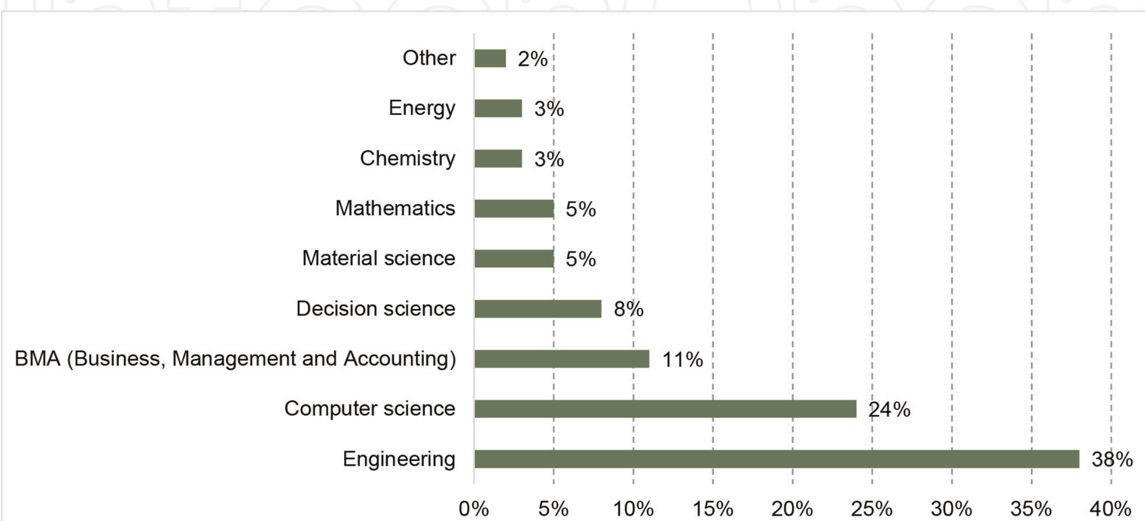

Figure 2.
Percentages of papers that have been published and focused on the Industry 4.0 for different subject areas.

On the other side, the Industry 4.0 framework also aims to face pollution problems through the proposal of green solutions and by the implementation of renewable energy systems. In this context, environmental pollution, which is one of the most critical global problems affecting today's world, has attacked the attention of many scientists aiming to provide successful solutions. Certainly, it is well known that the world's pollution (measured in terms of air quality) is in general produced due to the effects associated to the global greenhouse gas emissions, where carbon dioxide (CO_2) is the most dangerous gas produced by the use of fossil fuel and also produced in industrial processes, which has a concentration of about 65% only for the global greenhouse gas emissions; meanwhile, the remaining 35% of gases are composed by carbon dioxide, methane, nitrous oxide, among others. Therefore, cars, trucks, and/or industrial processes that are based on the use of fossil fuel are the main sources that contribute the environmental pollution, specifically, to the pollution of the air. In this sense, in the most recent decades, it has been noticed that electrification may be the key solution that can lead to the reduction of those high percentages of gas concentrations that increase the world's pollution and that endanger human health [9–11]. Accordingly, since electrification can be considered the most adequate solution to the reduction of environmental pollution, it may be understood as the reconversion of those traditional systems that are dependent on fossil fuel to new systems that only use electric drives. Hence, nowadays, new scientific and technological advances have made it possible to innovate as the readily technology is scalable; in this regard, the new trends are toward the manufacturing of electric vehicles if possible and/or hybrid vehicles to reduce the emission of polluting gases. Although the manufacturing of electric or hybrid vehicles has been promoted by technologically developed countries, some challenges must be faced; thereby, the energy storage and management are probably the most critical issues that are recently addressed. Certainly, the monitoring of the state-of-charge in batteries may be the key point that allows the characterization of the efficiency and/or autonomy in electric and hybrid vehicles [12–15].

In fact, the Industry 4.0 can be the solution to face actual problems and to overcome challenges that have not been addressed, thus, it should be highlighted that the Industry 4.0 is adaptable to a specific application. For example, for electromobility and electric vehicles, the most critical challenges are the range, charging time, and charging infrastructure. Consequently, most of the recent research has been focused on the condition assessment of the state-of-charge in batteries under the Industry 4.0 framework, which involves the general terms of automation, big data, cloud computing, autonomous Internet of Things (IoT), and data management. Moreover, the efficiency of electric vehicles is intuitively in terms of installed monitoring and diagnostic systems and depends on the number of available variables that can be acquired to assess the vehicle parameters. As illustrated below (**Figure 3**), under the Industry 4.0 framework, it is shown a general scheme where are presented different problems (challenges) to be solved under the Industry 4.0 framework.

Therefore, this work presents a systematic report related to the new trends and challenges that are associated with condition monitoring strategies used for assessing the state-of-charge in batteries under the Industry 4.0 framework. Precisely, in this work are presented those classic and significant techniques of analysis that have led to high-performance signal processing, as well as those artificial intelligence techniques that are implemented in experimental and model-based assessing approaches. Additionally, in this work are included the most important aspects that have to be theoretically considered whether a condition monitoring strategy is intended to be implemented for the assessment of the battery's condition.

