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# Contribution to a review of lithium-ion batteries diagnostic methods for space applications

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**Abstract** — Thanks to their excellent performance, lithium-ion batteries have become increasingly used in terrestrial and space applications. Despite the long lifespan, this type of battery is subject to inevitable aging dependent on electrochemical degradation phenomena. Defining a diagnostic method capable of estimating the state of health of a battery and predicting its end of life is therefore a priority to ensure proper functioning. Although considerable progress has been made in recent years in this research topic, most of the effort of the scientific community is concentrated in terrestrial applications. Of all the various existing approaches, both experimental and numerical, few are applicable within the limitations imposed by space applications. Hence, the main contribution of this paper is to provide an overview of the current state of the diagnostic methods adopted to estimate the aging of lithium-ion batteries used in satellites.

**Keywords** — *Lithium-ion battery, Degradation modeling, Space applications, State of health estimation.*

## I. INTRODUCTION

Among all commercially available battery types, lithium-ion technology stands out for its high energy density, high power density, and long lifetime [1]. Lithium-ion batteries were first used in space application during the STRV-1 mission organized in the UK by DERA in 1992 [2]. Another example of early successful applications is the Myriade platform whose development began in 1998 by CNES [3]. Before the adoption of this technology, the battery chemistries used in space application were nickel-cadmium (Ni-Cd), nickel-hydrogen (Ni-H<sub>2</sub>) and silver-zinc (Ag-Zn) [4]. Table I compares the characteristics of these chemistries and shows some examples of NASA applications [5].

TABLE I. CELL CHEMISTRIES USED IN SPACE COMPARISON [4]

Chemistries	Characteristics	Specific Energy (Wh/kg)	NASA Mission Example
Ni-Cd	High rate capability, long cycle life, high reliability	<50	Mariner 7 (1971)
Ni-H <sub>2</sub>	Long cycle life (>50 000 cycles), resiliency to abusive operating conditions	~50	ISS (1998)
Ag-Zn	Short cycle life (<100 cycles), high specific energy	~100	Apollo (1968)
Li-ion	Long cycle and operational life, high specific energy	>120	MER (2003)

An electrochemical lithium-ion cell, the elementary unit of a battery, consists of two electrodes, a positive one and a negative one, an electrolyte and a separator. The negative electrode is mainly made of a porous carbon/graphite, the positive electrode is mainly composed of transition metal oxides and the electrolyte is composed of lithium salt and carbonate solvents with good ionic conductivity. Depending on the materials used for the positive electrode, it is possible to have different cells chemistries. Table II summarizes the advantages and disadvantages of the most widely used lithium-ion cell types. Nevertheless, the performance of this type of battery, i.e., the energy it can store and the power it can deliver, inevitably declines with time (calendar aging) and use (cycle aging). This aging is generated by the electrochemical degradations of the cell components that depend on external factors, such as temperature, and battery use.

Today, lithium-ion batteries are widely used in space applications, particularly in Earth orbit satellites. Different types of missions correspond to specific operational conditions and work profiles. Therefore, the energy storage system must be chosen accordingly and its state of health must be estimated periodically to assure reliability [6]. Several diagnostic methods have been developed recently that can qualify and quantify the level of degradation of a battery. Although the possible approaches are varied and numerous, few of them are suitable for space applications. In fact, the inability to have access to a battery on a space mission, combined with the characteristic operational conditions and work profiles, makes most of these methods ineffective.

TABLE II. LI-ION CHEMISTRIES COMPARISON [4]

Cathode Chemistries	Cost	Discharge Rate Capability	Specific Energy	Safety
Lithium manganese oxide (LMO)	Low	High	Low	Good
Lithium manganese nickel cobalt (NMC)	Low	Good	High	Good
Lithium nickel cobalt aluminum oxide (NCA)	High	Low	Very high	Good
Lithium cobalt oxide (LCO)	Very high	Low	Low	Poor
Lithium iron phosphate (LFP)	Low	Very high	Low	Very good

Moreover, most of the research efforts are invested in the terrestrial applications, given the growing and wider market for electric vehicles. The objective of this paper is therefore to understand which of the main diagnostic methods discussed in the recent literature are suitable for space applications.

