Key Performance Indicators for the monitoring of large-scale battery storage systems

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Abstract

In the context of the fight against climate change, the electricity sector is experiencing a complete renewal. Power grids are undergoing a transformation from centralized and unidirectional systems to multilevel and more integrated networks with, among others, the insertion of intermittent Renewable Energy Sources (RES) on the production side and with the emergence of new consumer behaviors on the demand side. In this context, Battery Energy Storage Systems (BESS) are gaining momentum. Their excellent technical performances combined with a falling price make these storage solutions applicable to multiple scales and applications, ranging from the electrification of rural areas to the reinforcement of modern power grids.

Large scale BESSs are complex systems, for which the electrochemical cells are only the elementary building blocks. Such storage systems consist of a hierarchical assembly of these cells, a complex control structure, a precise thermal management and a reversible power conversion apparatus, cooperating to ensure a smooth and safe operation. To deal with this complexity, BESS owners and operators need synthetic indicators to quickly assess the operation of their storage systems. In this work, this question of the monitoring of large scale BESSs is addressed with a selection, implementation and discussion of Key Performance Indicators (KPI).

After a presentation of the multiple components constituting a BESS, a review of the main KPIs found in the literature is proposed. This preliminary phase concluded with the definition of four main categories covering the multiple aspects of the operation of a BESS: operation, performance, ageing and safety. Where needed, a choice was made to choose the estimation techniques offering the best tradeoff between accuracy, ease of implementation and computational load. Then, the overall implementation strategy used to take advantage of the large amount of data available was presented.

The results were obtained for actual large-scale Li-Ion BESS projects, covering multiple applications and chemistries. Based on these illustrative results, the robustness and the accuracy of the indicators was discussed. More importantly, a special attention was paid to the methodology, meaning and interdependencies of these KPIs to enable battery owners to better understand their system.

Sammanfattning

Inom ramen för kampen mot klimatförändringar upplever elsektorn en fullständig förnyelse. Kraftnät genomgår en omvandling från centraliserade och enkelriktade system till flernivå och mer integrerade nätverk, bland annat införande av intermittenta förnybara energikällor på produktionssidan och med uppkomsten av nya konsumentbeteenden på efterfrågesidan. I detta sammanhang får batterilagringssystem fart. Deras utmärkta tekniska prestanda i kombination med ett fallande pris gör att dessa lagringslösningar är tillämpliga på flera skalar och applikationer, allt från elektrifiering av landsbygden till förstärkning av moderna elnät.

Storskaliga batterilagringssystem är komplexa system för vilka de elektrokemiska cellerna endast är de grundläggande byggestenarna. Sådana lagringssystem består av en hierarkisk sammansättning av dessa celler, en komplex kontrollstruktur, en exakt termisk hantering och en reversibel kraftomvandlingsapparat, som samarbetar för att säkerställa en smidig och säker drift. För att hantera denna komplexitet behöver batterilagringssystem-ägare och operatörer syntetiska indikatorer för att snabbt utvärdera driften av deras lagringssystem. I detta arbete behandlas denna fråga om övervakning av storskaliga batterilagringssystem med ett urval, implementering och diskussion av viktiga resultatindikatorer.

Efter en presentation av de flera komponenterna som utgör ett batterilagringssystem föreslås en översyn av de viktigaste resultatindikatorer som finns i litteraturen. Denna preliminära fas avslutades med definitionen av fyra huvudkategorier som täcker flera aspekter av driften av en BESS: drift, prestanda, åldrande och säkerhet. Vid behov gjordes ett val för att välja uppskattningsmetoder som erbjuder bästa
avvägning mellan noggrannhet, enkel implementering och beräkningslast. Sedan presenterades den övergripande implementeringsstrategin som användes för att dra fördel av den stora mängden tillgängliga data.

Resultaten erhölls för faktiska storskaliga Li-Ion BESS-projekt, som täcker flera applikationer och kemister. Baserat på dessa illustrativa resultat diskuterades indikatorernas robusthet och noggrannhet. Ännu viktigare var att särskild uppmärksamhet ägnades åt dessa resultatindikatorer metodik, betydelse och beroende av varandra för att möjliggöra för varje batteriägare att bättre förstå sitt system.
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1 Introduction

1.1 Context

Since its domestication in the 19th century, electricity has been playing an increasing role in modern societies. It progressively transformed everyone’s life by boosting the productivity in the industry sector, increased the safety by replacing traditional flame-based applications, improved living conditions by replacing manual tasks with electricity powered machines and opened an infinite horizon of electricity-based applications omnipresent in our everyday life.

However, in 2019 slightly less than 1 billion people still lack access to this form of energy according to the United Nations [1] and the energy sector was in the spotlight during the 21st Conference of the Parties (COP21) as it is responsible for about two thirds of the global greenhouse gas emissions [2]. With 38% of carbon emissions of the energy sector in 2018, the electricity generation sector already has a high responsibility and is still expected to undergo a constant development in order to meet the ever growing demand in developing countries [3].

Worldwide, countries are setting ambitious goals for a greener electricity sector while continuing to address the economic and social challenges related to the access to this form of energy.

![Figure 1: Traditional organization of a power system. From the left to the right: power generation, transmission, distribution and consumption. Image from [4]](image)

Power grids are at the forefront of this transformation with fundamental changes in their structure and the way they are operated. The traditional organization with centralized large-scale power plants is challenged by the integration of local production units connected to the various layers of the grid including the distribution level that was not initially designed for this purpose. Fuel based power plants are progressively being replaced or coexisting with renewable energy sources, mainly wind and photovoltaic (PV) in Europe.

Finally, the demand side is changing from a passive to an active participant with new behaviors and technologies like self-consumption, net metering, flexible demand or Electric Vehicles (EV).

In this context of transformation, energy storage solutions are gaining attention. Even if the utility scale storage sector has been largely dominated by Pumped Hydro Storage (PHS) for decades, newcomers are entering the market. Among them, Li-ion battery systems have attracted lot of investments. Their versatility,
high efficiency and high energy density gave them the capability to expand beyond their traditional use in consumer electronics. Li-ion batteries are already powering new forms of electrical mobility and are becoming an asset to address the challenges of stationary applications from the electrification of rural areas to the transformation of established power grids.

More specifically, large scale Battery Energy Storage Systems (BESS) are progressively deployed to deliver multiple type of services, from frequency regulation to arbitrage and the smoothing of intermittent renewable production. This high level of versatility and performance is only made possible by the coordinated operation of the multi-layer electrochemical storage with its thermal management, power conversion system and control architecture. As a consequence, it is essential to reduce this multiphysics problem down to a set of indicators that can be easily interpreted by the operator and the owner of the system. This Master Thesis aims to address this need by proposing Key Performance Indicators (KPI) for the monitoring of utility-scale Li-Ion BESS.

1.2 EDF

The context of transformation is opening up new opportunities for all the actors of the energy sector, including the well-established power companies. Électricité De France or EDF is the first electricity producer and provider in France and the third largest in the world in terms of revenues in 2018 [5]. That year, the Group announced an ambitious plan to become the European leader for electricity storage. This “Electricity Storage Plan” set the goal of deploying 10 GW of storage globally by 2035, on top of the 5 GW already operated by EDF and its subsidiary companies. These figures include PHS but also BESSs for residential customers, businesses and network operators [6].

In order to improve the performance of today’s battery storage projects and prepare those of tomorrow, a team of researchers in EDF’s Research and Development (R&D) division is actively working on this topic with the Group’s industrial and academic collaborators. Among others, this team is involved in the monitoring of the BESSs currently operated by EDF’s subsidiaries and partners around the world. It is in this context that this Master Thesis was conducted.

1.3 Scope and aim

Li-ion batteries have been a popular research topic over the last decade. This focus has mainly been driven by the development of the electrical mobility and more particularly by the rise of Electric Vehicles. It is therefore not surprising that this specific application received most of the attention of academic and industrial researchers. The question of developing Key Performance Indicators has also been studied but in a very individual way. More specifically, the State Of Charge (SOC) and State Of Health (SOH) largely dominate the literature on this topic.

This Master Thesis aims at giving the reader a new perspective. First of all, it focuses only on the stationary applications of Li-ion batteries. This study case comes with its own distinctive features compared to mobility applications in the way these systems are structured and operated. Secondly, this work intends to meet the needs of system operators who wish to have a broad perspective of their system. This implies moving away from the traditional literature were only one indicator is studied in depth but in silo and favoring multiple and interdependent analyses. Lastly, this thesis work is very different from the academic literature because of its specific constraints. Unlike small-scale laboratory studies, this work relies on a huge amount of data coming from multiple large-scale systems. An adapted approach is therefore necessary.

Finally, it should be stressed that the objective of this work is not to evaluate the technical performances of the systems under study. Rather, its purpose is to propose a discussion about why, how and to what extent the proposed KPIs can provide the system operator with some relevant information. The emphasis will therefore be placed on the methodology and discussions rather than on the numerical results themselves.
1.4 Thesis structure

This Master Thesis report is organized as follows:

2. Literature review: The first part of this section aims at giving the reader all the background necessary to understand the context and the technology itself. From there, the main KPIs selected in this work will be introduced and their corresponding literature will be summarized.

3. Methodology: This section will discuss the methodology that guided this thesis work. It includes a preliminary diagnosis based on the objectives and available data as well as the choice of the estimation technique for the complex KPIs. The working environment and the overall implementation strategy will also be presented.

4. Results and discussions: The implementation of the KPIs will be detailed and the illustrative results obtained will serve as a basis for the discussion. Where relevant, a simulation was preferred to the analysis of actual data to ensure a better demonstration.

5. Conclusions: To conclude, the key learnings of this study will be reminded. In addition, future steps and possible applications of this work will be proposed.
2 Literature Review

2.1 Battery storage systems

2.1.1 Definitions

In order to clarify the specific vocabulary used in the following sections, a couple of notions are introduced. First, the elements constituting BESS are briefly presented. Second, the main technical terms related to the battery technology are introduced.

2.1.1.1 Components

This paragraph gives a first overview of the generic elements forming a BESS. This general introduction is meant to allow a better understanding of the various battery technologies. The detailed description and analysis of the large-scale Li-ion BESS will be conducted in 2.4.1.

When one think about battery energy storage, one often thinks about cells. After all, this is the physical part responsible for storing the energy under the form of electrochemical potential. In our everyday life, what is called a “battery” in a smartphone or a laptop is one or multiple cells assembled together. A rechargeable battery, or secondary cell, is based on an oxidation-reduction pair that allows a reversible reaction. In a basic representation, a cell is made of an anode (where the oxidation takes place), a cathode (where the reduction occurs) and an electrolyte. A separator is also located between the electrodes to prevent any direct contact. These elements are illustrated in Figure 2.

The cells are the elementary building blocks of a BESS. They are responsible for storing the electrical energy under the form of chemical energy. It is the technology chosen for the cells that defines the technology of the overall system. For example, if the cells are of Li-Ion chemistry then the overall BESS is described as a Li-Ion BESS. In large-scale applications, hundreds of thousands of cells are organized in multi-layer configurations, allowing the overall system to reach high energy and power capabilities.

However, multiple cells left on their own are not able to deliver any service. Their operation is orchestrated by the EMS (Energy Management System) and the BMS (Battery Management System). Depending on the application, a PCS (Power Conversion System) may convert and condition the power output. A complete thermal management system featuring sensors, controllers and active heating/cooling systems is also
necessary in large scale applications. Finally, since safety is a critical issue for any industrial project, specific equipment such as fire detection systems and surveillance devices compose the overall system.

2.1.1.2 Characteristics

Regardless of its scale and technology, a battery system and its operation can be described by a couple of characteristics.

- **Nominal Capacity [Ah]**: The maximum amount of electrical charge being released by the system during a full discharge at a given C-rate and temperature.
- **C-rate [h⁻¹]**: During a constant current charge (resp. discharge) phase, it is defined as the ratio between the input (resp. output) current and the nominal capacity. A 50 Ah cell charging at a constant 100 A is said to undergo a charge at 2C.
- **Rated Power [W]**: The maximum electrical power output.
- **Energy [Wh]**: The maximum amount of electrical energy being released by the system during a full discharge at a given CP-rate.
- **CP-rate [h⁻¹]**: During a constant power charge (resp. discharge) phase, it is defined as the ratio between the input (resp. output) power and the nominal energy. A 200 Wh cell discharging at a constant 100 W is said to undergo a discharge at 0.5CP.
- **Energy efficiency [%]**: Over a complete cycle, it is defined as the ratio between the energy output and the energy input. The energy efficiency can be considered at different points of the system (DC-DC, AC-AC etc...).

2.1.2 Technologies

This section proposes a brief introduction to the main electrochemical and redox-flow battery technologies. The other forms of storage such as kinetic, mechanical or thermal storage are out of the scope of this work.

2.1.2.1 Lead-acid

Invented in 1859 by Gaston Planté, the lead acid battery technology remains today the most widely used form of electrochemical storage [7]. Its success is mainly due to its widespread use in the automotive industry. In the early days of this industry, some concept cars were fully powered by lead-acid batteries as it was the case for the first car to reach the 100 km/h in 1899, “La Jamais Contente”. Nowadays, lead-acid batteries are used as starters in cars or motorcycles, in emergency power units or in some electric vehicles such as golf cars or forklifts [8].

Its physical principle is based on the electrochemical couple Pb/PbO2. A battery block (12 V) is usually made of six 2 V cells connected in series. The positive electrodes (cathode) are lead grids with a layer of lead dioxide, the negative electrodes (anode) are made of sponge lead and the electrolyte is a mixture of sulfuric acid (H₂SO₄) and water. During discharge, lead and lead oxide react with the sulfuric acid to form lead sulfate (PbSO₄). The following table summarizes the chemical phenomena occurring during the charge and discharge phases.

<table>
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<tr>
<th>Cathode</th>
<th>PbO₂ + H₂SO₄ + 2e⁻ + 2H⁺ (\xrightarrow{\text{Charge Discharge}}) PbSO₄ + 2H₂O (\text{(1)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anode</td>
<td>Pb + H₂SO₄ (\xrightarrow{\text{Charge Discharge}}) PbSO₄ + 2e⁻ + 2H⁺ (\text{(2)})</td>
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*Table 1: Chemical reactions occurring in a Lead-Acid battery*

The main strength of the lead-acid technology is its low cost, around 50-200 €/kWh depending on the system features [9]. Another advantage of lead-acid battery is the wide range of applications that can be covered by adapting the design of its elements. For instance, a starter battery usually features a high number of thin plates to increase the exchange surface area and deliver high currents for a short period of time.
whereas a deep cycle battery is made of thicker plates allowing for extended charges and discharges phases [8].

When it comes to the performance, this type of batteries can reach 80% of energy efficiency with a lifetime up to 1500 cycles depending on the application. From the end-of-life perspective, lead-acid batteries have a well-established recycling industry with second-hand lead being competitive against raw material and representing more than half of the material used for new batteries [9]. However, lead remains a dangerous component for the environment and its low specific energy combined with the need for frequent maintenance prevented this technology from being present in other markets.