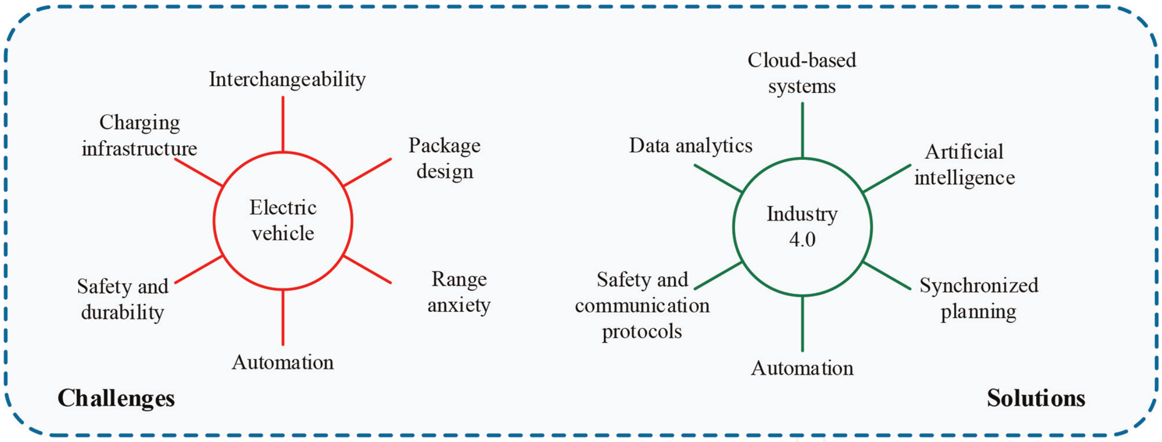

Figure 3.
Challenges to be faced under an Industry 4.0 framework presented in some published research works ([3]).

2. Theoretical background

In this section, a summary of the most common battery technologies nowadays, as well as an overview of the main components and functions that must be accomplished by a BMS (Battery Management System) to guarantee the proper operation of any battery system, is presented.

2.1 Different battery technologies

Batteries are electrochemical devices that can receive and store energy to be used at a later moment. Although there are more energy-storage devices, batteries have gained popularity due to their capability of providing high power and energy efficiency at a relatively low cost with a long life cycle and a rapid response [13]. **Figure 4** illustrates the general construction of any type of battery. It is composed of two electrochemical cells that can turn chemical energy into electricity. Each cell consists of a positive electrode, or cathode, a negative electrode or anode, and an electrolyte that is commonly a fluid that allows the flow of the ions (i+) from one electrode to another. This way, the electric current flows outside, and it can be used to feed any load.

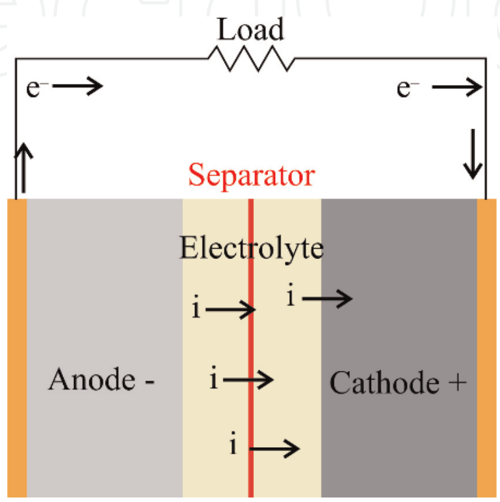

Figure 4.
Representation of the basic internal composition of a battery.

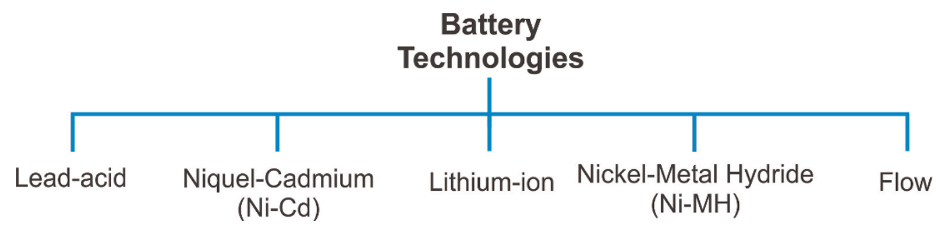

Figure 5.
Main technologies used in the internal composition of a battery.

Due to the key role that batteries play in important emergent technologies such as electric vehicles and renewable generation sources, a big effort is put into the development of a wide variety of batteries with different characteristics. This situation is achieved by using different chemical elements and construction strategies resulting in a wide variety of battery technologies. Next, the main technologies used in batteries are shown in **Figure 5** and also addressed and briefly described. Although there exist several battery technologies, the ones that are presented in this section represent the most used in applications such as renewable generation and electric vehicles.