This paper is organized as follows. Section II introduces the degradation phenomena typical of lithium-ion batteries. Section III explains the general battery work profiles and operational conditions in space application. Section IV lists the most common diagnostic methods used for battery degradation estimation while section V focuses on current examples used in space application. Finally, conclusions and outlooks are discussed in Section VI.

## II. LI-ION BATTERY AGING MECHANISMS

Battery aging is caused by external factors, which can act on a physical level, through mechanical and thermal stresses, or on a chemical level, through side chemical reactions, i.e., different from the main reactions necessary for the operation of the cell. The external factors that have an impact on cell degradation are as follows: time, high/low temperature, high/low cut-off voltage, State Of Charge (SOC) level, charge/discharge rate (C-rate), stoichiometry and mechanical stress [7]. While the physical meaning of time, temperature, voltage and mechanical stress are intuitive, it may be useful to introduce the other factors. The C-rate describes the electric current flowing in the cell compared to its total capacity. The cutoff voltage indicates the voltage at which the Battery Management System (BMS) stops the charge/discharge process to avoid overcharge/overdischarge phenomena and possible side reactions. The SOC is the percentage level of charge compared to its total capacity. The stoichiometry describes the quantitative relationship between reactants and products in a chemical reaction.

These external factors are the origin of degradation mechanisms, defined as the specific failures that lead to a change of the thermodynamic and kinematic behaviors of the cell [8]. These mechanisms can be physical or chemical in

nature, and they can manifest on different scales, both at the particle (micro) and cell (macro) level. These degradation mechanisms are not easy to identify or isolate experimentally. Nevertheless, it is possible to distinguish and categorize the consequences of these mechanisms, called degradation modes, defined as the measurable effects associated with the change of cell state [9]. Multiple external factors may contribute to the same degradation mechanism, and at the same time, one external factor may lead to several mechanisms. Similarly, different mechanisms and degradation modes are related in the same way. In addition, multiple external factors can simultaneously interact on the cell, and multiple mechanisms can interact with each other in positive/negative feedback loops [10]. Because of the complexity of these phenomena, only those that have the greatest impact on cell health are often considered.

Finally, on a practical level, these degradation modes have as their ultimate causes the loss of capacity and the loss of power. Fig. 1 lists the external factors, the degradation mechanisms and modes and the final effect on the cell thermodynamic. These are the main values that help define the battery State Of Health (SOH), defined as the ratio between the actual and initial capacity. In applications where power matters most, the SOH indicator is calculated from the ratio of the actual and initial impedance.

## III. BATTERY USAGE IN SPACE APPLICATIONS

During the past 10 years, the lithium-ion battery has been used extensively as an energy storage system in satellites thanks to its high energy density and long service life [11]. Along with the battery, solar panels are the other energy source for the system. They provide electricity to the satellite and recharge the battery during the windows of time when the sun is visible, called sunlight phases. On the other hand, the battery provides electricity to the satellite during the windows of time when the sun is not visible, called shadow phases or eclipses, or when the power system needs power peaks [12]. Just as the earth follows its orbit around the sun, so the satellite