### 2.1.2.2 Sodium Sulfur (NaS)

Sodium Sulfur batteries have the distinguishing characteristics of operating at high temperatures, usually around 300-350 °C. As its name suggests, a cell is made of a Sodium (Na) anode and a sulfur (S) cathode organized in tubes as presented in the following picture:

![Sodium Sulfur batteries structure](image)

**Figure 3: Sodium Sulfur batteries structure. Image from [10]**

During the discharge, Na atoms give out electrons and migrate through the selective electrolyte membrane. At the cathode, electrons combine with S atoms to form sodium polysulfide. The overall discharge/charge process can be described as follows:

\[
2 \text{Na} + 4 \text{S} \xrightarrow{\text{Charge Discharge}} \text{Na}_2\text{S}_4
\]  

(3)

The need for high temperature stems from the fact the cathode and the anode must be in the liquid state and the ceramic electrolyte (beta-aluminum solid electrolyte) must be at sufficiently high temperature to ensure efficient ionic conduction. Even though the charge and discharge cycles produce heat, additional heaters can be included in the system to maintain the electrodes in a molten state. These temperature requirements make NaS batteries primarily adapted to large-scale stationary storage and its applications such as peak shaving or stabilization of intermittent renewable energy (RE) sources.

Over 560 MW and 200 projects have demonstrated the technology that is today mainly produced by the Japanese company NGK [11]. To date, the largest NaS installation is located in Japan with a 50 MW/300 MWh system dedicated to peak shaving and balancing of a PV plant.

When it comes to the cost, Sodium Sulfur battery systems were amongst the cheapest several years ago, with an energy cost between 300 and 450 €/kWh. However, this price has not diminished over the last years and is nowadays higher than redox-flow and lithium-ion. In addition, its low efficiency (<70%) and safety concerns due to its high operating temperature make it less attractive than the competing technologies [11] [12].
2.1.2.3 Redox-flow

Unlike other technologies, flow batteries feature tanks storing the active chemicals that are located outside of the cell where the reaction takes place. A system of pumps and pipes is used to channel the chemical components to the cell where the ion and electron exchange occur. This unique configuration with separated tanks and a cell allows an independent sizing of power and energy. While the surface areas of the electrodes in the cell determines the power, the volume of chemical components stored in the tanks decides the energy. The name “redox” refers to the reduction-oxidation reactions taking place in the cell, at the membrane, during charge and discharge phases [13].

![Redox Flow batteries, working principle. Image from [13]](image)

Redox-flow batteries are most suited for large scale applications (>1 MW and >2 h) and benefit from economies of scale thanks to their cheaply scalable auxiliary components such as storage tanks or flow regulation system. In addition, redox flow batteries have very good announced cycling capabilities (over 30 000 cycles) with no capacity loss over time and an acceptable energy efficiency (higher than 70%) [12]. However, the low concentration of the active material in the electrolyte results in low energy density and limits its deployment to stationary applications where the floor space is not a limiting factor [13].

Several chemical elements can be used but Vanadium Redox Flow batteries are currently the reference and large-scale projects are in operation in Asia. Zinc-Bromine is a more recent technology offering innovative designs such as membraneless cells or single tank configurations enabling further cost reduction but at the expense of a lower efficiency [9]. Other designs make use of organic materials, either as the active material or as the electrolyte. Research about redox-flow batteries is very active and the first large scale projects (>400 MWh) are expected to go online by 2020 [14].

2.1.2.4 Li-ion batteries

The Li-ion technology only gained market maturity in the early 1990’s in the low power applications but is nowadays a leading technology in high power industries as well [15]. Its physical principle is based on the reversible exchange of Li+ ions between a metal oxide cathode and a graphite anode (most frequent configuration). Current collectors are usually made of aluminum for the cathode and cooper for the anode.
During the charging phase, lithium atoms release an electron and migrate to the carbon anode. The opposite reaction occurs during the discharge phase.

Li-ion batteries exhibits very good performances in terms of energy density (up to 200 Wh/kg), efficiency (up to 99% for DC-DC), cycling (up to 10000 cycles) and self-discharge (which can be lower than 1% per month). On the other hands, Li-ion batteries should be carefully operated when it comes to temperature and solicitations as these aspects strongly affect the rate of deterioration of the cells. In turns, the available capacity slowly decays over time in a process called ageing [9] [15] [14].

In the early days of Li-ion batteries, metallic lithium was used to exploit its high energy density. However, its unstable behavior especially during the charging phase was responsible for incidents and induced a reorientation towards non-metallic lithium batteries using lithium ion. A careful monitoring of cell temperature and voltage is essential to prevent any accelerated ageing but mainly to avoid element meltdowns, flames or gases release [17] [12]. That being said, Li-ion batteries are nowadays one of the safest technologies with billions of cells manufactured every year to cover a broad range of applications.

### 2.2 Applications of Li-Ion batteries

Thanks to their versatility, Li-Ion batteries are ubiquitous in our everyday life. They are mainly known for powering our smartphones and laptops but nowadays they also drive multiple forms of electrical mobility and play an increasing role in both developing and mature electrical grids around the world. This section gives a brief overview of the applications of Li-Ion batteries.

#### 2.2.1 Consumer electronics

In 1991, Sony introduced the first rechargeable Li-ion battery to power its cameras [18]. Its usage progressively spread to cell phones and laptops. Its high energy content permits to supply energy to a wide range of portable devices with a minimum weight and volume.
The ambition to improve the user’s experience drives the current development in Li-ion cells. For instance, smartphones manufacturers are heading towards thinner, lighter and longer-lasting batteries. However, sometimes this race can be run at the expense of safety. For example, in 2016, a few weeks after releasing its new Note 7, Samsung was under the spotlight after reported battery explosions. These faults pushed the company to recall its devices and resulted in significant economic losses and consumer mistrust [19]. Nowadays, despite some isolated incidents Li-Ion batteries are a safe power source and are widely spread in consumer electronics. For example, the development of the Internet of Things (IoT) is partly based on Li-Ion batteries that are embedded in smartwatches, connected speaker and other small rechargeable devices.

2.2.2 Electrical mobility

Since the 2010’s, the main driver for the development of Li-ion batteries is the electrical mobility. As climate change and air quality problems in urban areas are gaining public attention, new forms of mobility are often seen as a relevant solution. Electrical mobility encompasses all means of transport powered by electricity. One can mention electric trolleys, bike, scooters but also larger vehicles like cars, trucks and buses. The fastest developments are taking place in the automotive industry. Car manufacturers are currently operating a progressive transformation from thermal to electrical power. The Internal Combustion Engine (ICE) invented in 1859 has long been the reference design to drive vehicles [20]. But today in the context of growing environmental and health concerns, ICE vehicles are facing new competitors. Thanks to the sharp decline in the price of Li-Ion battery packs (see 2.3) and progresses made in design and safety, Electric Vehicles (EV) are becoming a competitive alternative to ICE vehicles. Electric vehicles can be classified in Battery Electric Vehicles (BEV), Plug-in Hybrid Electric Vehicle (PHEV) and Hybrid Electric Vehicles (HEV). All these categories are powered by Li-Ion battery packs, but the role and size of the battery depends on the configuration. In all cases, the high energy density, power density and efficiency make Li-Ion batteries the most frequent technological choice [21] [18].

2.2.3 Stationary Applications

The two applications presented above can be classified as embedded storage systems. On the other hand, stationary energy storage systems are the family that covers all the static applications of battery storage.

2.2.3.1 Small scale stationary applications

An Uninterrupted Power Supply (UPS) is an electrical apparatus able to provide power to a load when its primary power source fails. It nearly instantaneously delivers power to the system and does so for a limited amount of time while waiting for a return of the primary source or the activation of a secondary source of power. They are mainly used in applications where the loss of power could have devastating consequences like hospitals, safety architectures, power stations or computer systems. The UPS is usually made of a battery bank connected to the source and to the load by converters (inverter and rectifier). A switching apparatus is in charge of the connection and the overall switching process can take as little as tens of milliseconds [22]. In these applications, the main requirement is a high calendar lifetime since UPS batteries are only supposed to operate a limited number of cycles per year. UPS batteries can also be designed to provide other services while always keeping energy to deliver its primary backup function [23].

The rise of Renewable Energy Sources (RES) like Photovoltaic (PV) resulted in the growth of decentralized power production. In developed countries, this trend is accompanied by new consumer behaviors like self-consumption. This approach intends to give households a partial or even a total autonomy from the grid and is often referred to as Behind-The-Meter applications. In the general case of a PV plus battery systems, the power generated by the PV panels is directly consumed by the domestic loads while the excess energy is stored in the batteries for later use. In the developing world, PV + battery kits are giving access to electricity to millions of people. In both cases, the power rating of the battery systems is in the 10W to 10kW range with a couple of hours of autonomy at nominal power.
2.2.3.2 Production/Consumption optimization

The following sections 2.2.3.2, 2.2.3.3 and 2.2.3.4 deal with large scale applications of stationary BESS. In this work, large scale defines BESS with energy and power ratings in the range of MW/MWh and above.

Thanks to its high level of maneuverability and symmetric operation, ESS can be used to optimize the production and consumption in terms of economic gains. Arbitrage and peak shavings are two of these applications.

Simply put, arbitrage consists in storing energy when it is cheap and selling it back when the price is higher. In the electricity market, the price is fluctuating on an hourly basis (or more frequently in intraday markets). Its dynamics reflects the balance between the production and the consumption.

Figure 6 illustrates these fluctuations with the example of California. The prices are low (<30 $/MWh in the day-ahead market) during low demand periods typically during the night and in the middle of the day. On the other hand, the prices peak around 19-20 when everyone is coming back home and connecting its appliances. Arbitrage aims at taking advantage of this price difference. Of course, the profitability of this strategy is function of the spread of the prices that the storage system can tap into and the predictability of this price. When it comes to price spread, the example of California is both very specific and very interesting. Due to the very high share of PV in its electricity mix, the production can temporarily exceed the demand and the electricity price can become negative. The California Independent System Operator reported that over the first six months of 2017, day ahead prices were negative about 2.5% of the time [24], offering clear opportunities for battery arbitrage. In Europe, the increasing penetration of Wind and Solar causes the same negative price events. In Germany, the number of negative power prices increased by about 50% in 2017 compared to 2016 [25]. The case of arbitrage within a day is well adapted to battery ESS because the system is designed to store a couple of hours of energy at most. But arbitrage can also be performed at much larger time scales. Profitable price gaps can be targeted between days, weeks or even seasons. In these cases, Pumped-Hydro storage and dams are more adapted due to the larger amount of energy at stake.

Large industrial sites can also rely on BESS to reduce their electricity bill. Most of the time, industrial sites have a variable pricing contract. Part of their bill can even correspond to the maximum power demand recorded over a period. In a similar strategy to what was discussed for arbitrage, a smart usage of a BESS allows to reduce the net demand of the site during peak periods. This approach is commonly referred to as peak shaving.
2.2.3.3 Grid related services

The operation of power systems notably requires maintaining the balance between generation and demand. It means that all the power produced equals all the power consumed (consumers and losses), at all times. For the Transmission System Operator (TSO), this constraint is both a challenge during the live operation of the grid but also what guides its investments in the future development of the network. In both cases, large scale BESS can play a major role.

During the live operation, the variation of frequency of the grid is the reflection of the balance between the supply and the demand. When the production exceeds the demand, the frequency increases in proportion to the power imbalance. From a physical standpoint, the surplus energy is stored in the synchronously connected generators under the form of kinetic energy: the rotational speed of the rotors increases and since this rotational speed dictates the frequency, it increases too. The frequency should be kept within its nominal range of \(50 \text{ Hz} \pm 50 \text{ mHz}\) for the European Continental grid) to ensure of smooth operation of the power system.

In order to maintain the balance, the TSOs rely on dedicated power reserves organized in what is called frequency ancillary services. One of them are the Frequency Containment Reserves (FCR) or Primary Control. They are fast acting entities able to automatically increase or decrease their power output within a few seconds to maintain the short-term balance between the generation and the load. Traditionally, this regulation is performed by thermal plants which dedicate part of the power to the service. They regulate their power output in proportion to the measured frequency deviation or by following a signal provided by the TSO. However, new services are appearing to take advantage of the high level of reactivity of BESSs to reinforce the stability of the grid. In 2016, the TSO of Great Britain, National Grid, introduced a new service called Enhanced Frequency Response (EFR). Even though its technical requirements did not specify the type of power project, the criteria of being capable of responding to frequency deviations within one second and the price-based selection were such that all of the successful tenders were battery systems [26]. An illustration of the behavior of the BESS as a function of the frequency is proposed by Oudalov et al. [27] in Figure 7.

Figure 7: Typical power - frequency (p-f) characteristic of a BESS for FCR services

BESS can also be a relevant solution to relieve congestion problems in the power system. The electricity grid is organized as a net of power lines and nodes. Since all these components have load limits, the system operator needs to ensure that the power flow does not exceed the local capabilities of the network. A congestion can thus be defined as a situation where the capabilities of the network are not sufficient to meet the requests of the grid users. As power grids were initially designed to accommodate centralized production and unidirectional flows of power, the integration of RES at every levels of the power systems is one of the
reasons for the increases of the frequency and the intensity of these congestion problems [28]. The evolution of the demand when it comes to its level and geographical distribution is another contributing factor. To address these local congestions, the system operator needs to reinforce its infrastructure. In this context, BESS can bring an alternative to the reinforcement by postponing the investment or even replacing it. Indeed, BESS are distributed solutions that can be deployed locally to permanently relieve the constraints or to bring a temporary solution until the strengthening becomes economically viable. This postponement of the investment is called asset upgrade deferral [9, 21].

To conclude on the services provided to the grid, one can also mention the black start capabilities and the regulation of the voltage. Black starting defines the process of restarting a power plant or a grid without external energy input. This task requires a primary and self-sustained power source that can typically correspond to a BESS. For example, in 2017 a 33 MW/20 MWh Li-Ion BESS successfully kick-started a combined cycle gas turbine in California [29]. Voltage ancillary services are meant to maintain the voltage of a network within its nominal range. Contrary to the frequency that is the same in all points of a synchronous network, the voltage is locally controlled by the flux of reactive power. For this service, a distributed BESS is once again well adapted [30].

### 2.2.3.4 RES integration

BESSs can also be an ally to meet the objective of integrating more RES. This can be observed directly at the scale of a project where batteries can be combined with wind or solar to increase the overall economic and technical performance of the hybrid system. In addition, BESS are also a very important player in microgrids where they act as a buffer between RE production and consumption.

First, BESS can be combined with PV or Wind farms to build hybrid systems. Adding a storage system comes with a cost but it also opens new opportunities.

- PV and Wind plants are intermittent sources which power greatly fluctuate with the variations of their resource. The rapid changes in their power output can deteriorate the stability of the network they are connected to. In addition, the variability of weather conditions makes the power output of PV and Wind farms hard to predict accurately. In this context, BESS are able to bring stability and predictability by smoothing the power output. This technique is called power smoothing or capacity firming. Depending on the study case, such a hybrid configuration can be more economical than power curtailment. If the local grid regulation imposes limits in terms of guaranteed power output or maximum rate of change of power, BESS may even be indispensable.

- The presence of a BESS in a hybrid system also opens up new operation strategies. Apart from curtailting a potential excess power, the controllability of the PV and Wind farms is limited. In the case of constant feed-in tariffs, flexibility is not necessary as the profits are independent of the instant of production. However, in the case of a dynamic pricing, storing the energy enables the plant operator to perform arbitrage and shift part of the production to the high price periods.

The transition towards a higher share of renewables brings new challenges in microgrids. Microgrids are small self-sufficient electricity networks and not connected to a larger grid. A perfect example of microgrids are the islands but the term can also describe remote communities on the mainland. To illustrate this transformation, one can take the example of France. In 2015, the country set ambitious goals for its islands in terms of the share of renewable energies in the electricity mix. They should cover 50% by 2020 and 100% by 2030, starting from an average of about 16% in 2016 [31]. To achieve these goals, BESS are already being introduced in combination with Energy Management Systems (EMS) to minimize the role played by diesel generators and facilitate the integration of RES while maintaining the stability of the power network [32].