2.2 Lead-acid batteries

This is one of the oldest technologies used for the development of batteries. Therefore, the lead-acid technology for batteries is mature and widely spread. These types of batteries are characterized to be low cost and very reliable; thus, it is a proficient technology for applications that require an uninterrupted power supply with high quality [16]. In lead-acid batteries, the positive electrode (cathode) is composed of lead dioxide (PbO_2) and a negative electrode (anode) of metallic lead (Pb). Additionally, they consider a sulfuric acid solution (H_2SO_4) as an electrolyte. At the anode, the Pb reacts with a sulfate ion to obtain lead sulfate ($PbSO_4$) as shown in Eq. (1):

$$Pb + SO_4^{2-\rightarrow 2e^{-+PbSO_4}} \tag{1}$$

It is observed in Eq. (1) that two electrons are released at the lead electrode conferring it the negative charge. On its part, the PbO_2 of the cathode reacts with the electrolyte yielding $PbSO_4$ and water according to Eq. (2):

$$PbO_2 + 4H^{++SO_4^{2-+2e^{-\rightarrow PbSO_4+2H_2O}}} \tag{2}$$

Finally, the total reaction can be expressed with Eq. (3):

$$Pb + PbO_2 + 2H_2SO_4 \Leftrightarrow 2PbO_2 + H_2O \tag{3}$$

Eq. (3) shows that the reaction is reversible allowing the battery to be repeatedly charged and discharged. Commonly, a lead-acid battery is composed of several pairs of electrodes that are placed in separate compartments. Each one of these compartments is called a cell. The negative electrode of each cell is connected with the positive electrode of the next cell leaving free the cathode of the first cell and the anode of the last cell, and the result is a battery whose voltage is the sum of the individual voltages of each cell. It is important to mention that each cell of a lead-acid battery handles typical voltages of $E_0 \approx 2.048V$ and typical configurations consider three, six, and 12 cells for a complete battery [17].

2.3 Lithium-ion batteries

This technology is more recent, it was first introduced in the 1990s, but it is recently widely used in electronic devices, smart grids, and electric vehicles [18]. Lithium-ion batteries have gained a lot of popularity because they are the main type of storage system used by all mobile devices as smartphones and tablets. Notwithstanding, they are also highly used in electric vehicle applications as well as in grids containing renewable energy generation. These types of batteries can provide a higher energy density than most of the other available technologies since they operate at voltages around 4 V per cell, while other systems operate at 2 V per cell [19]. Lithium-ion batteries use anodes and cathodes based on insertion-compound materials. In the case of the anode, a carbonaceous material [20] is required; therefore, the preferred compound is graphite formed by one lithium atom per six carbon atoms LiC_6. On its part, for the construction of the cathode, it is used a metal oxide and the available materials are mainly three: the layered $\lim O_2$ ($M = Mn$,Co and) [21], spinel $\lim n_2O_4$ [22] and olivine $LiFePO_4$ [23]. Additionally, these batteries use water-free organic liquid electrolytes such as $LiPF_6$ salt dissolved in a mixture of ethylene carbonate (EC). In fact, the use of this type of electrolytes is the reason why lithium-ion batteries are capable of handling 4 V per cell. Finally, this technology incorporates a separator that allows only the lithium ions to flow from one side to another in the battery. During the charging process, some of the lithium ions leave the positive electrode and flow through the electrolyte to the negative electrode. When the lithium ions reach the graphite, they are inserted between the atomic layers of that material, where they recombine with the electrons, leaving the lithium deposited there. When the ions stop flowing, the battery is completely charged. On the other hand, when the battery is discharging, the lithium ions flow back through the electrolyte from the graphite anode to the cathode.

2.4 Niquel-Cadmium (Ni-Cd) batteries

This is another technology that has been on the market for many years. These batteries use a cathode of nickel hydroxide and an anode of cadmium hydroxide. In this case, the electrolyte is an alkaline substance and the charge and discharge process can be described by Eq. (4):

$$2NiOOH + 2H_2O + Cd \Leftrightarrow 2\ni(OH)_2 + Cd(OH)_2 E^0 = 1.29V \tag{4}$$

where E^0 represents the voltage of a single Ni-Cd cell.

These batteries are famous because they can operate at a wide temperature range and they are easy to maintain. However, their manufacturing is complex, making these batteries expensive. But probably the biggest issue related to this technology relays in the fact that it contains cadmium, which is a heavy metal well known for its toxicity [24].

2.5 Nickel-metal hydride (Ni-MH) batteries

This type of battery operates in a way similar to the Ni-Cd one, and this technology is preferred in hybrid electric vehicles (HEV) due to its high-power density and tolerance to overcharge/over-discharge processes [25]. In this case, the Ni-MH technology considers that the active material of the positive terminal is nickel oxyhydroxide (NiOOH) and the active material that constitutes the negative terminal is hydrogen in the form of a metal hydride, which allows the hydrogen produced during the charging process to be stored and released during the discharge process [24]. This type of electrode is responsible for providing greater capacity per volume unit compared to a Ni-Cd battery. A common metal alloy (M) in Ni-MH batteries is an alloy made up of a mixture of zirconium or titanium hydride with another metal such as nickel, cobalt, or aluminum. And the electrolyte in these batteries is mainly made up of potassium hydroxide, which also makes it a type of alkaline battery. The chemical reaction that occurs inside these batteries is described by Eq. (5):

$$MH + NiOOH \Leftrightarrow M + (OH)_2 E^0 = 1.35V \tag{5}$$

Again, as in the Ni-Cd battery, the term E^0 refers to the voltage of a single battery cell. Compared to its cadmium counterpart, this technology is less harmful to the environment. However, its disposal at the end of its lifecycle must be cautious since it still uses corrosive salts.