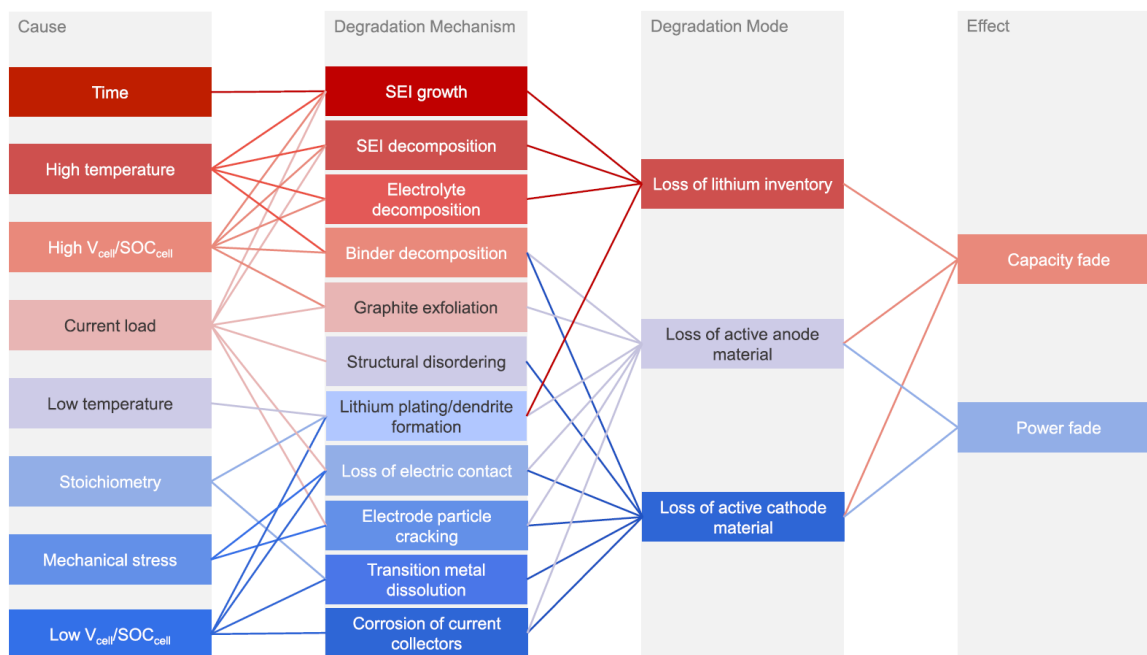


Fig. 1. Causes and effects of the main phenomena underlying the degradation of electrochemical cells [7]. SOC: State Of Charge, V: Voltage, SEI: Solid Electrolyte Interphase.

follows a predetermined orbit around the earth. In fact, shadow phases occur when the earth is between the sun and the satellite. These periods vary in duration depending on the height of the satellite's orbit.

The height of the orbit in turn depends on the type of mission assigned to the satellite. The most common missions for earth-orbiting satellites involve applications in meteorology, navigation, remote sensing, telecommunications, data transmission, and military defense. Each of these has its own optimal orbital height. Three categories can be distinguished: Low Earth Orbit (LEO), Medium Earth Orbit (MEO) and Geostationary Earth Orbit (GEO) [6]. Table III summarizes the mission specifications and battery requirements for these satellites. Fig. 2 shows the size comparison between LEO, MEO and GEO and computer images of examples of satellites on these orbits.

Thus, batteries in different applications have different work profiles. The alternation of sunlight and shadow phases defines three processes in the battery: discharge, charge and shelve state (period when the battery is not used) [14]. Among them, the battery main process is the discharge, since this is the one in which the battery is effectively the only satellite energy source. This process is partial and variable: partial

because the satellite battery cannot be fully discharged for safety reasons; variable because the duration of the process gradually changes with time since it depends on different factors. For example, shadow phases for GEO satellites vary from about 21 minutes to 72 minutes, according to the solar declination angle (the angle made by the sunrays with the equator of the earth). The charging process occurs as soon as the satellite enter a sunlight phase and lasts according to the level of SOC after discharge [15]. The shelve process, requires no battery participation and lasts until the sunlight period ends. Work profiles are therefore more or less dynamic depending on the applications. During each of these three processes, characteristic electrochemical reactions occur in the battery, which affect differently the degradation.

In addition to work profiles, operational conditions also have a strong impact on battery degradation. In space, the main factors are radiations, vacuum, temperature, and vibrations [15] [16]. Radiation consists of energetic particles capable of damaging the spacecraft at both the electronic and atomic structure level. Through the use of shielding layers, it is possible to protect the satellite. Vacuum can affect the battery through the electrolyte leakage and outgassing phenomena. The latter consists in the formation of gas inside the battery that can escape and contaminate other sensitive

TABLE III. MISSION SPECIFICATIONS AND BATTERY REQUIREMENTS FOR CLASSICAL SATELLITES [13]

Specifications and Requirements		LEO	MEO	GEO
Mission specifications	Altitude range (km)	250–2000	2000–36,000	36,000
	Orbital period	90 minutes (60 minutes sunlight 30 minutes eclipse)	2-24 hours	24 hours (coupled with the earth's orbital rotation)
Battery requirements	Lifetime (years)	2–15	up to 14	up to 18
	Cycles per year	~5500	~180	90
	Charge current (C-rate)	C/3	C/10–C/15	C/10–C/20
	Cycle Depth Of Discharge (DOD) (%)	10–40	60–80	60–80
	Discharge current linked to cycle DOD (C-rate)	C/2–C/1.5	C/2–C/1.5	C/2–C/1.5
	Temperature range (°C)	0–40	10–30 eclipse season (due to battery cycling) 0–30 solstice periods	10–30 eclipse season (due to battery cycling) 0–30 solstice periods
Mission Example		International Space Station	Galileo	OneSat