### 2.3 Economics

The increasing role played by Li-Ion BESS (LBESS) in modern power systems is explained as much by the versatility of technology as by its declining cost. In the context of a booming energy storage market, the fall of its manufacturing costs is expected to continue, making LBESS a major actor in the energy sector of the...
next decades. This section aims at giving an overview of the energy storage market before focusing on the specific case of LBESS.

### 2.3.1 Energy storage: Current market and forecasts

As discussed in 2.2, storing the energy can be performed at multiple scales, from small electronic devices to multi-MW systems. This section will only cover mobility and grid related applications of battery storage.

Energy storage is not a newcomer in the power systems. Since the moment grids were commissioned, the need for energy storage led to the development of the technological solution. For decades, Pumped Hydro Storage (PHS) has been the dominant technology in terms of deployed capacity. As its name suggests, PHS are hydropower plants able to operate reversibly between an upper and a lower reservoir. During the charge, water is pumped from the lower reservoir to the upper one. When power production is needed, the PHS plant operates like a regular hydropower station. The result of this domination is the current distribution of energy storage power capacity, presented in Figure 8 (left-hand side).

![Figure 8: Global operational grid-connected stationary storage capacity per technology, mid-2017. Taken from [33]](image)

In 2017, PHS represented about 96% of the 176GW installed capacity worldwide, according to the International Renewable Energy Agency (IRENA) [33]. The remaining 6.8GW are shared between thermal storage (mainly from Molten Salt in Concentrating Solar Power plants), batteries (dominated by Li-ion) and electromechanical systems.

When it comes to the forecasts, two scenarios are investigated by the IRENA. The Reference scenario is based on current trends and energy policies already introduced by the countries. On the other hand, the REmap Doubling scenario is a more aggressive roadmap complying with the 2°C objective set by the Paris Agreement [34, 33].
In both cases, PHS is still expected to dominate the sector by 2030 but the higher growth rate of alternative forms of storage reduces its overall share. The shift towards electric mobility and new CSP plants coming online are expected to be the main drivers to the rise of energy storage. One can notice the significant difference between the reference and doubling scenarios. This discrepancy illustrates the determining role played by energy policies and regulations in the future development of energy storage applications.

2.3.2 The economics of Li-Ion BESS

The economics of Li-Ion batteries is characterized by two main interwoven trends: a booming demand and a falling cost.

The demand is mainly driven by the ongoing transformation of the transport sector, with Electric Vehicle (EV) featuring Li-Ion batteries entering the market. Between 2013 and 2017, the International Energy Agency (IEA) estimates that the demand for EVs increased with an annual growth rate of 40 % [35]. And this trend is expected to continue with the expansion of the EV fleet around the world that is projected to reach between 50 and 200 million vehicles (light duty vehicles and buses) by 2030 [36].

This rapid increase of the demand imposes a corresponding growth of the manufacturing capacities. In 2017, the global manufacturing capacity reached 200 GWh and is expected to increase threefold by 2022. In this race for battery production, China is leading with a 73 % share of the manufacturing capacity in 2017 and the country is continuing its investment [35].

The other consequence of the raising manufacturing volume is a sharp decrease of the cost. This trend can be explained by economies of scale, progresses made in manufacturing processes and incremental improvement brought to the technology itself. The impact of the production volume on the cost is often described by a learning rate. It corresponds to the cost reduction (in %) for every doubling of the production. With this metric, the current trend in battery cost exhibits a 15-20% learning rate [36, 37], comparable to the one experienced for PV with 24% over the last four decades [38]. This trend is illustrated in Figure 10 with the forecast of Bloomberg on the future cost of a battery pack:
The future looks thus promising for Li-Ion batteries in mobility applications. The other beneficiaries of this diminishing cost are the large-scale stationary applications. LBESS are expected to grow from 2 GWh in 2017 to about 100GWh by 2025 and then up to 150 to 400GWh by 2030 in most of the forecasts. It should be mentioned that the IEA expects a much slower growth with only 8 GWh by 2030 [36] [39]. Even if the stationary application market is expected to boom, the forecasted cumulative capacity remains very small when compared to the expected 1 to 9 TWh deployed by the EV fleet by 2030 [36].

In the case of utility scale stationary storage, the cost of Li-Ion cells and packs are driving the cost of the entire system down. But the electrochemical storage is not the only component experiencing a downwards trend. In its study gathering multiple literature sources, the Joint Research Centre of the European Commission [36] proposed a cost structure and cost structure outlook for utility scale stationary BESS, represented in Figure 11.

In this scenario based on the 2018 Electric Vehicle Outlook and the 2018 New Energy Outlook of Bloomberg New Energy Finance, the overall cost of BESS is expected to decrease by more than 65% between 2017 and 2040 for both energy and power-oriented systems. In either case, the largest cost segment shifts from the battery pack to the category “Other” gathering the thermal management, the EMS, the BMS, Engineering, Procurement and Construction (EPC) costs and other soft costs.
In order to conclude on the economics of ESS, one should discuss the metrics used for the analysis. In this section, the price of storage solutions is quantified in terms of capital cost. This raw value gives a clear view on the ongoing trends, but it does not intend to measure the gains or losses occurring during the use phase. To answer these questions, other indicators have been proposed. One can for instance mention the Levelized Cost of Flexibility (LCOF) introduced by the IEA in 2014 [40] that represent how costly it is to make the production or the consumption of 1MWh more flexible. Another alternative is the Levelized Cost of Storage proposed by Lazard [41] that analyses the cost and revenue stream of representative storage projects in a way similar to the established LCOE. These metrics can offer alternative views on how to quantify the overall cost of a storage when it comes to providing a specific service and can help compare storage solutions to other flexibility levers such as flexible power generation, RE curtailment, network interconnections or demand-side management.

2.4 Lithium-ion battery systems: a closer look

Since the work conducted in this Master Thesis is based on data related to Li-ion BESS, this technology is further described. In the first section, the elements constituting such a system are detailed. Then, the ageing, the electrochemical mechanisms responsible for the progressive decline of the performance of a Li-Ion system will be explained and its consequences discussed.

2.4.1 System elements

A Li-ion battery storage system is a complex assembly of several interconnected elements. Even if the electrochemical storage remains the central component, auxiliary systems play a crucial role in the operation, performance and safety of the overall system.
Figure 12 provides an example of what a LIBESS can be made of. Each manufacturer has its own organization, but this schematic intends to give the reader an overview of the main elements. A LIBESS can be made of one or several containers. Adding these blocks permits to scale up the overall LIBESS in terms of energy and power. Each container comprises the electrochemical storage but also a thermal management system to regulate the indoor climate, a set of safety equipment and a hierarchy of control and communication devices. The Power Conversion System can be partly or entirely housed in a container or even shared between containers.

The following subsections examine these components in greater detail.

### 2.4.1.1 Electrochemical storage

The cell is the elementary block of the electrochemical storage section. As its name suggests, a Li-ion cell is based on the reversible transfer of Li$^+$ ions between the anode and the cathode. Several cathode and anode materials exist and differ on their energy and power density, cycling capabilities, safety and cost. The choice of these materials defines the chemistry of a cell. There is no single best material as the choice is very much application dependent. Cathode materials are currently dominated by Lithium Cobalt Oxide (LCO), Nickel Manganese Cobalt Oxide (NMC) and Lithium Iron Phosphate (LFP) with these three active materials sharing more than 78% of total weight produced in 2015. NMC cathodes are expected to become the dominant material by 2025 [42]. Regarding the anode materials, Graphite remains by far the reference material more than 91% of total weight produced in 2015 [42].

The choice of the couple cathode/anode defines the voltage curve of a cell. For each charge level, the Open Circuit Voltage (OCV) of a cell is defined as the difference of potential between the anode and the cathode when the system is at electrochemical equilibrium (no current flowing and sufficient rest period). Figure 13 illustrates the difference of the OCV curve for four chemistries (four cathode materials against graphite in the anode) as a function of the specific capacity. One can notice the discrepancies in terms of shape and nominal voltage. These characteristics influence the operation of these cells since the voltage is a value that is monitored and regulated. This notion of voltage curve is fundamental for the operation and monitoring of battery systems and will be extensively exploited in this work.
Within the cell, the electrolyte is the part responsible for conducting the Li\(^+\) ions between the electrodes while preventing electrons from doing the same. The electrolyte should thus be a good ionic conductor but a poor electrical conductor to force electrons to go through the external electrical circuit. Another key constraint on the electrolyte is its window of stability. Indeed, due to the difference of potential between the electrodes, the electrolyte needs to be stable over the entire range of voltage where the cell operates. The same applies for the temperature. With all these constraints considered, the most frequent solution is the use of an organic liquid electrolyte containing lithium salts (for example LiPF\(_6\)) [44] [45].

The cell also comprises current collectors whose role is to recover the electrons and transmit them to the external circuit and vice versa. During the manufacturing process they also serve as a support for the coating of the electrode materials and remain the backbone of the electrodes all along the life of the cell [46]. The most standard combination is copper for the anode and aluminum for the cathode thanks to their high conductivity and their stability at their respective electrodes working potentials. The cells can have multiple shapes. The most frequent ones are cylindrical, prismatic (wounded electrodes) and pouch (stacked electrodes) [47].

From the choice of the electrode materials to the shape of the cell, there is a huge number of combinations possible to build one type of Li-ion battery cell. But the possibilities do not stop here since the cells are grouped into larger assemblies to increase the energy and power capabilities of the BESS.

The names used to call the successive levels of hierarchy of the electrochemical storage depends on the manufacturer. For instance, Samsung stacks cells into modules connected in series to form a rack [48]. A group of racks is called a bank. The composition of a rack (number of modules, number of cells per modules, number of cells in parallel or series) defines its characteristics. For example, a rack made of 5 modules in series containing 24 cells (50 Ah, 4V) organized in 12 parallel pairs in series will have a total nominal voltage of \(4 \times 12 \times 5 = 240\) V and a capacity of \(50 \times 2 = 100\) Ah. This scalability permits to match virtually any type of design requirement.

<table>
<thead>
<tr>
<th>Cells</th>
<th>Modules</th>
<th>Racks</th>
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Table 2: Illustration of cells, modules and racks. Images from [49]
2.4.1.2 Power Conversion System (PCS)

The PCS is the interface between the electrochemical storage and the application. In the case of MW scale systems, the external connection is the grid. The main task of the PCS is thus to transform the power from AC (grid side) to DC (storage part) and vice versa. To do so, multiple devices are required:

- The main DC bus transfers the power between the inverter and the electrochemical storage.
- The inverter is the piece of equipment that converts DC power to AC power. When the battery is being charged, it acts as a rectifier. Depending on the application, the inverter can operate in voltage source mode where it sets the reference voltage and frequency to the network or act in current source mode where it only injects power in a stable network [50]. The inverter is an active device. As a consequence, it consumes power to operate and this consumption is considered as a loss from the perspective of the overall BESS.
- In order to comply with grid requirements in terms of quality of the power injected (harmonic content), a filter may be needed in the conversion chain.
- A transformer can be needed to step up the voltage but also to isolate certain parts of the systems. In that case, the AC part of the BESS can be divided into a low voltage and a high voltage side.
- The main AC connection links the BESS to the point of connection (POC).
- A set of protection and control equipment like fuses, circuit breakers or switches can also be part of the topology.

The architecture of the PCS is a tradeoff between redundancy, flexibility of operation, efficiency, safety and cost. For example, the designer can choose to have one inverter per rack, bank or container (dedicated topology) that permit a differentiated operation or to have less inverters with a higher rating, connected in parallel (parallel topology) [51]. The same design considerations apply to multi-sources projects. For example, a PV + battery system can benefit from a shared PCS as both the PV and the battery have a primary DC output [52].

2.4.1.3 Thermal management

Controlling the temperature of the cell is a crucial task for two reasons. First, the temperature strongly impacts the ageing of the cell. For the same solicitation, a cell operating at a higher temperature would deteriorate much faster as illustrated in Figure 14. Maintaining the temperature of the cells within their nominal range has a direct impact on the life of a BESS.

![Figure 14: Impact of the temperature on the discharge capacity. Taken from [53]](image)

The second issue related to temperature management is safety. The main safety risk related to Li-ion batteries are the fires that can be triggered by a thermal failure. The process called Thermal Runaway describes...
the chain of self-sustained exothermal reactions taking place within a cell and which leads to the violent deterioration of the element. Among the consequences of a thermal runaway are the release of gases, explosions that may eventually lead to fire. This chain of reactions starts from a very temperature. This high temperature can be reached in reaction to an external mechanical stress, electrical failure or simply due to the accumulation of heat in normal operation. It is to prevent the later that an efficient heat dissipation system is required [54].

At container level the need for a thermal management apparatus results in the use of an HVAC system to regulate the indoor climate. This cooling equipment requires its own power supply and this consumption affects the overall back-to-back energy efficiency of the BESS. This global cooling solution is however not sufficient to prevent local hotspots from appearing. Indeed, it is the temperature of the cell that needs to be regulated, not the ambient air within the container.

As a consequence, heat dissipation elements are also implemented at rack and module levels. The simplest one features a fan that blows air on the cells inside the modules. The heated air is rejected to the container and is then further evacuated by the HVAC system. The effectiveness of this solution is very dependent on the internal configuration of the module. More complex solutions featuring phase change materials, heat pipes and liquid cooling are also gaining attention, especially for electrical mobility applications. Indeed, these methods permit a more homogeneous cooling and can meet higher dissipation rates [55].

2.4.1.4 Control and communication

In order to coordinate the operation of the multiple parts of the BESS, several systems are required.

The Energy Management System (EMS) is the system-level controller. It is located at the interface between the BESS, the application and the system owner and acts like the brain of the storage system. From external signals or objective functions, the EMS is responsible for deciding the power flow in and out of the BESS, distributing the load between the sublevels and communicating the overall state and performance of the system [51]. The EMS can be integrated within a Supervisory Control and Data Acquisition (SCADA) solution to build multi-sources systems [56].

The Battery Management System (BMS) is the control architecture built in parallel with the electrochemical storage layout. It monitors, controls and protects the successive layers of the battery, from the cells to the banks to implement the instructions of the EMS. It is often built in a master-slave configuration with a master BMS (e.g. rack BMS) controlling multiple slave BMSs (e.g. Modules BMS). The highest level of the BMS reports to the EMS. Among the multiple functions of the BMS one can mention the control of the charging and discharging phases, the monitoring of the voltage, current and temperature or the estimation of the live indicators (charge, health) [57] [58]. Another crucial role of the BMS is to ensure a good balancing of the cells within a module (and modules within a rack). The objective of balancing is to maintain all cells to the same voltage. Indeed, a poor balancing leads to a lower efficiency, a reduced useable capacity and most of all it induces an accelerated deterioration of the over- and under-voltage cells that causes a serious safety risk. Industrial solutions to achieve this balancing can be divided into passive and active balancing methods, if any balancing solution is integrated at all. Passive methods usually feature shunt elements used during the charge phase to bypass the over-charged cells and waste the corresponding excess energy. Active methods intends to redistribute the charging energy where it is needed to equalize the charge level [58] [59].