2.6 Flow batteries

This is a technology that considers systems of two connected tanks, both containing electrolytic liquids: one with a positively charged cathode and the other with a negatively charged anode. Electricity passes from one electrolytic liquid to another through a membrane between the tanks. There are two main types of commercial flow batteries: Vanadium redox batteries (VRB) and Zinc-Bromine (Zn-Br). The VRB uses sulfuric acid containing V5+/V4+ and V3+/V2+ redox couples as the positive and negative half-cell electrolytes. The reaction that describes the charge/discharge process is described by Eq. (6):

$$VO_2^{++2H^{++}V^{2+} \Leftrightarrow VO^{2++}H_2O+V^{3+}E^0=1.26} \tag{6}$$

In the case of the Zn-Br battery, its operation principle may be defined by Eq. (7) as follow:

$$Zn + Br_3^{- \Leftrightarrow ZnBr_2 + Br^{-E^0=1.85}} \tag{7}$$

Despite this technology having technical advantages, such as potentially separable liquid reservoirs and almost unlimited longevity over most conventional rechargeable batteries, current implementations are relatively less powerful and require more sophisticated electronics [26].

2.7 Battery management system (BMS)

To ensure the safe and reliable operation of any battery, it is important to keep the operating conditions within a range known as the safe operating area (SOA). **Figure 6** shows a diagram of the different operating conditions that can be observed in a battery.

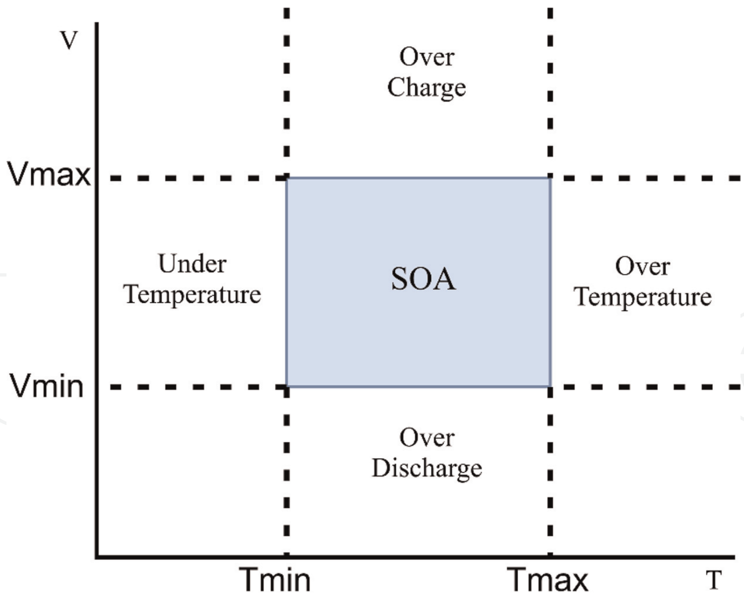

Figure 6.
Common diagram of the SOA for a battery that depicts different states during the charging procedure.

The SOA considers that the voltage and temperature of the battery must not exceed or fall below very specific values. These values are different for any battery, and they must be specified by the manufacturer. However, they can be addressed as the maximum voltage (Vmax), minimum voltage (Vmin), maximum temperature (Tmax), and minimum temperature (Tmin). If Vmax is exceeded, the battery presents an overcharge; when the battery reaches voltages lower than Vmin, it has reached the over-discharge state; for the case of a temperature superior to Tmax, the battery shows an over-temperature state; and finally, if the temperature is lower than Tmin and under temperature condition is achieved. All these last four conditions must be avoided because they can lead to severe damage to the battery, and they can result in safety risks for the final users. On the other hand and as observed, a single-cell battery delivers a small voltage value; therefore, a common battery is confirmed by a series of cells that can deliver a higher voltage together. This situation supposes some challenges, for instance, it is important to guarantee that all the cells perform the charge/discharge operations at the same rate so the complete system is balanced. Additionally, it is necessary to regulate the amount of current that is delivered or received by each cell to avoid damages associated with a misuse of the batteries. In this sense, the battery management system (BMS) plays an important role to keep the battery pack operating safely, reliably, and efficiently [27]. The BMS can be described as a black box model as depicted in **Figure 7**. To accomplish its purpose, the BMS takes the temperature (T), voltage (V), and current (I) of the battery pack and use them to perform different algorithms for controlling the operational conditions of the battery to extend its life and guarantee a safe operation. Additionally, the BMS provides an accurate estimation of the

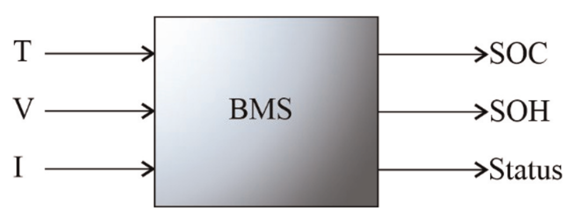

Figure 7.
Black box diagram of a BMS.