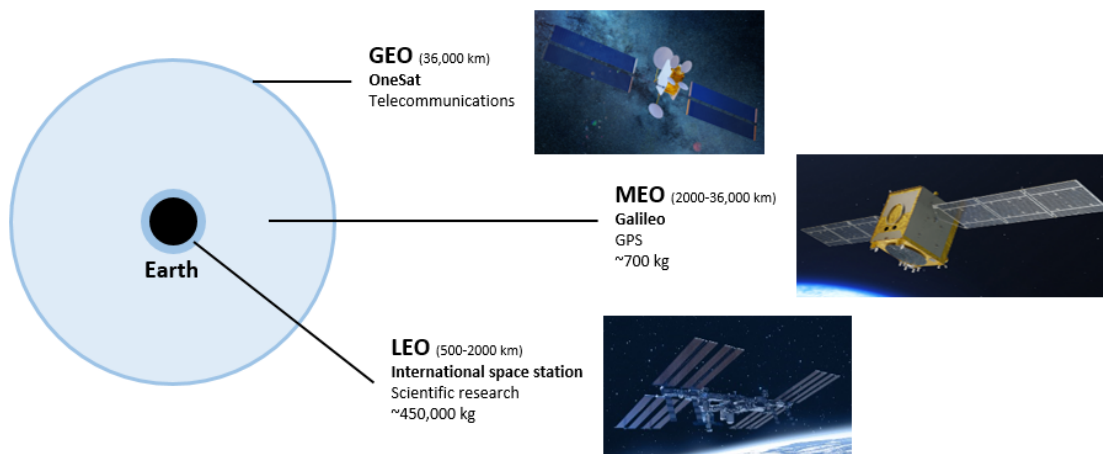


Fig. 2. Size comparison between LEO, MEO and GEO and computer images of examples of satellites used in missions with different orbits [© AIRBUS].

satellite components. To prevent these phenomena during the mission, batteries are tested thanks to thermal vacuum processes on ground. The battery temperature depends on the type of mission and can vary significantly and suddenly. Both high and low temperatures can increase the number of side chemical reactions that degrade the battery. To regulate the temperature, the satellite can expel excess heat or heat the battery when necessary. Concerning vibrations, even if they occur exclusively during the satellite launch, permanent mechanical damage to the battery is possible. As the previous cases, specific on ground tests control the stability of the battery.

Estimating and predicting the level of battery degradation before and during the mission is therefore a key aspect of managing satellite operations to ensure stable and safe work conditions.

#### IV. DIAGNOSTIC METHODS FOR LI-ION BATTERY

The diagnostic methods that estimate the degradation level of a battery can be divided into 3 categories: disassembly-based post-mortem analysis, curve-based analysis and model-based analysis [17]. A brief introduction to these methods is given below while Table IV lists their advantages, disadvantages and their ability to investigate the causes, degradation mechanisms, degradation modes and effects of aging.

##### A. Post-Mortem Analysis

This diagnostic method is based on a Disassembly Post-mortem Analysis (DPA). It consists of a destructive approach that studies the relationship between cell degradation and its morphology, crystallographic structure, and chemical composition. This approach requires strict disassembly protocols and multiple complementary methods, each one with its specific instrumentation. Nevertheless, it is the only way to directly observe the inside of an electrochemical cell [18].

##### B. Curve-Based Analysis

It is a non-destructive approach that consists of Open Circuit Voltage (OCV) and differential analysis measurements. By interpreting these curves and comparing how their key features change with aging it is possible to estimate the cell degradation mechanisms. The OCV of a cell is the measurement of the voltage between the two electrodes (V) in equilibrium condition and can be related to the cell capacity (Q), hence its degradation. This method is not applicable to real situations, where the battery is subjected to dynamic charge/discharge protocols [19]. Differential analysis consists of the differentiation of the curves that describe the evolution of different types of signals measured during the charge/discharge processes. The most frequently mentioned methods in the bibliography are Incremental Capacity Analysis (ICA), Differential Voltage Analysis (DVA), Differential Thermal Voltammetry (DTV) analysis and Differential Mechanical Parameter (DMP) analysis [20]. ICA and DVA study respectively the capacity gradient  $dQ/dV$  and the voltage gradient  $dV/dQ$  evolution [21]. DTV analysis studies the evolution of the temperature (T) gradient  $dT/dV$  [22] and the DMP analysis studies the evolution of the strain ( $\epsilon$ , a quantity used to measure deformations) gradient  $d\epsilon/dV$  [23]. Thanks to this differential transformation, it is possible to associate the curve peaks with the different electrochemical phenomena occurring in the electrodes. Given a cell, if measurements taken at different aging stages are superposed,