Because a BESS is not only made of the electrochemical storage part, the auxiliary systems also have their own management systems. The Thermal Management System is responsible for maintaining the temperature of the cells within their nominal range [51]. It receives data from the temperature sensors at acts on the cooling systems. The Conversion Management System controls the operation of the PCS devices. Even if conversion equipment is more robust, is still needs to communicate with the EMS to perform the basic operational functions like adjusting the power output (active vs reactive power), detecting and protecting the system from external faults or report on its status.
2.4.1.5 Safety Equipment

Finally, maintaining a high level of safety is of the utmost importance for a BESS. Just like any other power system LIBESS are subject to electrical, mechanical, climatic and human risks and these common risks won’t be examined in this work. What is worth discussing however, is the risk of thermal failure that is the main specific hazard facing a Li-Ion BESS. Such event can cause the release and the combustion of toxic gases, explosions and the propagation of this failure to neighboring elements. As discussed in section 2.4.1.3, this phenomenon is called Thermal Runaway and is further examined in this section.

A Li-Ion battery cell is stable within a fairly large window of temperature. Manufacturer datasheets set the range of acceptable voltage and temperature. While it is generally recommended to operate around 20-25°C, the safety range spans from negative temperatures to up to 60°C. In fact, the chemical components that constitute a cell are stable up to 80°C [60]. From 120°C, the Solid Electrolyte Interface (See. 2.4.2 for more details) starts to decompose in an exothermal reaction further increasing the temperature. Then, the electrolyte breaks down and the meltdown of the separator induces internal short circuits contributing to the increase of temperature and pressure within the cell [19]. When its threshold is reached, the safety vent of the cell opens and releases the gas. This gas contains Carbon Monoxide (CO), Carbon Dioxide (CO2) and Hydrogen (H2) that may self-ignite [60]. During the thermal runaway, the cell surface temperature can reach up to 400-700°C [19] and the heat generated during this chain reaction can trigger the same event in neighboring cells.

There are many factors that can cause such thermal failure. Even if in any case this failure needs a high temperature to be initiated, there are many causes that can bring the cell to this extreme temperature condition. Ouyang et al. [19] propose a classification of these factors into physical (shocks, stress, penetration), electrical (short circuit, inappropriate voltage), thermal (internal or external overheating), manufacturing defects and ageing.

To protect the BESS, both prevention and mitigation are required. From the design phase, choices have an impact on the probability and intensity of such events. For example, the choice of the cathode material strongly influences the chain reaction. For example, while Lithium Cobalt Oxide (LCO) decomposes in an exothermal process, Lithium Iron Phosphate (LFP) does not. At cell level, the presence or the absence of safety features like a gas vent, current interrupt device or fire retardant change the dynamics and the intensity of thermal failures. Finally, the configuration of the module is a key factor in the propagation of the failure with compact layouts fostering the spread from cell to cell [19].

During the operation of the system, a very efficient regulation of the temperature is crucial to prevent the accumulation of heat. In addition to the temperature, the voltage at cell level should be monitored closely. Indeed, a poor cell balancing may lead to cells being under- or over-charged. Apart from the fact that these operating conditions accelerate the deterioration of the cells, it can also cause an increase in temperature. It is the role of the BMS to guarantee a proper balancing within the modules.

In order to mitigate the impact of a failed cell, the container can include passive thermal barriers that prevent the propagation of the default. It can also feature active equipment like fire detection and extinguishing devices [54]. In addition, a global alarm system ensures a rapid handling of the incident by the dedicated teams.

When it comes to the regulatory framework, Li-Ion batteries (like other kinds of electrochemical batteries) are covered by many European and International regulations considering all phases of its life-cycle: raw material, design, transport, use and end of life [61]. Due to its multi-physics nature, BESS are governed by general guidelines related to chemical components, electrical equipment, machines, electromagnetic compatibility and so on [62]. In Europe, the European Battery Directive 2006/66/EC sets objectives in terms of ecological impact and consumer choice [63]. At international level, the standards developed under the IEC TC 120 (IEC 62933-62937) intend to define testing methods and guidelines for grid-connected ESS [64].
2.4.2 Ageing

2.4.2.1 Microscopic description

Unlike other forms of energy storage (mechanical, kinetic, thermal), a BESS is subject to ageing i.e. to a progressive decay of its performance over time. Even if the auxiliary equipment of a BESS is also prone to a slow deterioration, the ageing refers to the microscopic phenomena, occurring at cell level and responsible for the irreversible decline in capacity and power capabilities. Beyond performance, extreme ageing conditions can also be the cause of safety issues as discussed at the end of this section.

The ageing of battery cells is a natural process influenced by material choice, environment conditions and solicitation. To understand these deterioration phenomena, the main elements of a typical Li-ion cell and their role should be reminded. The cathode is a lithium-based metal oxide that releases Li+ ions during the charge. On the other side, the graphite anode has the ability to host the Li+ ions in its crystalline structure. The opposite reaction takes place during the discharge. It is the amount of Li+ ions being reversibly transferred that characterizes the capacity of the cell. Between the two electrodes, the electrolyte is an organic liquid that conducts Li+ ions while maintaining a good electrical insulation. The separator is a physical barrier located in the electrolyte that prevents any direct contact between the two electrodes that would induce a short-circuit. The force that drives the ion migration is the difference of potential (a.k.a. electromotive force) between the two electrodes.

The literature proposes the following classification of degradation modes [65] [66] [67]:

- The irreversible consumption of lithium ions in parasite reactions reduces the number of ions able to navigate between electrodes. It is referred to as Loss of Lithium Inventory (LLI).
- The second category gathers the mechanisms reducing the amount of electrode material able to participate in the reversible insertion of lithium ions. It is called Loss of Active Material (LAM).

The degradation process takes place both at the anode and at the cathode. The anode is home of two major ageing mechanisms: the Solid Electrolyte Interface (SEI) creation and evolution and the lithium plating.
The first phenomenon is caused by the intrinsically high reducing/oxidizing character of the electrodes. At the surface of the anode, part of the electrolyte is degraded resulting in the formation of a solid layer called Solid Electrolyte Interface (SEI). The SEI acts like a passivation film (protective barrier) allowing the electrolyte to operate with the anode being out of its stability potential. As part of the manufacturing process, the cell is subject to a few charges and discharges under controlled environment to permit the formation of this protective SEI. However, this SEI formation step is also responsible for a significant reduction of the cell capacity (up to 30% [12]) due to the irreversible consumption of Li ions in the process. Since the SEI is impermeable to the electrolyte molecules that reacted with the anode surface to form the layer at the first place, the SEI grows more slowly while in operation. The stability of this protective layer gives the Li-ion technology its remarkable cycling capabilities [68] [67]. Still, even if this process occurs at a very slow rate, Li ions are indeed continuously consumed throughout the life of the cell as the SEI continues to grow. For this reason, the growth of the SEI is classified as Loss of Lithium Inventory (LLI). Figure 15 proposes an illustration of the phenomena occurring in the SEI. To summarize, the SEI formation is an essential manufacturing step to ensure a good resistance to repeated cycling but the consumption of Li ions during the growth of this protective layer causes a progressive decline in capacity and an increase of the internal resistance.

Lithium plating is the second main degradation reaction happening at the graphite anode surface. It takes place under extreme conditions. Unlike the lithium intercalation mechanism that is the expected and reversible phenomenon, lithium plating is the permanent deposition of lithium under its solid form at the surface of the anode. At very low temperature, the intercalation process is slowed down to the point where plating occurs. Similarly, when the applied charging current is too high compared to the rate of the intercalation process, the accumulation of Li ions can cause deposition [69] [12]. The lithium plating is thus another mechanism responsible for the Loss of Lithium Inventory (LLI) but also prevents the use of some sites in the anode (classified as LAM). During sustained inappropriate conditions, solid lithium can even
build-up to form dendrites that can cause internal short circuits. To limit the extent of lithium plating, a careful monitoring of both temperature and current at cell level is crucial.

When it comes to the cathode, ageing phenomena include film formation, structural disordering and dissolution of the active material by the electrolyte.

First, in a manner similar to what happen at the anode, the decomposition of the electrolyte can lead to the formation of a thin membrane at the surface of the cathode (LLI and LAM), especially at the end of charge when the applied voltage is high [66] [68].

Second, at atomic level, the repeated insertion and extraction of Li ions is responsible for structural changes in the metal oxide crystal. This makes some sites unable to participate in the lithium intercalation process (LAM) and leads to deformations and mechanical stress at macroscopic scale. The mechanical stress can also induce local contact loss between the cathode and the current collector [65] [66].

The main driver for ageing at the cathode remains the dissolution of the active material by the electrolyte. Literature [66] [68] tends to indicate that manganese is the element most prone to dissolution and proves that the extent of metal dissolution is very chemistry specific. This disintegration of the cathode can either be driven by low potentials or by the reaction with HF that is a product of the hydrolysis of LiPF6, the main component of the electrolyte. In both cases, the degradation process leads to a loss of active material (LAM) at the cathode which results in a loss of capacity at cell level. These ions can then migrate to the anode where they further thicken the SEI or form dendrites [12] [68] [66].

These paragraphs mainly focused on the mechanisms responsible for the progressive loss of performance at the anode and at the cathode. However, it should be mentioned that other phenomena take place at the binder (material at the interface between the electrode and the current collector) and at the current collector surface, resulting in loss of capacity, impedance increase or other safety related issues.

Birkl et al. [65] (Figure 16) proposed a summary of the main ageing phenomena observable in a Li-ion cell.

![Figure 16: Schematic of the main ageing mechanisms taking place in a Li-ion cell. Taken from [65]](image)

2.4.2.2 Macroscopic considerations

The previous paragraph detailed the electrochemical mechanisms driving the progressive deterioration of the cells. Of course, the extent and the rate of deterioration is very dependent on what the cell experiences during its operation and this can be monitored at the macroscopic scale.

From a macroscopic perspective, the overall ageing process is described as being the result of the contribution of a calendar ageing and a cycling ageing. Calendar ageing basically describes the role played by time on the spontaneous degradation of the cell. High temperatures and high voltages are aggravating...
factors. On the other hand, cycling ageing is a consequence of the solicitation of the cell. It is influenced by the solicitation they face (cumulative charge, current, voltage) and the temperature [70]. This discussion can be summarized by Equation (4):

\[
\text{Ageing} = \text{Calendar Ageing} (\text{time}, I, V, T) + \text{Cycling Ageing} (Q, I, V, T)
\]  

(4)

Even if ageing is a microscopic phenomenon, its impact is visible at the scale of the system. The Loss of Lithium Inventory, the Loss of Active Material and the other degradation mechanisms induce a decline of the available capacity and an increase of the internal resistance. This progressive decay of the performances requires smart design choices to be able to deliver the expected service and a precise operation is needed to avoid the safety risks.

Ageing affects both the energy and the power capabilities of a BESS. Indeed, the energy available is reduced in proportion to the diminution of the capacity and the maximum power is lowered by the increased internal resistance at cell level. In order to guarantee the same level of service all along its lifetime, the BESS designer should thus offset the impacts of ageing. This can be performed in two ways:

- The electrochemical storage part can be oversized (energy and power). It thus operates at a lower rating. As for the auxiliary systems (Thermal Management, PCS), they are normally dimensioned. The margin between the capabilities of the system and the service requirements slowly decreases as ageing goes on.
- An alternative to the general oversizing is the punctual reinforcement. In this approach, parts of the electrochemical storage (entire racks or banks) are replaced by new ones during the operation in order to maintain a sufficient overall performance at all time.

The live operation of the BESS is also impacted by the ageing. Beyond the simple generalized decrease in performance, problems of homogeneity also appear due to the imperfect manufacturing process and discrepancies in operation.

Depending on the homogeneity of the manufacturing process, cells can be slightly different. As a consequence, even if they all experience the same solicitation, they will have different ageing rates. On the other hand, if the cells are strictly identical but the BMS fails to evenly distribute the load or the temperature, the cells will also deteriorate at different rates. In both scenarios, the result is a system operating with cells having different characteristics.

Let’s illustrate this point with the consequences for a module made of cells in series with different ageing conditions. In terms of performance, it means that the capacity of the string is decreased. Indeed, the string capacity is set by the weakest cell as all cells in series see the same current. A lot of energy is thus not usable anymore. In terms of operation, it means that balancing features are required to ensure a uniform distribution of the charge level despite the discrepancies in capacity.

As it has already been discussed in 2.4.1.3 and 2.4.1.5, thermal management is paramount to reduce the risk of thermal failure. In this context, ageing is an aggravating factor. Directly, the deterioration of the cell manifests through a growing internal resistance (destruction of the electrolyte, electrical contact loss …) that leads to an increase of the heat generation via ohmic losses. Indirectly, and in the absence of a good BMS, ageing increases the unbalance between the cells that in turns raise the likelihood of extreme temperatures, over-voltage and under-voltage. These abuses can be responsible for internal failures such as internal short circuits that may trigger the thermal failure of the cell.

To summarize, the ageing of a cell is driven by microscopic phenomena, but this progressive deterioration has multiple macroscopic repercussions. The decrease of the performance should be considered from the design phase, it influences the operation of the overall system and it should be regarded as a safety threat.
As a conclusion, it is now clear that LIBESS are complex systems. They gather in a same project multifaceted engineering challenges ranging from the chemical phenomena occurring at microscopic levels to the need for a performant thermal management via the necessity to operate all elements of the system in a coordinated way. From this section, the need of a detailed monitoring arises, to make sure that the system meets its performance and safety objectives throughout its lifetime.

2.5 The need for a close monitoring

2.5.1 Project stakeholders

Just like any other large-scale energy project, a BESS is the result of the cooperation between multiple stakeholders. In this section, the main actors in the operation of a BESS for grid services are presented and their roles are described. For the sake of simplicity, the parties involved in the financial and economic aspect of the project are not studied. As a result, the stakeholders in the development and operation of a BESS are the following: the TSO that is at the origin of the competitive tender for grid-related services, the battery manufacturer that conceived the BESS and the system owner that is also considered as being the project developer and the system operator in this illustrative example.

In the case of grid applications, the TSO first identifies a need for a specific service. To address this need, opening a competitive tender is a traditional choice for the procurement of energy projects. In this kind of process, developers are competing against each other through a multistep procedure to meet a set of requirements with the lowest price [71]. To illustrate this process, one can focus on the opening of the new Enhanced Frequency Response (EFR) service initiated by the TSO of Great Britain National Grid. After a preliminary phase of expression of interest in 2015, 64 participants were prequalified. The invitation to tender took place during the spring of 2016. It resulted in 37 submissions being received by National Grid from which 8 tenders were selected based on their average price for the service [26].

From the perspective of the tender participants, a competitive procurement process is a very intense preparation period aiming at designing a system meeting the requirements and with the lowest price. It is very usual that the developer is not a producer of the technology. In this situation, the developer also initiates a sub call for tenders with manufacturers based on its design requirements. The solution eventually proposed by the developer is thus made of parts it owns and other it obtains from sub-contractors. For example, a BESS developer may have its own EMS, but the electrochemical storage may be bought from a battery manufacturer. The developer and the manufacturer are linked by a contract that specifies requirements and warranties. An intermediate actor, called a system integrator can also play a role in between but this player will be omitted in this simplified scheme.

During the operation of the system, the main three stakeholders remain very active. In the example of frequency regulation, the TSO can impose the operation of the system by a collection of fixed rules or via an active signal to follow. To make sure the expected service is delivered satisfactorily, score functions can determine the remuneration and penalties can be given if the availability is below the contracted one.

To maximize the profit, the operator should hence ensure a smooth operation of the system. During live operation, a chain of command controls the BESS. In this control chain, some parts may belong to the developer/operator and some may be the responsibility of the sub-parts manufacturers. A robust communication protocol is thus crucial. When it comes to the maintenance, each component can have its own maintenance team, associated to the manufacturer.