State of Charge (SOC) and the State of Health (SOH) of the battery pack, and based on all these parameters, the BMS can deliver information regarding the status of the battery pack and detect if a fault condition is present in the storage system.

The SOC is a parameter that can be defined both: in terms of the battery capacity or energy consumption. In renewable energy generation and EVs applications, it is more common to define the SOC as the ratio of the remaining energy (E_r) and the total energy (E_T) of the battery pack, and it is expressed as a percentage. The mathematical definition can be observed in Eq. (8):

$$SOC_E = \frac{E_r}{E_T} \times 100 \tag{8}$$

On the other hand, the SOH can be defined as the current total capacity that can be performed by the battery compared with the total capacity of the battery at the beginning of its life. As in the case of SOC, this parameter is defined as a percentage, and it is mathematically defined by Eq. (9):

$$SOH = \frac{C_T}{C_{BOL}} \times 100 \tag{9}$$

Where C_T is today's total capacity, and C_{BOL} is the capacity at the beginning of life. In the following section, the most common approaches for the implementation of BMS are presented. A more detailed diagram of how a BMS is composed can be observed in **Figure 8**.

3. Approaches and technologies for the implementation of BMS

In order to ensure the reliable and safe operation of electric vehicles, the accurate application of fault diagnosis schemes over the battery system is mandatory, in which the most relevant elements are composed of the sensors, the systems and components, and the actuators. Hence, different methods have been reported in the literature to

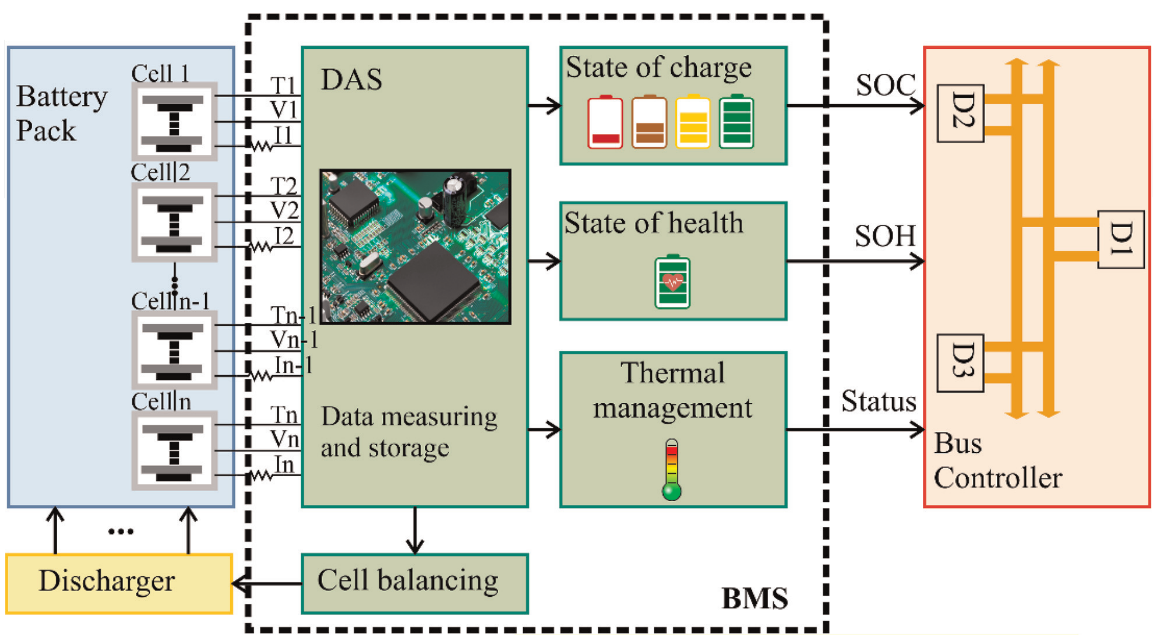

Figure 8.
Detailed diagram of a BMS showing the main and minimal components.

implement different tasks that must be performed by a BMS. In general, all the developed methodologies can be classified into two groups: experimental approaches and model-based approaches. The first one considers that several tests must be performed several times to obtain the information regarding the condition of the battery pack, whereas the second one considers that there exists a series of parameters that describe the battery state, and they focus on finding such parameters [28].

3.1 Experimental approaches

First, it is important to mention that most of the BMSs focus on performing an accurate estimation of the consumed capacity. If this task is correctly performed, it is possible to estimate the SOC and the SOH of a battery pack accurately and reliably. Therefore, most of the works reported in the literature pay special attention to this matter. The most common solution for this issue is the method known as the Coulomb counting [29], which considers the used capacity as the area behind the curve defined by the discharging current over time. When this value is subtracted from the total capacity, it is possible to know the remaining capacity in the battery pack. This method can be mathematically described by Eq. (10):

$$SOC(t) = SOC(t_0) - \frac{1}{C_T}\int_{t_0}^{t} i(t)dt \tag{10}$$

Where $SOC(t)$ is the current SOC; $SOC(t_0)$ is the initial SOC that is commonly considered as 100%; C_T is the nominal capacity of the battery; and $i(t)$ is the discharge current extracted from the battery. Accordingly, the implementation of the aforementioned method can be experimentally performed by means of following the flowchart of **Figure 9**, where the SOC starts by carrying out the real-time data acquisition,