the features of the peaks, such as height, width and position, can be compared and it is possible to interpret the degradation level. In order to properly analyze the degradation modes, ICA and DVA have to be based on the pseudo-OCV measured at very low current and with a constant temperature. Indeed, when the C-rate is increased, the peaks amplitude of the ICA are modified [24]. DTV and DMP, on the other hand, need specific sensors on the cell surface, which is not always possible [20].

##### C. Model-Based Analysis

The objective of a model is to define mathematical relations that describe the aging of a cell with a non-destructive approach. Models can have exclusively theoretical basis, be built starting from experimental data or be in the middle of the spectrum. In the bibliography, the most frequently mentioned methods are the electrochemical models, the Equivalent Circuit Models (ECM), the empirical models and the data-driven models.

The construction of an electrochemical model is based on the understanding of the physicochemical phenomena that occurs inside the cell [25]. From the laws of conservation of mass and charge that underlie thermodynamic, kinetic, and transport phenomena theories, nonlinear and partial differential equations are constructed to describe these phenomena. The goal is to identify and compare the equations parameters, observe their dependence on external parameters and finally associate their evolution with aging mechanisms. Although it is the ideal approach to physically interpret the cell aging, the analytical resolution requires a considerable amount of calculation. Moreover, the theoretical knowledge to describe certain phenomena may be lacking. Finally, the equations and parameters are related to the cell chemistry: an electrochemical model is therefore specific.

It is possible to build an equivalent circuit model to simulate the static and dynamic behavior of the cell. This ECM represents a good compromise between complexity, precision and physical meaning [26]. It is composed of electrical components (i.e. voltage source, second-order RC network) and, sometimes, it is coupled with an aging model in order to take into account the influence of aging mechanisms on these components. The values of these components are usually identified and calculated thanks to the Electrochemical Impedance Spectroscopy (EIS) method. By interpreting the EIS results in the frequency domain, it is possible to distinguish specific electrochemical phenomena thanks to their different time constants. Given a cell at different times of its life, it is possible to identify the degradation modes by monitoring the value of the cell impedance computed at different stages of aging [27]. This type of modeling is intuitive, flexible and accurate. However, its simplicity cannot answer for all the phenomena and interactions that take place in the battery.

The empirical models aim to identify and evaluate parameters correlations starting from the analysis of data obtained from experiments [28]. To build the model, it is initially necessary to identify internal parameters, called Health Indicators (HI), which are assumed to depend on health ageing, and study their evolution with respect to defined external parameters. Through the application of regression methods, empirical relationships that correlate HIs and external parameters are obtained [29]. Empirical models are easy to perform and provide basic information on the degradation behaviors, provided that the number of external

parameters considered is limited. Nonetheless they are not linked to the physical meaning of the electrochemical phenomena. Moreover, changes in the cell chemistries or external parameters, such as different environmental conditions, makes the model obsolete and requires a new set of measurements. Finally, if it is not possible to apply nominal conditions, it is necessary to refer to laboratory aging tests, which cannot always reproduce the real aging of the battery.

Data-driven methods use historical data to estimate and predict degradation behavior using numerical resolution methods [30]. Concerning battery ageing, one of the most investigated data-driven approach is Machine Learning (ML). ML allows to fit the nonlinear behavior of battery aging by finding correlations between the degradation levels and different HIs. The functioning of an ML algorithm can be summarized in the following steps: training and testing. Training, in particular, consists of data collection, features extraction and correlations definition [20]. If the model is self-adaptive, once new data is received, periodic updates and retraining are possible [31]. Some examples of ML methods cited in the bibliography are: Artificial Neural Network (ANN), Support Vector Machine (SVM), Relevance Vector Machine (RVM), Gaussian Process Regression (GPR) and

Auto-Regressive Integrated Moving Average (ARIMA) [20]. Pure data-driven models do not provide interpretations of the degradation mechanisms and the amount of data needed for them to work is fundamental to get accurate results. Also, the computational load is considerable, and this could be a limiting factor when integrating these models into a battery management system. Nonetheless, these methods can provide precise estimation, are versatile and can be used in parallel with other models, via hybridization, in a complementary way.