During the lifetime of a BESS project, having a clear understanding of the state of the system is of the utmost importance for the owner. This comprehension concerns both the live performance of the system and its progressive degradation with time. These indicators are necessary to make sure the contracts with the contractor and the manufacturers are respected. To achieve this goal of accurate monitoring, the owner can rely on a huge amount of data generated by the BESS.
### 2.5.2 The increasing role of data

The global industry is undergoing a change towards more simulation and data, and the energy sector is no exception to this.

During the design phase, the developer can rely on numerical models to simulate the dynamic behavior of the system. The main objective in this case is to specify its characteristics. The simulation can also have the ambition to evaluate how the system will age with time and with the service it provides. These long-term forecasts can be based on empirical data produced during ageing tests: in a controlled environment, cells are solicited in an accelerated way to quantify its ageing. From these lab data, empirical rules can constitute an ageing model able to predict the ageing of the system as a function of its solicitation.

Data is also and most importantly generated during the use phase of the BESS. Indeed, such a complex system requires sensors at every level (cell, module, rack, bank, and container) for operational but also for safety reasons. In addition to the raw measurements, secondary variables are also generated. They are processed and/or non-physical variables such as state indicators, control variables or status flags.

In order to give an order of magnitude to the amount of data generated by a BESS, one can consider a 1 MWh system where only the information at cell level is processed. Assuming average cells of 200 Wh each, about 5000 of them are required. If one only considers the voltage monitored every second for one year, it represents:

$$5000 \times 60 \times 60 \times 24 \times 365 = 1.6 \times 10^{11} \text{ points/year}$$

In a 64bits system, it corresponds to about 1,2 TB of data and this is a conservative estimate for a rather small system. This example illustrates two points. First, in order to have an overview of the system, this huge amount of data should be reduced to a collection of synthetic indicators. These indicators are presented in the next section 2.6. The second conclusion is the need to run these analyses within a framework adapted to the volume of data at stake. This question will be addressed in the section 3.3.

### 2.6 Key performance indicators

Key Performance Indicators (KPI) are synthetic variables designed to provide an overview of the performance of the system and to quantify its ageing. This section introduces the main KPIs under study in this thesis work from a theoretical standpoint. For the complex KPIs, a literature review a proposed.

In this work, four categories of KPIs have been investigated. They mainly cover the electrochemical storage part of a BESS. First, operational indicators will be studied through the State-Of-Charge and the balancing. Then, several definitions of the efficiency and a quantification of the availability will be proposed in the section related to the performance indicators. Ageing will be regarded with the number of cycles and the State-Of-Health. Finally, some analyses regarding the thermal management of the BESS will be presented.

#### 2.6.1 Operational indicators

Unlike traditional power plants producing electricity, BESS are only able to store it. The amount of charge available within the system at a given time is what decides its capability to meet a demand and what governs its operational decisions (to charge, wait or discharge). Having a reliable indicator to indicate the State Of Charge is thus crucial. The quality of the operation of a BESS can also be evaluated by looking at the balance of the components of the electrochemical part. The notion of “balancing” will therefore be explained.

##### 2.6.1.1 State of Charge

The State Of Charge (SOC) is probably the most intuitive indicator when one thinks about a battery. Any smartphone or laptop user always keeps a close eye on the gauge illustrating the charge still available in the battery. This gauge, often in percent is the SOC.
The SOC is defined as the ratio between the capacity available in the battery at a given instant $Q$ and the maximum capacity at that instant $Q_{\text{max}}$. At the beginning of its life, this maximum capacity is simply the nominal capacity $Q_{\text{nominal}}$. However, as the cell ages, the capacity decreases ($Q_{\text{lost}}$) and the denominator is updated to account for this loss.

$$\text{SOC} \left[\% \right] = \frac{Q \left[\text{Ah} \right]}{Q_{\text{max}} \left[\text{Ah} \right]} = \frac{Q \left[\text{Ah} \right]}{Q_{\text{nominal}} - Q_{\text{lost}} \left[\text{Ah} \right]}$$ (6)

The SOC is probably the most important variable when it comes to the live operation of the system. Indeed, it represents the charge available in the battery at any given time and thus quantifies the ability of the system to perform a given task. Typically, the EMS computes its commands based on the SOC to decide whether to charge or to discharge and the corresponding rate. The SOC also materializes the operation range of the system. Extreme SOC levels (close to 0% or 100%) forces the EMS to adapt its instructions to make sure that the system is never over- or under-charged.

Even if the SOC is very intuitive and fundamental to the operation of the system, it is still one of the hardest indicators to compute accurately. The following paragraphs introduce the reader to the main approaches proposed in the literature.

**Coulomb Counting:** Coulomb Counting (CC) is the simplest way to compute the SOC. As its name suggests, it consists in counting the charges flowing in and out of the battery in a cumulative way. The indicator is initialized from a reference instant where the SOC is known ($\text{SOC}_{t=0}$).

$$\text{SOC} \left( t \right) = \text{SOC}_{t=0} + \frac{1}{Q_{\text{max}}} \int_{0}^{t} I \left( \tau \right) d\tau$$ (7)

Coulomb Counting is often seen as a reference for short term estimates. Indeed, its implementation closely follows the definition of the SOC. However, as examined by Rivera-Barrera et al. [72], the CC method is limited on the long run due to the accumulation of small errors. This cumulative error causes the SOC to deviate from its exact value and this process is often referred to as drift. In addition, the technique depends on the accuracy of the initial value chosen. Any initial error will cause an offset that is kept in the indicator value until a new update is performed. As a consequence, the standard CC approach is rarely used alone and is more frequently used as a building block for a more robust estimation.

**Corrected Coulomb Counting:** One way to work around the issue of CC drift is to implement a corrected version of the Coulomb Counting. This kind of approach was first proposed by Ng et al. [73]. A complete framework with SOC initialization and live estimation was suggested. The key difference with the standard technique is the use of test data to establish a law for the coulombic efficiency and the other possible sources of imbalances. The coulombic efficiency will be discussed in greater details in section 2.6.2.1, but for now it can be seen as the quantification of the deficit of capacity released during the discharge compared to the capacity absorbed during the charge. The corrected CC approach thus becomes:

$$\text{SOC} \left( t \right) = \text{SOC}_{t=0} + \frac{1}{Q_{\text{max}}} \int_{0}^{t} I \left( \tau \right) \eta_{\text{coulombic}} \left( I \right) d\tau$$ (8)

In their experiment, Ng et al. introduced an adjusted correction coefficient $\eta_{\text{coulombic}}$ that maintained the SOC error below 3% while it cumulated to reach 9% after 27 cycles in the standard version [73].

**Voltage based estimates:** An alternative to Coulomb Counting is to use the voltage of an element to deduce its SOC [74, 75]. Indeed, the voltage is the image of the charge contained in a cell. During the

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1 This definition can be updated to integrate the State Of Health as presented in the corresponding 2.6.3.2 section.
charging process, Li\textsuperscript{+} ions migrates from the cathode to the anode and electrons transit through the external circuit as they are driven by a voltage source. The result of this displacement of electrons is an electrical current, that can be monitored and converted in a cumulative way into charge and thus into State Of Charge. But the displacement of charges also induces a buildup of a potential difference between the two electrodes resulting in the measured voltage. Unlike Coulomb Counting that is a cumulative process, using the voltage to estimate the SOC is thus an instantaneous process since one single value of the voltage can provide an estimate of the corresponding SOC.

During the operation of the cell, the measured voltage is the image of the State Of Charge, but it is also influenced by the current and the temperature of the cell. First, the current leads to the apparition of various overpotentials resulting of the thermodynamic inefficiencies affecting the reversible reaction. This phenomenon is usually described with an equivalent internal resistance. These overpotentials causes a voltage hysteresis: during the charge, a slight over-voltage is necessary to drive the reaction while the overpotentials are responsible for a voltage-drop during the discharge. Figure 17 illustrates this point. For a given capacity, the measured voltage is reduced when the discharge current is increased. When it comes to the temperature, the impact is fairly similar. A low temperature leads to a lower voltage (for the same constant discharge rate) and a reduced capacity. The opposite is true for temperatures higher than 25°C, the usual nominal working temperature.

As a conclusion, the voltage measured in operation is the image of the charge contained in the cell, but it is also a function of the C-rate and of the temperature at which it is operated. In order to directly estimate the SOC from the measured voltage in operation, correlation tables can be used. These tables, obtained from extensive testing campaigns establish direct links between the measured voltage, current, temperature and the SOC.

This technique has long been the standard in the industry. Indeed, it is easy to use and does not require any complex computation tool. However, its empirical nature comes with a cost. A test campaign is required every time a new battery model is produced as these maps are model specific. In addition, even if these maps can be very accurate at the beginning of the life of the system, the degradation mechanisms that drive the ageing of the cell may be different from the ones reproduced in the lab tests which can cause a progressive deterioration of the accuracy of the technique.

A variant to this extensive voltage-SOC mapping is to work with the Open Circuit Voltage (OCV). As its name suggests, the OCV is the voltage measured at the cell terminal when the latter is not loaded and has
been in this state of rest for a sufficient duration, typically several hours. In these conditions, the measured voltage (OCV) reflects the electrochemical state of the cell, including its charge level. If one also keeps the temperature of the cell at its nominal value during this period of rest, the previous problem to estimate the SOC as a function of three variables (voltage, current and temperature) is reduced to one: the OCV. Measuring this Open Circuit Voltage gives access to the SOC via a reference curve called OCV-SOC characteristic.

Of course, by definition this method cannot be used for under-load estimations of the SOC. Still, this technique can be applied for systems experiencing long periods of rest like EV during the night or large-scale BESS if they are not solicited. The result is only a temporary estimate of the SOC, but this one-time evaluation can be used to initialize or readjust a cumulative technique like Coulomb Counting.

**Equivalent Models:** The previous paragraphs illustrated the limits of cumulative methods on the long run. Then, voltage-based estimates showed that they are not affected by this CC drift, but they come with their own drawbacks namely the cost of building exhaustive correlations for voltage-SOC maps and the impossibility to use the robust OCV approach for live operations.

To address these constraints, equivalent models can be implemented. These models intend to represent the dynamics of the system to estimate the useful variables such as the SOC. They can be defined as phenomenological models by opposition to the purely mathematical models discussed later on (Artificial-Intelligence and statistics-based approaches).

One family of phenomenological models are the electrochemical ones. They aim at simulating the behavior of the cell by describing the phenomena occurring at the microscopic level such as the migration of ions or the transfer of electrons. In these electrochemical models, the mechanisms can be described by local migration, diffusion and kinetics laws adjusted by parameters [72, 78, 79]. The fitting of these parameters can be the result of lab measurements or empirical data.

This kind of approach has the merit of representing the physics driving the reversible exchange of Li$^+$ ions. However, the tuning of the parameters requires in depth analysis as it is not provided by the battery manufacturers. In addition, the complex partial differential equations governing the model are computationally expensive to solve and make this approach poorly adapted to live calculations. Still, these models can be very useful for the process of design of new cells as they can help to understand the influence of new chemical compositions [74] [80].

The other major family of equivalent models are the Equivalent Circuit Models (ECM). Unlike their electrochemical counterparts, ECMs are focused on the macroscopic description of the dynamics of the cell. To do so, an electrical circuit model made of a voltage source and impedances is employed. To illustrate this point, Figure 18 provides the examples of a Thevenin and a first order ECMs.

![Figure 18: Thevenin (left) and first order (right) ECMs. Taken from [81]](image)

A typical ECM is the first order one represented on the right-hand side. It indicates that the total measured voltage $U$ is the sum of three voltages. The main contributor is the Open Circuit Voltage represented by a voltage source ($U_{OCV}$) which is only a function of the SOC as discussed in the paragraph about OCV-based estimations. Then, a resistor $R_Ω$ embodies the internal resistance responsible for the voltage hysteresis during
the charge and discharge phases. Finally, one or several RC blocks account for the dynamic behavior of the system (inertia, relaxation etc.). This third voltage contribution is often referred to as polarization voltage. Note that each of these elements can be a function of the temperature if the parameter is considered relevant.

Several methods exist to estimate the value of the impedances constituting the ECM. The most generic one is called Electrochemical Impedance Spectroscopy (EIS), which is a non-destructive experimental technique. From an initial state of either complete rest or constant current load, the cell is stimulated with a sine current with the frequency ranging over multiple orders of magnitude, typically from 0.01Hz to 10kHz [82]. The analysis of the cell voltage during this experiment gives access to a characterization of the impedance of the cell which is then translated into the values of the parameters constituting the chosen ECM [74, 82, 83]. Note that this technique can also be used to find the parameters of an electrochemical model. Another simpler way to estimate the parameter of a first order ECM is to stimulate the cell with a crenel current. The induced voltage drop is proportional to the internal resistance by the Ohm’s law and the product RC corresponds to the characteristic time of the voltage variation [84]. Finally, one should mention that the internal resistance of a cell and, less frequently, the other impedances can be provided by the cell manufacturer as part of the characteristics.

With regard to the problem of estimating the SOC, ECM can be seen has the intermediary step between live measurements and OCV-SOC maps. Thanks to the first order equations governing the ECM, the measured current gives access to the Ohmic voltage drop and to the polarization voltage. Indeed, these voltages are only a function of the current when the impedances are known. By subtracting them to the total cell voltage measured (U), the Open Circuit Voltage is estimated. Then, the SOC can be obtained from a direct correspondence with the OCV [72].

This straightforward method has the benefit of being algorithmically light. It is easily implementable in small controllers and its low computational cost make the method adapted to ex-post analyses where a long period of time is studied at once. In addition, this instantaneous approach does not suffer from the accumulation of error and can thus be used to reset the cumulative Coulomb Counting method. However, the reliability of this method is very dependent on the model and the accuracy of its estimated parameters. In addition, an ECM remains a simplified version of the actual dynamic behavior of the cell. If the cell is subject to a hectic load, the estimated SOC may contain noise. Last but not least, as the battery ages the values of the ECM also evolve and a regular update of the parameters is required via, for example, the techniques previously mentioned (IES, current pulses etc.).

**Adaptive algorithms:** Adaptive algorithms address the need for a continuous update of the parameters constituting an ECM (or virtually any kind of model). Their self-adjusting capabilities and good robustness to parameter estimation errors have attracted a lot of attention in the literature [85, 86, 87, 88, 75, 89]. This type of method consists of two steps:

- A prediction step. During this first phase, a model predicts the current state of the system based on live input measurements and on the knowledge of the previous state. The model mentioned here is very often an ECM, the type discussed in the previous paragraph, but it can also be more general such as mathematical fit of curves or empirical relations.
- An update step. The difference between the estimated state and the actual one serves as input to a correction algorithm. Several steps (depending on the algorithm chosen) permit to update the model parameter for the following step.

A general flowchart of model-based adaptive filters is proposed in Figure 19. The inputs and state variables depend on the specific application. For the task of SOC estimation, the measured current and temperature can serve as inputs to the battery model that predicts a voltage and SOC level. The update step then intends to reduce the difference between the estimated voltage and the measured voltage by feeding a correction algorithm with this error. More sophisticated approaches can feature other inputs and state variables.
When it comes to the correction algorithm themselves, one can first mention the widely used Kalman Filters (KF). Kalman filtering is for example used in navigation applications to track the evolution of a dynamic system over time. The real-time update of the parameters is performed by minimizing the root mean square error between the expected and actual outputs while accounting for the measurement noise [84, 87]. While linear systems can be followed with a standard KF, non-linear systems require more complex formulations such as the Extended Kalman Filters or the unscented Kalman Filters. Another solution is the Recursive Least Square (RLS) method that uses past sampling points to converge towards the parameters minimizing an error function [90, 90, 72]. RLS methods can also feature multiple Forgetting Factors to take into account the various dynamics of the system (kinetics, operation, ageing etc.). To conclude on the large variety of adaptive methods, one can also mention the Sliding Mode Observers based on the theory of Sliding Mode control [91, 92] and the Proportional-Integral Observers applying the fundamentals of control theory [93].