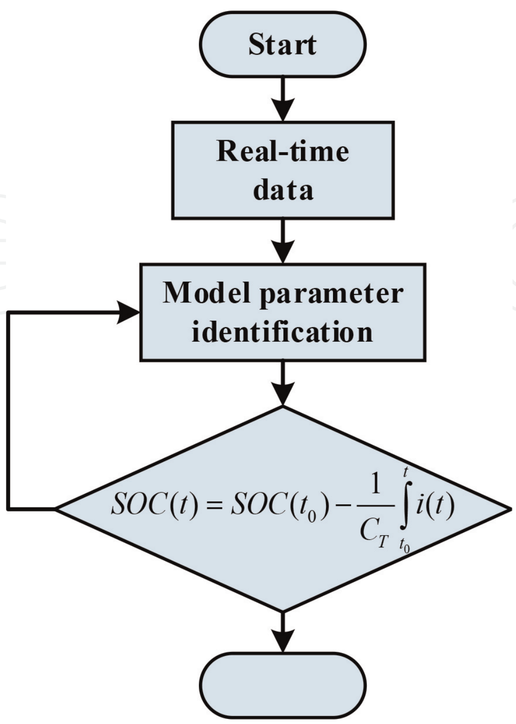

Figure 9.
General flowchart that may be followed to apply the assessment and achieve the SOC in batteries through experimental-based models.

then in a second step, the model parameter identification is achieved, and subsequently, the SOC is estimated in terms of the collected data by applying Eq. (10). Despite this approach being preferred, the implementation of this method has a technical drawback that is related to the use of a sensor for the current measuring. The sensors used for this purpose are usually shunted resistors or Hall effect transducers. These types of instruments introduce an error in the estimation due to the drift. Therefore, the Coulomb counting must be complemented with another technique to compensate for this effect. In this sense, the use of the open circuit voltage (OCV) [30] allows the analysis of energy changes in the electrodes of the battery, and therefore, there exists a direct relationship between the OCV and the SOC of the battery. In the experimental approaches, the OCV is sometimes obtained from the specifications given by the manufacturers. Notwithstanding, the information given by the manufacturer is not as detailed as required to perform an accurate estimation of the SOC.

Thus, the use of methodologies such as the low current test and the incremental current test results is helpful to solve this issue. The low current test considers that the battery must be initially charged using a constant current rate of 1C, considering that 1C means that the complete energy of the battery is taken in intervals of 1 hour. Next, the battery is discharged at a constant rate of C/20, and then, recharging the battery uses this same last rate (C/20). In this test, the voltage between electrodes is constantly measured and recorded during the entire test. This process is repeated several times and the average of all the tests is taken as the OCV [31]. On its part, the incremental current test considers that the battery must be completely charged to represent a 100% SOC. Then, a negative pulse current relaxation is used to discharge the battery and the voltage between terminals is measured every 10% of the discharge. When the battery has been completely discharged, the process is applied in reverse, i.e., the battery is charged with a positive pulse current and the voltage between terminals is measured every 10% of charge. This process must be repeated several times and the OCV curve is obtained by linear interpolation [32]. These techniques provide a good approximation of the OCV that can be easily related to the SOC and SOH of the battery. However, they are considered aggressive tests that may cause damage to the batteries; moreover, they suffer from the polarization effect due to the constant current discharge. In this sense, another widely spread methodology for the estimation of the SOC and SOH in batteries is the use of the impedance measurement [28]. This method takes advantage of the fact that the internal resistance of a battery determines its power capacity. Thus, the internal resistance is calculated using Ohm's law considering the voltage drop over the electrodes when a current is demanded. The so far mentioned algorithms calculate the SOC and SOH directly using their definition stated by Eqs. (8) and (9), respectively. But there is also possible to perform an indirect estimation of the SOC and SOH of the battery using the incremental capacity analysis (ICA) and the differential voltage analysis (DVA). These techniques allow to find a curve coming from the gradient of charged/discharged capacity concerning the cell voltage according to Eq. (11) and another one derived as the gradient of the cell voltage for the battery capacity as shown by Eq. (12):

$$IC = \frac{\Delta Q}{\Delta V} = \frac{dQ}{dV} \tag{11}$$

$$DV = \frac{\Delta V}{\Delta Q} = \frac{dV}{dQ} \tag{12}$$

Where IC is the incremental capacity feature, DV is the differential voltage feature, Q is the cell capacity, and V is the cell voltage. These curves present peaks at specific values and locations, and as the battery degrades, the amplitude and location of the peaks change. This situation is used for determining the SOH of the battery accurately and reliably [33].