Based on what was presented in this section, Table IV also identifies which methods are suitable for space applications. DPA is not possible since satellite batteries are recovered only rarely. Curve-based analysis, instead, requires specific sensors and battery work profiles that do not correspond to nominal conditions. The model-based analysis is therefore the approach most suitable for space applications.

#### V. BATTERY DEGRADATION ASSESSMENT FOR SPACE APPLICATIONS

The operational conditions and work profiles to which a battery is subjected are thus key factors influencing degradation phenomena and the methods by which these are

TABLE IV. ADVANTAGES AND DISADVANTAGES OF THE PRESENTED METHODS AND THEIR ABILITY TO INVESTIGATE THE CAUSES, DEGRADATION MECHANISMS, DEGRADATION MODES AND EFFECTS OF AGING. SPACE APPLICABILITY IS ALSO PRESENTED

Methods	Advantages	Disadvantages	Cau- ses	Deg. Mec. <sup>a</sup>	Deg. Mod.	Eff- ects	Space Appl.
Disassembly-based post-mortem analysis [18]	- The only way to directly observe the inside of a cell	- Destructive - Strict disassembly protocols - Multiple complementary methods necessary to characterize the cell - Each method requires specific instrumentation and expertise	✓	✓	✓	✓	
	OCV [19]	- Effective for qualifying and quantifying degradation modes through capacity - Not applicable to real situations	✓		✓	✓	
	ICA / DVA [20]	- Works for partial charging/discharging conditions - Limited to low current rates - Noise handling problems (requires filtering) - Sensitive to operational temperature	✓		✓	✓	
Curve-based analysis	DTV / DMP [20]	- Not limited by current rates - Need additional specific sensors - Sensitive to external temperature variations (DTV) - Not applicable to all cell designs (DMP)	✓		✓	✓	
	Electrochemical [25]	- Can physically interpret the battery behavior and degradation phenomena - High number of equations and parameters increases complexity - High computation cost - Requires a good understanding of the electrochemical phenomena - Specific to the cell chemistry	✓	✓	✓	✓	✓
	Equivalent circuit [27]	- Intuitive and flexible modeling - Cannot interpret all battery behaviors	✓		✓	✓	✓
Model-based analysis	Empirical [28]	- Easy to perform - Provide basic practical information - Extensive laboratory tests - Not linked to degradation mechanisms - Specific to the cell and tests conditions - Not always possible to apply nominal conditions	✓			✓	✓
	Data-driven [20]	- Very versatile - Possibility of hybridization with other methods - High computation cost - Not linked to degradation mechanisms - Requires high amount of data	✓			✓	✓

<sup>a</sup> Deg. Mec.: Degradation Mechanisms, Deg. Mod.: Degradation Modes, Space Appl.: Space Applicability

qualified and quantified. In the case of satellites, both operational conditions and work profiles are strongly conditioned by the space applications specificity. Once the satellite has been launched into space, one of the most impactful limitations in battery degradation assessment is that only voltage, current and temperature measurements can be made through telemetry [32]. Moreover, the classic methods that need specific experimental tests to measure the capacity or internal resistance, such as a total discharge, cannot be made as this would result in the loss of the satellite [33]. For the remaining methods, however, indirect estimation of these values is complex given the dynamic battery work profile and operational conditions. The range of methods that can be applied is therefore reduced. Given these limitations, to date the approach used to evaluate the aging of a battery on a mission consists in correlating the evolution of the battery telemetry data with a preexisting model. However, this approach shows significant uncertainties since the defined and limited Depth Of Discharge DOD (which refers to the size of the range usually used for discharge) prevents to observe the whole profile of voltage with respect to the SOC [33]. Below are a few recent examples of degradation estimation in satellite batteries.