The two major strengths of adaptive algorithms are their self-adjusting capability and their accuracy. The resulting SOC error is reported to be below ±3% in most studies and proved to quickly converge regardless of the initial SOC guess [84] [85] [93] [94] [95]. However, these performances come with a higher computational burden, limiting their use in ex-post applications where a huge amount of data needs to be computed at once. In addition, the correction function and the model require a fine tuning to ensure the stability and a good convergence of the approach [72]. These constraints make adaptive algorithms more suited to the in-depth study of a specific type of cell than to replicable performance analyses.

**Artificial-Intelligence and statistics based approaches:** This category gathers data-driven monitoring solutions where no modelling step is required [72] [74] [87]. Artificial Neural Networks are multi-layers graphs with weighted coefficients able to link input variables to output values after a learning phase. Support Vector Machine is a method aiming to transforming a non-linear model into a higher order linear one. Genetic Algorithms replicate the biological processes of selection, mutations and crossovers to convert a collection of random values into adjusted variables.

These methods can be considered as being “black boxes”. Indeed, the mathematical operations ruling them are not controlled by the user and does not require a preliminary knowledge of the physics of the system. This disconnection from the physics of the system is very convenient to overcome the difficulty related to accurate modelling, especially if one wants to simulate complex problems. However, in the context of battery monitoring, this feature is prohibitive because it does not provide information to fully understand the mechanisms that govern the system and its evolution.

### 2.6.1.2 Balancing

In an ideal battery system, each of the elements constituting a serial assembly have the same voltage. For example, it can be the multiple cells mounted in series in a pack. However, in real systems this voltage homogeneity is never fully achieved. This is heterogeneity has its origin in the imperfection of the
manufacturing process, producing cells with slightly different characteristic. During the operation the differences can be further accentuated if the BMS fails in ensuring an evenly distributed load and working environment. In that case, some elements can be over-solicited compared to others, leading to exacerbated imbalances. The result is that in a serial assembly, the elements may not all have the same voltage, i.e. not the same charge level as illustrated in Figure 20.

A poor balancing, characterized by a voltage imbalance between elements connected in series, causes both a reduction of the performance and some safety issues. First, if the BMS regulating a chain of cells in series is programmed to stop the charge or discharge when the first cell reaches the voltage boundaries then the overall capacity of the chain is limited by these extreme cells. The greater the imbalance, the greater the loss of performance. Second, a poor balancing can be at the origin of safety issues if the cells are operating out of their nominal voltage range as illustrated in Figure 20.

The balancing of the cells in an assembly is thus a multifaceted problem but with a simple objective: to maintain a similar voltage in all the elements constituting the assembly. This task is performed by the Battery Management System (BMS) at a given level (module, rack, pack etc…). However, even if a good balancing enhances the performance and the safety of the battery, the BMS may not be equipped with an equalizing apparatus at all, since it comes with additional costs.

With that in mind, assessing the homogeneity of the voltage is thus both a question of operational performance and of safety. One way to quantify the uniformity of the voltage is to study the maximum voltage spread within an assembly at a given time, for example between the extreme cells in a module. This spread can be compared to the average cell voltage at that instant to obtain a relative value.

\[
\mathcal{V}_{\text{module, max}}(t)[\%] = \frac{U_{\text{cell, max}}(t) - U_{\text{cell, min}}(t)}{U_{\text{cell, mean}}(t)} \times 100
\] (9)

### 2.6.2 Performance indicators

BESSs are complex systems but their core principle remains to store energy through a reversible electrochemical reaction. Evaluating the efficiency of this process is thus a relevant indicator. To address this question, three definitions of the efficiency will be presented. The performance of the system can also be analyzed at a more macroscopic scale with the notion of availability. An adapted version of this concept will be proposed.

#### 2.6.2.1 Efficiencies

In this thesis work, the efficiency is studied at the level of the electrochemical storage of a BESS (cell, module, rack ...). This DC-DC efficiency is only a component of the overall AC to AC efficiency. This system level round trip efficiency requires to integrate additional losses such as the consumption of the auxiliaries and the losses in the power conversion equipment, but the corresponding data was not available in this work. However, this electrochemical efficiency is what distinguishes BESS from other forms of energy storage and production. It therefore deserves a specific analysis.
The first definition of the efficiency is the most intuitive one and is called round trip efficiency or DC-DC energy efficiency. It is defined as the ratio between the discharged energy and the charged energy, typically over a full cycle.

However, these quantities are functions of the solicitation profile due, among other, to the effect of the internal resistance. For this reason, an exact definition the energy efficiency implies to explicit the profile considered for the assessment (C-rate, CP-rate, profile, rest time etc…).

\[
\eta_{\text{energy,exact}} [\%] = \frac{\int_{\text{discharge profile}} U(t) \times I(t) \, dt}{\int_{\text{charge profile}} U(t) \times I(t) \, dt} \times 100 = \frac{E_{\text{discharge profile}}}{E_{\text{charge profile}}} \times 100 \tag{10}
\]

where U and I are the measured voltage and current of the element during the test. The constraint imposed by the predefined solicitation profile ensures a fair comparison between cell models as it is a rigorous benchmark. However, this strict protocol also makes this first definition limited to lab experiments where the operation can be fully controlled.

For online application, an average approach is proposed and privileged. The constraint of a specific profile is removed, and a long period of time is analyzed to obtain an average value of the efficiency. This period necessarily spans between two instants with the same state, for instance a fully charged battery.

\[
\eta_{\text{energy,average}} [\%] = \frac{\int_{\text{period}} U(t_{\text{dis}}) \times I(t_{\text{dis}}) \, dt}{\int_{\text{period}} U(t_{\text{cha}}) \times I(t_{\text{cha}}) \, dt} \times 100 = \frac{E_{\text{discharge over period}}}{E_{\text{charge over period}}} \times 100 \tag{11}
\]

where \( t_{\text{dis}} \) and \( t_{\text{cha}} \) correspond to the instants were the system is discharging or charging.

Because the solicitation is not controlled by the user, this value of the efficiency is case specific. For example, the same system would have a lower round-trip efficiency if it is operated at high powers than if it were at lower levels due to higher ohmic losses among others. As a consequence, this value can hardly be exploited to compare one BESSs to another if their operations differ significantly. Nevertheless, this average value of the efficiency can give an overview of the performance of one individual BESSs.

One can notice in Equation (11) that the energy efficiency is in fact the simultaneous contribution of the current and the voltage. Therefore, two additional definitions can be introduced: the voltaic efficiency and the coulombic efficiency.

The voltaic efficiency illustrates the impact of voltage hysteresis on the energy efficiency. Indeed, the charge voltage is always higher than the discharge voltage due to the effect of overpotentials. An illustration of the voltage hysteresis over a full charge + discharge cycle is proposed in Figure 21.

\[
\eta_{\text{voltaic,average}} [\%] = \frac{\int_{\text{period}} U(t_{\text{dis}}) \, dt}{\int_{\text{period}} U(t_{\text{cha}}) \, dt} \times 100 \tag{12}
\]
The **coulombic efficiency** on the other hand quantifies the share of the input charges that are returned by the storage system.

$$\eta_{\text{coulombic average}}[\%] = \frac{\int_{\text{period}} I(t_{\text{dis}}) \, dt}{\int_{\text{period}} I(t_{\text{cha}}) \, dt} \times 100$$  \hspace{1cm} (13)

In a first order approach, it can be approximated that the energy efficiency is then simply the product of these two secondary efficiencies [96] [97]:

$$\eta_{\text{energy}} = \eta_{\text{voltaic}} \times \eta_{\text{coulombic}}$$  \hspace{1cm} (14)

From these two components, the voltaic efficiency is by far the greatest contributor to energy losses. Even if its value depends on the type of cell, solicitation profile and temperature conditions, its typical value ranges from 85 to 98%. On the other hand, the coulombic efficiency is frequently reported to be higher than 98,5 % [98] [99] [100] [101].

In a rather counter-intuitive way, it is the coulombic efficiency that is the main challenge for the monitoring of BESSs. Indeed, several indicators have their calculation relying on an accurate Coulomb Counting (SOC, number of cycles, SOH ...) and this counting of exchanged charges is necessarily associated to the notion of coulombic efficiency. For instance, if the SOC is monitored through a corrected Coulomb Counting technique, a 0,5% error in the coulombic efficiency that acts as corrective coefficient would induce a 5% SOC drift after only 10 cycles. The interaction between SOC estimation and coulombic efficiency will be further discussed in the result section.

### 2.6.2.2 Reliability, Availability

Battery Energy Storage Systems are inherently linked to the notion of service provision. Beyond the traditional firm energy supply, BESSs can also provide specific services to the grid (frequency and voltage regulation), to industrial sites (Uninterrupted Power Supply, peak shifting) and to power projects (Wind and PV smoothing) thanks to their unique capabilities. Quantifying “how well” this service is delivered is thus an important task. To address this question, two notions are widely used but often confused: the reliability and the availability.

**The reliability** quantifies how long an element can perform its function without experiencing any failure. The reliability is often expressed with the Mean Time To Failure (MTTF) defined as the ratio between the
duration during which the system is operable ($\tau_{\text{operative}}$) and the number of failure that occurred during the total period under study. Note that for non-repairable devices, the MTTF corresponds to its average lifetime

\[
MTTF [s] = \frac{\tau_{\text{operative}} [s]}{n_f \text{ailures} [-]}
\]  

(15)

A complementary metric is the Mean Time To Repair (MTTR) defined as the ratio between time during which the system is not operable after a failure ($\tau_{\text{not operative, failure}}$) and the number of failures that occurred during the total period under study. Not that the MTTR contains all the steps necessary to bring the system back in operation. This includes diagnosis, the corrective maintenance and the return to normal operation.

\[
MTTR [s] = \frac{\tau_{\text{not operative, failure}} [s]}{n_f \text{ailures} [-]}
\]  

(16)

Together, they form the Mean Time Between Failure (MTBF) defined as:

\[
MTBF [s] = MTTF [s] + MTTR [s] = \frac{\tau_{\text{total}} [s]}{n_f \text{ailures} [-]}
\]  

(17)

The notion of reliability is disconnected from the notion of preventive maintenance. MTTF, MTTR and MTBF are values corresponding to an operation strategy only based on corrective maintenance.

The availability on the other hand is defined as the ratio between the time during which the system is operable or uptime, and the total duration of the period under study. No specific distinction is made on the reason why the system is not operable. It thus encompasses corrective maintenance due to failure but also preventive maintenance such as cleaning, lubrication or replacement of elements. One can introduce the Mean Time Between Downing Events (MTBDE) and the Mean Down Time (MTD) to encompass both failures and preventive maintenance in a category of “downing events” [102].

\[
A [%] = \frac{\text{uptime} [s]}{\text{uptime} [s] + \text{downtime} [s]} \times 100 = \frac{MTBDE [s]}{MTBDE [s] + MDT [s]}
\]  

(18)

Of course, the availability only makes sense when the system is expected to deliver a service. It does not necessary mean that the system is delivering the service but rather that the system is capable of delivering it if needed. Since large-scale stationary BESS usually provide a continuous service, the total time (uptime plus downtime) in the previous definition is simply the calendar time.

Availability and reliability are hence closely related notions. While the reliability is focused on the notion of failure, the availability is a more comprehensive indicator that also accounts for the maintenance strategy. For systems operated with corrective maintenance only, the downing events are only the failures and the availability and reliability are link through the following relation:

\[
A = \frac{MTBDE}{MTBDE + MDT} = \frac{MTTF}{MTTF + MTTR} = \frac{MTTF}{MTBF}
\]  

(19)

In the specific conditions mentioned in Equation (19) one can notice that the availability is directly influenced by the repairability of the system. As long as the MTTR is negligible in comparison to the MTTF, the availability remains close to 100%.

Note that these availability and reliability indicators can be used for both the monitoring of actual system (operational availability) and simulation purposes (predicted availability). In the first case, the above definitions can be directly applied based on the system's status history. To obtain representative indicators,
the study period should be as large as possible. When reliability and availability are simulated, these notions are ruled by probabilistic laws as described in [103].

All these indicators are related to time. They consist in quantifying how one element operates with time considering failures and maintenance. Due to their hierarchical nature, the notion of availability can be applied to the multiple levels of a BESS. For example, a container can be under maintenance while the others are still operating. As a consequence, the previous definitions based on a binary state (up or down) is not well adapted to BESSs because at one given time, some elements can be operating while others are not.

It thus seems relevant to introduce an additional definition to quantify the availability along a hierarchical structure. One can propose a new notion, called Live Level Availability (LLA) defining the share of the operable elements at a given level of hierarchy (container, pack, module etc.) and at a given time:

\[
LLA(t)[\%] = \frac{n_{el, operable}(t) [-]}{n_{el, total}(t) [-]} \times 100
\]

(20)

where \(n_{el, operable}\) is the number of elements operable at a given level of hierarchy at a given instant and \(n_{el, total}\) is the total number of these elements. This LLA thus offers an overview of the state of the system at any given time. It offers a “vertical” analysis of the availability to complement the traditional “temporal” calculation. This notion is particularly interesting for large systems with highly parallel configurations. In that case, the failure of a component does not impact its parallel neighbors. Similarly, this value can be a relevant operational indicator for decentralized battery systems operated as one (virtual power plants) as it quantifies their live overall serviceability.

From this instantaneous availability, one can build a variant of the standard definition of the availability. The Average Level Availability (ALA) is simply the average of the LLA over the period of study (\(\tau_{period}\)):

\[
ALA[\%] = \frac{1}{\tau_{period}} \int_{\tau_{period}} LLA(t) \, dt
\]

(21)

The LLA and the ALA will be further illustrated and discussed in the results section.

2.6.3 Ageing indicators

As discussed in 2.4.2, ageing is a fundamental notion for BESSs. The progressive deterioration of the system influences both the technical and the financial performances of a project. For this reason, continuously monitoring the health of the system is crucial. To achieve this objective, two main notions can be followed: the number of cycles performed by the system and its State-Of-Health.

2.6.3.1 Number of cycles

The ageing mechanism can be described as the contribution of calendar ageing and cycling ageing. As its name suggests, the cycling term accounts for the effect of repeated solicitations. The main factor inducing solicitation fatigue is the cumulated charge exchanged. Indeed, every time the reversible exchange of Li\(^+\) ions is performed, elementary damages are caused to the cell. These damages build up and the macroscopic result is a progressive decrease of the available capacity and an increased internal resistance.

One way to quantify this cumulative exchange of charge is to talk about the number of equivalent full cycles. A straightforward way to compute this number of cycles is to divide the total discharged capacity (\(Q_{dis, total}\)) over a given period by the nominal capacity (\(Q_{dis, nominal}\)).

\[
N_{cycles} = \frac{Q_{dis, total}}{Q_{dis, nominal}} = \frac{\int I_{dis}(t) \, dt}{Q_{dis, nominal}}
\]

(22)
One may wonder why it is necessary to specifically use the discharge phases. The reason for that are the coulombic losses inducing a slight imbalance between the electrical charges being absorbed and the ones being released. This notion of coulombic efficiency has been detailed in the corresponding section 2.6.2.1. In addition, the manufacturers provide the nominal capacity of a cell defined in discharge (at a given temperature and C-rate). For these reasons, this convention is adopted.