3.2 Model-based approaches

The experimental methods provide a good tool for BMS to perform its task. However, they present the disadvantage of requiring a repeated number of tests to deliver their results. Therefore, they are not recommendable for an online implementation since BMS is expected to monitor the condition of the battery in real time, the model-based solutions seem to be a more appropriate tool. These approaches consider that certain parameters as the capacity and resistance of the battery can be calculated based on a mathematical model. In this regard, batteries have been described using an equivalent circuit model (ECM). This methodology states that a battery can be described by three main parameters: resistance, inductance, and capacitance. By finding these parameters, it is possible to determine the SOC and SOH of the battery in the function of the variations in the nominal values of the parameters. Here, the Kalman filter algorithm turns out to be particularly good for the estimation of the parameters of the battery [34]. This model delivers good results; however, it does not consider what happens inside the battery and may lead to errors if parameters such as the temperature are not taken into account. To overcome this situation, some works propose the development of an electrochemical model (EM). This way, the operation principle of the battery and its dynamic are modeled getting a more reliable and accurate representation. But this increment in the accuracy is not for free, the complexity of the model and the number of parameters increase, making the proper parameter identification more difficult. For instance, in [35], the use of different types of parameters: geometric, transport, kinetic, and concentration is proposed. The result is a mathematical model that comprises a total of 26 parameters. With this model, the SOC and the SOH are calculated considering not only the electric performance but also the composition and internal reactions of the battery. Thereby, SOC and SOH are commonly proposed and/or designed as a condition monitoring scheme that accomplishes stages such as data acquisition or monitoring, feature extraction or signal processing, and the fault diagnosis task in which the fault detection, isolation, and estimation are executed. **Figure 10** shows the flowchart of a condition monitoring scheme used for the implementation of a SOC.

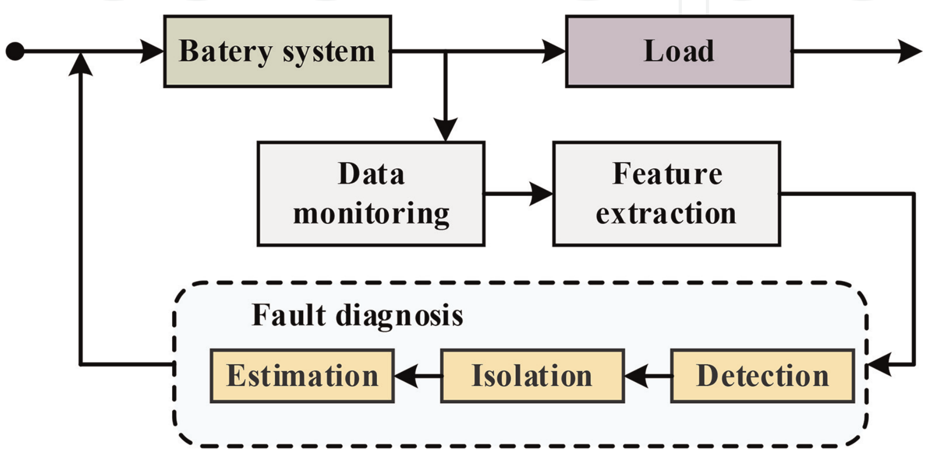

Figure 10.
Flowchart of a condition monitoring-based scheme used for performing the fault diagnosis in battery systems.

Another approach that is gaining popularity is the use of data-driven methodologies based on machine learning. These methodologies model the battery as a black box and develop software that uses example data or past experiences for learning how to solve a problem [28]. Here, support vector machines (SVMs) have proven to be effective for the estimation of parameters such as the SOC of a battery. For instance, in [36], the authors use voltage, current, and cell temperature as inputs of an SVM and with a least square algorithm, they estimate the SOC based on the behavior of the input parameters. A similar implementation is carried out in [37], the difference is that in this work the use of an SVM and the least square approximation are replaced by a deep neural network that estimates the battery condition using as inputs the voltage, current, and temperature. On their part, the authors in [38] propose the use of an ECM, and they use a fuzzy logic system to perform the parameter estimation. At this point, it is important to mention that all the machine learning approaches can be appreciated as a hybrid of the experimental and the model-based methods because they require a series of previous experiments before being implemented; additionally, they use a mathematical model but the model does not describe the system but the conditions required for the system to meet a specific state.

4. New applications and trends in BMS devices

According to recent research works and studies, it has been determined that the BMS (Battery Management System) is the key element in applications such as electric vehicles and renewable energy, this assert is due to the BMS being responsible for managing the energy consumption totally or partially, and it is also responsible for managing the energy storage. Although there exist different types of BMS that allow achieving an effective energy exploitation, nowadays new trends are emerging aiming to contribute to the development of innovative solutions. In this regard, the trend of new research will continue to consider a general diagnostic framework, and these will be based on the flowchart of **Figure 11** as a common base, where the data monitoring, data processing, data analysis, and diagnosis comprise the four general steps.