L. Gajewski et al. developed a non-intrusive battery health monitoring method based on the impedance spectroscopy principles [33]. During nominal battery operation, the current is randomly perturbed by sources inside the satellite, such as on-board thermal control for example. The battery voltage response to these current perturbations can be studied on the frequency domain and the impedance is then calculated indirectly through current and voltage telemetry. The result is then compared with an on ground reference, which consists of an identical battery to which the same work profiles are applied. Since the degradation levels of the reference battery in the laboratory are known, it is possible to make assumptions about the SOH of the battery on the mission. This study is a good example of how methods used in the terrestrial domain are adapted to space applications, where it is not possible to integrate onboard components that perform specific measurements such as EIS. Being an on-ground reference necessary to estimate aging, the application of this method to satellites with different batteries and work profiles requires as many references, which is not always possible.

J. Yang et al. proposed a novel health indicator for the SOH estimation of satellite batteries based on the discharge curves [34]. Thanks to extensive experimental measurements, it was possible to investigate the effects of the DOD, discharge rate and temperature on the voltage discharge profile. From these results, a model was built and a hypothesis of HI was extracted. Finally, the SOHs of batteries with different aging were characterized according to this new HI and a correlation was derived. The batteries studied for this empirical model are of the LCO type, the HIs obtained may therefore not be valid for other types of cell, such as NMC.

Y. Song et al. proposed an iterative updated approach to improve the RVM long-term prediction performance of a satellite battery Remaining Useful Life (RUL) [35]. It is a hybrid approach based on the RVM method, the Kalman filter and a physical degradation model. The outputs of the RVM method were optimized by the Kalman filter based on a degradation model. These optimized outputs were then added to the training set used by the RVM method to make its predictions. Thanks to RVM iterative re-training it was

therefore possible to dynamically adjust the outputs of the algorithm to obtain more accurate RUL predictions. Although supported by a physical model, this method does not provide an understanding of the real events occurring in the cell.

F. Bard et al. provided with their work a quantitative study on the in-orbit batteries performance of the Galileo constellation satellites (MEO) [36]. Their objective was to compare the past and present telemetry voltage profiles to the predictions made by the simulation tools provided by the batteries manufacturers: SAFT and ABSL. In particular, SAFT's tool SLIM (Saft Li-Ion Model), consists of a macroscopic electrochemical model. This model was built from extensive experimental measurements based on the DPA method applied to batteries with different levels of aging (fresh, calendar, GEO/LEO cycling). This way, correlations between the parameters that most influence aging and the chemical changes that take place at the electrode level were found. Given a defined mission and a specific SAFT battery, SLIM can provide reliable RUL prediction [37]. Since this model is specifically for SAFT products, it cannot be applied to satellites with different batteries. Given the fast and competitive development of the lithium-ion cells industry, a more versatile model may be preferable.

## VI. CONCLUSIONS AND CHALLENGES

Based on recent scientific literature, this article summarizes the basics of lithium-ion battery degradation phenomena and associated diagnostic methods. The specificities of space applications, such as operational conditions and work profiles, were introduced in order to understand how they affect aging and its quantification.

To sum up, DPA methods by definition are only applicable in laboratory and, unfortunately, it is not always possible to recover batteries at the end of the satellite mission. The ICA/DVA methods are not easily applicable to space applications due to the battery nominal work profiles, the DTV and DMP analysis instead require specific sensors that cannot be integrated in real batteries. Nevertheless, both DPA and curve-based methods are essential to understand, through laboratory testing, the aging phenomena inside the cell. Regarding the different types of models, each of them has interesting properties for spatial applications. In fact, since only the measurements of voltage, current and temperature are possible through telemetry, the approaches most used by the scientific literature consist of comparing this data with models, both experimental and numerical. In particular, the application of data-driven methods looks promising due to their versatility, accuracy and hybridization possibilities. Alongside numerical models, which have seen significant uptake thanks to their effectiveness, the electrochemical approach seems necessary for a deep understanding of the degradation phenomena. The construction of an electrochemical model based on a precise cell characterization associated with periodic parameter updates through telemetry, seems a promising approach. Finally, the identification of new HIs and the adaptation of the many methods existing for terrestrial application are areas of research that need to be explored further.

In conclusion, there is no single method that can provide a complete estimation of the battery degradation. Nevertheless, the variety of approaches, each with its advantages and disadvantages, allows for a hybrid approach to the problem. The understanding of space battery aging is thus an open



research field whose challenges require a wise use of the existing methods and an innovative vision to develop new ones.

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