### 2.6.3.2 State Of Health

Quantifying the number of cycles performed by the system is precious as it gives an insight on one of the main causes of ageing. However, what really matters to the system owner is more the consequences than the individual causes. The consequences of this deterioration process are mainly a loss of capacity and an increase of the internal resistance.

To quantify these degradations, the State Of Health (SOH) is introduced. It aims at portraying the current condition of the system. However, the ageing causes both the energy and the power capabilities of the cell to fade. As a consequence, two definitions of the SOH can be found in the literature.

The first one is related to power. As the systems ages, the internal resistance of the cell increases. The consequence is that for a same current, the voltage drop caused by the internal resistance is greater for a degraded system and by the product $P=U\times I$, the power ends up being reduced. To quantify this decline of the power capabilities, a first definition of the SOH is based on the evolution of the internal resistance.

$$SOH_R[\%] = \frac{R_{EOL}[\Omega] - R_{current}[\Omega]}{R_{EOL}[\Omega] - R_{BOL}[\Omega]} \times 100 \quad (23)$$

It this equation, $R_{BOL}$ is the internal resistance at the beginning of life (BOL), $R_{EOL}$ is the internal resistance at the end of life (EOL) and $R_{current}$ is this same internal resistance at the moment the estimation is performed.

This definition can be useful for power-oriented applications. Indeed, if only the peak power performance is at stake, the minimum power requirement can be converted into a maximum internal resistance ($R_{EOL}$) and this definition can be meaningful.

However, for battery applications, the main performance indicator remains the available energy more than the power. For EVs for example, the energy decides the maximum range of the vehicle. When it comes to stationary applications, the energy limits the duration of the service provided. More specifically, when one talk about batteries, one should focus on the capacity rather than on the energy. Indeed, while the energy is a convenient notion at system level, the capacity is what truly describes the physics of the cells with the reversible exchange of electrons and ions. The commonly accepted definition of the SOH compares the maximum capacity available at the instant of estimation ($Q_{max}$) to the nominal capacity of the cell ($Q_{nominal}$).

$$SOH_Q[\%] = \frac{Q_{max}[Ah]}{Q_{nominal}[Ah]} \times 100 = \frac{Q_{nominal}[Ah] - Q_{loss}[Ah]}{Q_{nominal}[Ah]} \times 100 \quad (24)$$

Once again, it should be reminded that these values of capacities refer to discharge capacities, just like it was the case for the number of cycles. Compared to the previous definition based on the increase of the internal resistance, quantifying the health of the system on the decline of its capacity does not require to compute a lower bound. It is naturally 0% when the cell cannot store charges anymore.

**From now on, the State Of Health refers to its definition in terms of capacity $SOH_Q$. $SOH_Q$ is hence simply written SOH.**

Now that the definition of the SOH is explicit, one can link it to the State Of Charge (SOC). In the definition proposed page 28, the SOC includes the capacity lost due to ageing to take into account the decline of the maximum capacity. With the newly introduced notion of SOH, the SOC can hence be written again as:
\[ \text{SOC} \% = \frac{Q \ [Ah]}{Q_{\text{max}} \ [Ah]} = \frac{Q \ [Ah]}{Q_{\text{nominal}} \ [Ah] - Q_{\text{lost}} \ [Ah]} = \frac{Q \ [Ah]}{Q_{\text{nominal}} \ [Ah] \times \text{SOH} \%} \] (25)

This new formula for the SOC is the most convenient one as it breaks the problem of estimating the SOC into two sub-tasks: assessing the SOH (or equivalently \(Q_{\text{lost}}\) or \(Q_{\text{max}}\)) and evaluating the current charge level \(Q\). From this equation it is now clear that an accurate SOC indicator requires a precise SOH estimate.

However, it should be stressed out that the SOC and SOH have two very different time characteristics. The SOC is a live variable, illustrating the current quantity of charges contained in the battery. It evolves with the solicitation it experiences and the characteristic time typically ranges from the seconds to the hours. The SOH on the other hand is a long-term indicator illustrating the decay of the ability of the system to store electrical charges. The rate of this degradation is influenced by calendar and cycling factors and typically varies within months or years.

The link between the two variables can be illustrated with the Figure 22.

The case A illustrates a new and fully charged battery. Both SOC and SOH indicators are at 100 %. A couple of hours after (Case B), half of the capacity has been consumed. The SOC equals 50 % but the SOH remains at 100 % since the degradation experienced is negligible. Case C takes place a couple of months later. Time and service have eroded the maximum capacity that is down to 80 % of the nominal capacity. The SOH is thus 80 %. Even if the SOC indicates 50 %, the amount of charge available is actually 20 % lower than in case B due to the decreased maximum capacity. This simple example illustrates from an engineering perspective a classic consumer problem: a smartphone with an old smartphone battery “lasts less” than it did at the beginning of its life.

Computing the SOH is thus important for the calculation of the SOC. But the purposes of the SOH do not stop here. As macroscopic indicator of the ageing of the system it quantifies the progressive decline in performance and the changes in operation it imposes. The SOH also reflects the expected lifetime of a BESS and thus its profitability. Finally, this variable is also a safety indicator. Indeed, a very deteriorated system is more prone to thermal runaway and other dangerous behaviors as discussed in 2.4.2.2. For all these reasons, estimating the SOH has been the focus of multiple researches both in the industry and in the academic field.

The methods can be classified into five main categories. The first one gathers the complete and partial applications of the Coulomb Counting principle. Secondly, multiple analyses aiming at linking the voltage curves to the SOH will be presented. Then, the families of the adaptive algorithms and AI based methods similar to the ones discussed in the section related to the SOC will be reminded. Finally, the notion of ageing model will be introduced.

**Coulomb Counting Based:** The SOH quantifies the reduction of the available capacity. And when it comes to estimating the capacity and just like it was the case for the SOC, the standard way is to count the charges exchanged by the system. The Coulomb Counting technique can be applied in two different ways.

First, the SOH can be estimated during a “capacity test”. As its name suggests it is the reference checkup protocol to quantify the remaining capacity. The system is diverted from its normal operation to undergo a first residual discharge until it is completely empty, followed by a complete charge and a complete discharge.
These steps are carried out within the framework of a strict protocol in terms of profile (Constant Power and/or Constant Current and/or Constant Voltage phases), timing (rest periods), rate (C-rate, CP-rate), voltage range and temperature. The capacity $Q_{\text{max}}$ is obtained by computing the total charges released during the complete discharge phase.

This direct approach is the reference in the industry as it strictly applies the definition of the SOH. In that case, the available capacity is not estimated but measured in a controlled experiment. However, this strict protocol imposes to stop the normal operation of the system for a couple of hours and this comes with a cost since during this period the system is not remunerated.

In order to estimate the SOH while keeping the system in normal operation, the Coulomb Counting technique can also be applied to partial discharge phases. The core assumption required for this technique is that as the cell ages, the decline of its capacity induces a homogeneous “shrinkage” of its voltage curve.

Figure 23: Voltage Capacity curve for a 1.10Ah LCO cell at different ages. Image from [104]

Figure 23 illustrates this idea with the charge and discharge voltage curves of a 1.10Ah cell at different SOH. One can notice that after 800 cycles, the capacity is decreased to about 0.70Ah and the slope of the curve seems to follow the deterioration. For this reason, one can reasonably consider that the total capacity can be extrapolated from a portion of this voltage curve.

To do so, one needs to define two reference states based on a measurable value. For instance, in Figure 23 one could choose the voltage range $[3.4; 3.8]$ V and perform a CC between these states. The partial charge obtained can be compared to the partial charge obtained at the beginning of the life of the cell and thanks to the assumption of a homogeneous shrinkage of the curve one can estimate the SOH.

$$SOH = \frac{Q_{\text{max}}}{Q_{\text{nominal}}} = \frac{Q_{\text{max}, [3.4, 3.8]V}}{Q_{\text{nominal}, [3.4, 3.8]V}}$$

(26)

This approach suffers from two limitations. The first one is related to the central assumption that the voltage curve is homogeneously compressed as the cell ages. This assumption cannot be exact due to the physical meaning behind the voltage curve. Each slope and plateau of the voltage curve materialize the multiple mechanisms driving the intercalation/de-intercalation and migration processes occurring in the cell.
Assuming a homogeneous compression of the curve implies to consider a regular degradation of these mechanism. However, this is not the case and one can observe an uneven deformation of the voltage curve [105]. The second limitation is the need for a reliable value to define the reference states between which the CC is carried out. One cannot use the SOC as this indicator implies a knowledge of the SOH. One could use the total voltage but since it contains the impact of the internal resistance, it is polluted by the current (voltage drop proportional to the current) and the aging level (increase of the internal resistance). Eventually, the most reliable value to define a reference state remains the Open Circuit Voltage or the total voltage with a very small current that correspond to an approximated OCV.

Even if this approach does not exhibit a high degree of precision, it can bring one significant benefit compared to a capacity test. The technique can be applied without imposing any change of operation. If the system is frequently at rest, local CC can be performed between these phases where the total voltage equals the Open Circuit Voltage. Even more, if the system is continuously under load but an adjusted model (electrochemical, ECM, empirical …) is able to provide a live estimate of the OCV, this technique can be applied anytime.

Analysis of voltage curves: In the Coulomb Counting based techniques, the charge is systematically quantified, and the SOH is computed based on its direct definition. In order to disconnect the estimation of the SOH from the calculation of the remaining capacity, several approaches proposed to study the shape of the voltage measurements over time under specific conditions. The patterns extracted from these temporal voltage curves can be associated to the SOH via a preliminary phase of establishment of correlations.

In [106], Guo et al. proposed a methodology to estimate the remaining capacity based on the analysis of the temporal evolution of voltage during the Constant Current (CC) charge phase. Analyzing the voltage under specific load profiles has also been a focus in the industry with several patents. For instance, Renault proposed in 2015 a method relying on two voltage measurements during the charge phase and on an empirical formula linking the voltage difference to the SOH [107]. In a similar fashion, the Commissariat à l'énergie atomique et aux énergies alternatives patented a technique based on the measurement of the relaxation time [108].

It is no surprise that analyzing the voltage curve under specific profiles is an appealing option for industrials. Undeniably, these approaches are very light to implement and do not require an in-depth knowledge of the ageing phenomena. Indeed, macroscopic variables such as the voltage can be directly connected to the SOH through empirical formulas.

Adaptive Algorithms: This type of self-adjusting models has already been introduced in the section about the State-Of-Charge. The adaptive algorithms can also be applied for the estimation of the State-Of-Health. To do so, a parameter should be introduced in the model to account for the decline of the capacity. This parameter would then be updated like the other variables but with a much higher time constant.

IA and statistics-based approaches: Data-driven techniques have the advantage of being able to “learn” from any kind of phenomenon. These approaches can thus also be applied to the estimation of the SOH as long as the learning data includes that specific matter.

Ageing Models: These models are based on empirical rules linking the main causes of ageing (number of cycles, temperature, SOC, C-rate) to their consequences (capacity fadeout, increase of the resistance). The approach often privileged relies on the notion of cumulative damage i.e. that the system ages with the accumulation of elementary degradations [70] [109]. Unlike the aforementioned methods that construct their SOH estimate on the analysis of the measured response of the system (charge, voltage, temperature …), ageing models only need the solicitation of the system to quantify its SOH over time. In other words, ageing models can operate independently of the battery they represent. As a consequence, they can also be used in simulation tools to estimate the ageing of a system under various loads. However, this versatility has a cost. The establishment of the empirical rules governing an ageing model requires an extensive campaign.
of laboratory tests and data treatment. In addition, the empirical rules are cell specific so the process should be repeated for each cell type.

**Other techniques related to the study of ageing:** Estimating the remaining capacity of a battery is not the only engineering task related to the ageing of Li-Ion cells. Understanding the electrochemical processes responsible for the degradation of the battery is another challenge. The techniques permitting to investigate these mechanisms are out of the scope of this thesis work since they cannot be directly applied to online large-scale systems but the knowledge they provide can directly be applied to the construction of various models. Briefly, one can mention the electrochemical characterization techniques such as the Electrochemical Impedance Spectroscopy, the analysis of voltage curve patterns via Incremental Capacity Analysis or Differential Voltage Analysis and the postmortem analyses of aged cell.

### 2.6.4 Safety indicators: thermal management

During the normal operation of a BESS, heat is generated. This production corresponds to the energy lost in the ohmic resistances composing the overall electrical architecture and the cells. If the power electronics, the cabling and the auxiliaries generate heat, the major contributor remains the battery cells especially at high currents [110] [111] [112]. The heat generated within a cell is responsible for the increase of its temperature. High temperatures are responsible for an intensification of the ageing and can lead to serious safety risks if it is not properly controlled (thermal runaway). The removal of the heat generated is thus a crucial task. This duty is locally performed by integrated cooling features such as cooling fans in the racks and in the modules as well as by the HVAC system at container level. The overall process of thermal regulation is controlled by the Thermal Management System (TMS).

Since temperature is such a key factor for ageing and safety, this section proposes some analyses to assess its regulation in large scale BESSs. This can be done in two ways. The first approach is to look at the temporal distribution of the temperature to try and identify abnormal behaviors. The other perspective is to analyze the physical distribution of the temperature in order to assess the effectiveness of the cooling process.

#### 2.6.4.1 Temporal analysis

A temporal analysis is necessary to detect abnormal temperature deviations. In a posteriori analyses, such check does not require complex calculations and simple implementations are sufficient. The temperature history can be inspected through direct plotting or this process can be automatized by filtering the temperatures measured out of their expected range. The same idea can be applied to the rate of change of the temperature. These thresholds can also be implemented for the live operation of the electrochemical storage system. For instance, if the temperature or its gradient exceed some thresholds defined by the designer, the dangerous element can be disconnected by the BMS to prevent any risk of thermal failure.

On the long run, the analysis of the temporal distribution of the temperature can also be a source of information for the battery operator. For instance, one could study the total duration during which a specific module is operating above a certain threshold to link this value to the rate of degradation. Finally, the thermal balancing of the system can be assessed through the estimation of the temperature difference between its elements.

#### 2.6.4.2 Physical distribution

The question of the physical distribution of the temperature within a container is primarily addressed during the design phase. System integrators often use of 3-dimensions models of their containers to design the ideal flow of air through CFD simulation [111]. But the notion of physical distribution of the temperature can also be studied via the analysis of temperatures measurements collected in the field. In this work, the vertical temperature gradient inside a container will be highlighted through the temperature of the modules constituting a vertical rack.
3 Methodology

This section discusses the methodology that guided this thesis work. From a preliminary diagnosis based on the objectives and available data, a set of Key Performance Indicators with their respective estimation techniques were chosen for their relevance and compatibility with the study. Then, the working environment has been chosen to meet the need for flexibility and the amount of data to process. Finally, the way the results should be illustrated has been carefully thought in order to ensure an easy interpretation and discussion.

3.1 Expectations and available data

As discussed in 2.5, a BESS project is the result of the cooperation between multiple entities ranging from the manufacturer to the end customer. Among them, the system owner and operator (same entity in this simplified scenario) is responsible for a smooth and safe operation of its system, and for maintaining a level of performance guaranteeing the profitability of the overall project.