Accordingly, regarding the ***Data monitoring*** step, the most accepted approaches are those that perform the assessment by means of experimental and/or model-based implementations, which are also known as data-driven approaches. Despite these proposals differing whether experimental data and/or simulated data are used, in both cases may exist similar aspects that are taken into account and that lead to new proposals. In case that data are acquired through experimental tests, the monitoring procedure consists of recording physical magnitudes such as voltage levels, current consumption, and reached temperature; in fact, these signals are commonly acquired for the whole battery

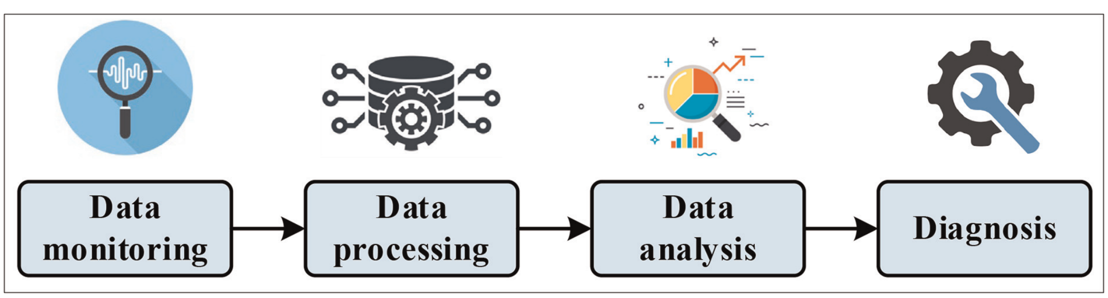

Figure 11.
General flowchart that may be followed to perform the assessment of batteries.

bank and are also individually acquired for each cell [39]. On the other side, equivalent circuit models are considered into account as the theoretical models when the data used are generated through simulation procedures, where the battery dynamics remain the most important aspect to be considered during the simulation [40].

Subsequently, the ***Data processing*** step may probably represent the most important stage since all the acquired data are processed with specific techniques, in this sense, the data processing may consider the simplest signal processing procedures such as the data normalization, data sub-sampling, data organization and may also consider the most complex signal processing procedures such as those techniques based on time domain, frequency domain, and time-frequency analysis [41]. The main objective of the Data processing step relies on the characterization and modeling of the acquired data, therefore, the processing of each acquired signal is performed in order to achieve a specific task, for example, the voltage signal may be processed aiming to give the current percentage or level of charge of the bank battery, the current signals are used to estimate the energy that may be supplied to all cells of the bank battery during the charging process and/or to estimate the energy consumption during the discharge procedure; and the temperature signals are taken into account as an additional variable that is implemented in most of the state-of-health monitor approaches to take care of the current state of the battery bank and to extend its useful life as much as possible [42].

Afterward, the ***Data Analysis*** and ***Diagnosis*** steps are commonly implemented as a part of the process that leads achieving the state estimation of the bank battery, as well as the remaining useful life, the level of charge, or in general is implemented to provide the SOH (state-of-health). Commonly, the *Data Analysis* stage includes Machine Learning techniques to process the available data [43], whereas the *Diagnosis* stage comprises intelligent algorithms to perform the automatic assessment task, in this regard, the most used techniques and algorithms are dimensionality reduction and/or feature extraction techniques, Support Vector Machines (SVM), Neural Networks such as Recurrent Neural Networks (RNN) and Fed-Forward Neural Networks (FNN), as well as regression models that may be based on Fuzzy algorithms; additionally, the use of genetic algorithms (GI) as a part of the assessing structures when the optimization of parameters is required [44]. On the other hand, it should be mentioned that for both stages, *Data analysis* and *Diagnosis*, most of the proposed approaches compute numerical values such as the Maximum Absolute Error (MAE), the Root Mean Square (RMSE), the Mean Square Error (MSE), and the goodness-of-fit R2, where these values are used as a quantitative measurement that depicts the effectiveness of the designed approaches [45]. An important aspect that must be also highlighted for the *Data analysis* stage is the estimation of the most representative set of features that allows a high-performance characterization of the processed signals. Finally, the use of Neural Networks is preferred in most of the designed predictors or SOH approaches due to their versatility and the low computational burden for their implementation in real-time applications. Thus, the selection of an appropriate signal processing technique, the use of Machine Learning techniques, and the implementation of Artificial Intelligence may represent the most important aspects to be considered during the proposal of novel strategies applied to assess the state-of-charge in batteries for multiple applications.

5. Conclusions

Modern society is undergoing an important transition toward new forms of transportation and energy generation that are sustainable and that allow reducing the emission of gasses that cause the greenhouse effect and global warming. In this sense, batteries play an important role because they allow energy storage with high power and energy efficiency at a relatively low cost. However, to ensure their proper operation and to extend their lifecycle as much as possible, the use of a BMS is mandatory. BMS allows the battery pack to perform its task safely and reliably by estimating parameters that provide information regarding the condition of the batteries. Several methodologies have been developed to allow the BMS to fulfill its task reliably and accurately. The experimental approaches can provide an estimation of the battery status using a simple but effective method. However, they require the implementation of several tests to properly work becoming these techniques suitable mainly for offline implementations. On the other hand, the model-based approaches can perform the same task that the experimental techniques robustly and reliably can be implemented for online condition monitoring, at the cost of higher complexity. Finally, the machine learning techniques provide a hybrid between the experimental and the model-based methodologies that uses artificial intelligence techniques for identifying the condition of the batteries based on the behavior of some inputs that are commonly the electric parameters of the battery pack. These implementations require a set of experiments to be performed before they can be implemented; however, once they have been properly trained, they can operate in online systems. All the methodologies used for BMS deliver accurate and reliable results, and this work aims to be a tool for the readers to know different options so they can select the one that better fits their needs.

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Conflict of interest

The authors declare no conflict of interest.

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