To achieve these objectives, the system owner does not even have full control over its system. Indeed, most of the time, it signed with a sub-contractor (solution integrator or manufacturer) to obtain a turnkey solution. In this configuration, the owner may not have the control over the sub-layers of the BESS. Typically, within the architecture of a BESS, some levels are controlled by the owner (for instance the EMS) but the commands are then interpreted and transferred to sub-levels of the BESS for which the owner only specified the characteristics but has no direct control over. For example, the system owner can decide of the overall strategy via the EMS (to charge or to discharge as a function of external indicators) but the way this command is distributed is managed at container, rack and module level by the multiple layers of the Battery Management System developed by the manufacturer.

To monitor the operation, the system owner usually has two sources of information at its disposal. First, the sub-layers of the system continuously report operational indicators to superior levels in order to communicate with the EMS. These signals typically include the SOC and the SOH that are estimated by the BMS. They will be referred to as “provided” indicators in the rest of the work. The other source of information is the measurement history of the multiple sensors distributed over the system. It usually contains the time series of physical measurements (current, voltage, power, temperature) and non-physical values (status, flags) for multiple elements composing the BESS.

The exploitation of this raw measurement data can be a valuable source of information for the system owner. First, it permits to verify the live indicators reported by the sub-layers (mentioned above as the first source of information). Indeed, if the BMS is found to report wrong estimates, the overall operation of the system would be deteriorated, and safety issues might arise. Second, the study of the raw time series enables the creation of additional KPIs, not proposed by the system manufacturer. To summarize, the raw data can help the battery owner assess the reliability of the information provided by its sub-contractors and make its own opinion on the operation of the system.

The key question addressed by this work is thus: How to choose, implement and evaluate relevant Key Performance Indicators to give the owner an overall assessment of its system?

In order to answer this question, a database of raw measurements gathering data from several projects with different chemistries, configurations and applications was exploited. More precisely, the data available only covered the sensors integrated in their electrochemical storage part, not their auxiliaries. As a consequence, the development of the KPIs is centered on the electrochemical part of the BESS which correspond to its core component.

3.2 Choice of the KPIs

After a preliminary phase where the expectations have been identified and the raw data presented, the next task is to choose the most relevant KPIs.
3.2.1 Literature review
The preliminary stage concluded on the need to establish synthetic indicators that could cover the multiple aspects of a BESS in operation. To answer this question, a first phase of comprehensive literature review permitted to gain an in-depth knowledge about Li-Ion Battery Energy Storage Systems. A summary of this learning phase has already been proposed in section 2.4 (Lithium-ion battery systems: a closer look).

3.2.2 Overall categories
In a second phase of literature review, the specific question of the Key Performance Indicators was addressed. In order to provide a comprehensive analysis of the electrochemical storage system, every perspective should be encompassed. For this reason, four axes of study have been selected: operation, performance, ageing and safety.

- **Operation**: BESS are complex systems, for this reason a smooth operation is by itself a marker of performance. This notion thus represents a first category. In addition, the execution of the command used by the EMS is the responsibility of the sublayers of the BESS. As mentioned above, the owner has no control over this execution, and it is valuable to investigate how well this task is performed.
  
  In this category, the State-Of-Charge provided by the manufacturer will be verified. Indeed, the SOC is a fundamental variable for the live operation of the system. The balancing of the elements in terms of voltage is another indicator of the effectiveness of the Battery Management System and will be investigated. Eventually, a discussion about the link between these two indicators will be proposed.

- **Performance**: The performance of a BESS is often seen as the priority for the system owner. Indeed, a service properly provided is a prerequisite for the profitability of a project. In this study, performance will be studied under technical and maintenance perspectives. The technical performance can be estimated through the assessment of the efficiency of the electrochemical storage. In fact, storage systems are reversible machines which operation is conditioned by their ability to return the energy they stored. But the performance of a BESS can also be limited by its availability. This variable assessing the reliability of the components and the performance of the maintenance strategy will also be explored thanks to a newly introduced notion of vertical availability.

- **Ageing**: Ageing is an inevitable process inducing a progressive decline of the performance of the BESS. This behavior, unique to electrochemical storage systems, requires a close monitoring as it influences all the other aspects of the lifetime of a BESS.
  
  As discussed in 2.4.2, the cumulative charge exchanged by the system is what drives the cycling part of the overall ageing phenomenon. Quantifying the number of cycles hence assesses one of the several causes of the progressive degradation of the electrochemical performance. One can also evaluate a consequence of the ageing mechanism. In this work, the gradual decline of the capacity is quantified with the State-Of-Health.

- **Safety**: Finally, an overview of the condition of a BESS could not be complete without the notion of safety. The section “Thermal management” stressed the need for an efficient evacuation of the heat dissipated by the batteries during their operation to reduce the rate at which the cells age but also to prevent any dangerous thermal failure that could lead to gas vent or fire.
  
  In this work, the effectiveness of the thermal management is investigated with the analysis of the temperature from temporal and spatial perspectives.
All these KPIs have been defined in the section 2.6 Key performance indicators. While some of them have definitions enabling a direct implementation, some require a more complex evaluation procedure. This is the case of the SOC and the SOH for which the literature review also covers the different techniques permitting their evaluation.

3.2.3 The case of SOC and SOH

The SOC and SOH are fundamental indicators attracting a lot of attention in both the academic and the industrial world. However, their implementation is complex and multiple techniques can be found in the literature.

In this thesis work, the objective is not to establish a comparative study of the SOC and SOH estimation techniques but rather to propose a more general analysis of the operation, performance, health and safety of BESSs and how all these aspects interact. SOC and SOH are thus only two KPIs among others. As a conclusion, not all the existing approaches can be evaluated, and a phase of selection is necessary. This selection was performed on the following criteria:

- **Accuracy**: A satisfactory precision for the indicator is of course a prerequisite.
- **Ease of implementation and modification**: The selected approach should permit a rapid implementation and modification. Indeed, monitoring activities are rarely case specific, and the analyst needs to rapidly deploy the same technique on multiple systems with a minimum effort to adjust the technique, in order to save time and money. In addition, as this thesis work aims at covering multiple aspects of BESSs, the time to implement one KPI should not be prevent the implementation of the others.
- **Computational load**: Unlike live applications where the SOC and SOH are only updated at every time step, ex-post analyses require the simultaneous computation of a long period of time. The complexity of the technique should permit this type of calculation.
- **Physical meaning, knowledge gain**: If the implementation of the technique can help the analyst to gain a better understanding of the physics of the BESS, it would be a plus.
- **Link with laboratory data**: For some methods featuring physical values (efficiencies, internal resistance), these parameters can be confronted to laboratory data.

From the knowledge gained in the literature review phase and based on the criteria presented here, the following qualitative comparison can be proposed for the SOC estimation techniques.
Table 3: Qualitative comparison of the SOC estimation techniques

From this comparative analysis, the Corrected Coulomb Counting technique was selected for several reasons. First, it features an excellent tradeoff between complexity and accuracy. This guarantees a fast implementation and computation. Then, it can help the user to better understand the system through the link with the notion of coulombic efficiency. Finally, it gives the opportunity to evaluate the impact of the main weakness of the Coulomb Counting technique, namely the SOC drift.

A similar comparison can be proposed for the SOH estimation techniques.

Table 4: Qualitative comparison of the SOH estimation techniques

When it comes to the SOH, a clear choice had to be made between ease of implementation and accuracy. Indeed, while the partial coulomb counting can be universally applied, its accuracy is reduced compared to its competitors. On the other hand, the other techniques are poorly adapted to a thesis work where the...
objective is to propose a broad set of indicators rather than a tailored solution to the estimation of the SOH. For instance, building an ageing model or empirical voltage curve correlations require to use experimental facilities which is not possible in this work. Numerical only methods such as the adaptive model have proven to deserve a full thesis work to be properly explored, implemented and validated [113]. For this reason, the partial coulomb counting approach was selected for implementation and discussion.

3.3 Choice of the working environment

Once the theoretical description of the KPIs is performed, they can be implemented. To do this, a working environment needs to be chosen. For scientific programming, Matlab and Python are often seen as the two main options. They are both very versatile programming languages and can perform all the stages required for this work: import, process and export the data.

For this study, Python was chosen. This programming language has several strengths including:

- It is a free and open source language
- Its popularity resulted in a large amount of online resources
- Finally, Python includes several specialized libraries which were extensively used in this work.

The first library is Pandas. It proposes a user-friendly framework for the analysis of large datasets with Python. Pandas can work with tabular data (SQL table, Excel spreadsheet), ordered and unordered time series and any other form of labelled data. The working elements of the Pandas library are called Series (1D) and Dataframes (2D) and permit a wide variety of operation from the simple sum to more complex user-defined functions [114].

The other fundamental library used in this work is Matplotlib. It is a plotting library converting structured data into a variety of figures like line plots, scatter plots, histograms, bar charts and many more. Its direct compatibility with Pandas and its user-friendliness makes Matplotlib a powerful tool to illustrate results [115].

Among the other libraries used in this work, one can mention NumPy, specialized on the processing of multidimensional arrays [116] and SciPy, dedicated to numerical calculations, linear algebra and statistics [117].

3.4 Implementation of the KPIs

The implementation of the KPIs corresponds to the execution phase of the thesis project. This phase requires a minimum background about the mathematical and statistical notions related to the analysis of time series. The concepts of numerical integration and statistical distributions are reminded. Finally, the overall implementation strategies for each type of the indicator is discussed.

3.4.1 Mathematical background for time series analysis

The notion of numerical integration is basic but yet fundamental for the analysis of time series. These techniques are required to evaluate the integral for sampled functions or functions that cannot be analytically integrated. Two approaches have been applied in this work, the bar method and the trapezoidal method.

The rectangle or bar method approximates the integral of a function over an interval by multiplying the length of the interval by the value of the function on one point of the interval. For example, the backwards rectangle method is expressed as:

$$\int_0^1 f(x) \, dx \approx h \sum_{j=1}^N f(x_j) + O(h)$$

where the interval $[0;1]$ is divided into N intervals of width $h$ and delimited by the $[x_0; \ldots; x_N]$. This method is first-order accurate which means that the error is proportional to the width of the grid.
The trapezoidal method is based on the linear interpolation of the function on each interval. The trapezoidal rule is second-order accurate.

$$\int_0^1 f(x) \, dx \approx h \sum_{j=1}^{N} \frac{f(x_{j-1}) + f(x_j)}{2} + O(h^2)$$  \hspace{1cm} (28)

Reminding the formulas of these numerical methods permits to bring an interesting topic on the table. In the case of time series analysis, the size of the grid $h$ is the time step between each measurement $\Delta t$. Unlike in numerical simulation where the user can modify this variable to meet its needs, in the case of time series analysis this value is fixed by the frequency of the measurement and cannot be modified. The accuracy of the integral thus only depends on the shape of the function $f$. More specifically, the time step $\Delta t$ should be at least equal to the characteristic time of fluctuation of the function $f$ or lower. This is a minimum requirement for a proper calculation of the integral.

This idea is illustrated in Figure 25. In this example, the current is sampled every 5 seconds whereas its values can vary within a second. In this configuration, the fast variations occurring between 10s and 15s would not be captured.

![Figure 25: Influence of the characteristic time on the accuracy of a numerical integral](image)

In this study, the time series have a time step of 1 second which is equivalent to the fluctuation capabilities of a BESS. This time step ensures a reliable integration of variables like current and voltage. For the temperature, the time step could be raised to the minute since the temperature varies more slowly than its electrical counterparts during normal operation.

The concepts related to the notion of statistical distribution are also very convenient in the analysis of time series [118]. Among them, one can remind the construction of the standard deviation $s$ for a dataset made of $N$ points and of mean $\bar{x}$:

$$s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N - 1}}$$  \hspace{1cm} (29)

One can also introduce the z-score that quantifies “how far” a point is from the mean of its dataset by normalizing with the standard deviation:

$$z_i = \frac{x_i - \bar{x}}{s}$$  \hspace{1cm} (30)
3.4.2 Type of analyses and visualization

The Key Performance Indicators proposed in this study cover the multiple perspectives of the operation of an electrochemical storage. This diversity is also materialized in the type of calculation they require. In order to classify the KPIs, the following categories can be proposed:

- **Direct vs. Processed**: Some KPIs are the result of a direct analysis of the time series. They do not need a complex calculation. This is typically the case of thermal indicators, directly derived from raw data. On the other hand, “processed” KPIs are the result of multiple-steps calculations.

- **Continuous vs. intermittent/statistical**: Another axis of differentiation can be drawn on the notion of time. While some KPIs are time-dependent, others are considered as independent from the notion of time and are only estimated in a punctual way. The classification as time-independent only means that their characteristic evolution time is much greater than the temporal window needed for their assessment. For example, the SOH of an element decreases as the system ages. However, this deterioration typically spans over several years, so the SOH can be considered as constant over a window of a couple of days.

These categories can serve as introductory discussion to decide the strategy of implementation.

<table>
<thead>
<tr>
<th></th>
<th>Continuous (time-dependent)</th>
<th>Interim / Statistical (time-independent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct</td>
<td>Temporal distribution of Temperature</td>
<td>Physical distribution of Temperature</td>
</tr>
<tr>
<td>Processed</td>
<td>SOC, availability, cumulative number of cycles</td>
<td>SOH, efficiency, balancing</td>
</tr>
</tbody>
</table>

*Table 5: Classification of the KPIs in 4 categories*

The display of time dependent KPIs is intuitive. Continuous KPIs require to be represented with the time as x-axis. If one wants to verify the sensitivity to some calculation parameters, one need to compare the **temporal results** (difference of values, temporal average …).

On the other hand, intermittently estimated KPIs are guided by the notion of **statistical distributions** rather than by the concept of temporal evolution. This difference is particularly important for processed KPIs. For example, one can illustrate this discussion with the efficiency. To get a single estimate of this value, one window allowing one calculation is enough. However, the estimate would be affected by an error. One could assume that this error approximately follows a normal distribution centered on zero with a standard deviation representing the precision of the calculation process. In this situation, the law of large number states that as the number of experiment increases, the mean of the experimental values converges towards the actual mean. In other words, if the estimation technique is accurate (error centered on zero) but subject to noise then the mean of a large number of estimates should be very close to the actual value.

This approach is what governs the implementation strategy for processed and statistical KPIs. Based on the available data, the calculation should be performed as many times as possible to benefit from the convergence provided by the law of large numbers.
4 Results and discussions

This section corresponds to the implementation phase of the thesis work. From the literature review and the methodology section, the definition of the KPIs and the general execution strategy were set. The following paragraphs propose a discussion about the sensitivity of the selected estimation techniques. A strong emphasis is also put on the interpretation of these KPIs and on how they interact to provide a global assessment of a BESS.

The data used to test the KPIs originates from several projects with different chemistries and applications. In addition, the objective of this work is to discuss the methodology rather than the exact values of the KPIs. For these reasons, in the case of the availability and of the number of cycles for which the data was not sufficient to lead a productive discussion, an illustrative simulation was preferred. In other KPIs based on actual data, the sensitive values are normalized while still permitting a relevant analysis.

4.1 Operational indicators

4.1.1 SOC

The State Of Charge is a fundamental operational indicator quantifying the “amount” of charge available within an element. The notion of SOC can be applied to virtually every level of an electrical storage, from the elementary cell to the containers. In practice, this indicator is not computed for every cell as the small gain in accuracy (compared to average assembly level estimates) would be largely outweighed by the increased computational burden and the costs of additional sensors that might be required. In addition, it should be kept in mind that the SOC is first and foremost a control variable. For this reason, it is sufficient to compute the SOC at the level where the distribution of the load is performed, not in the sublevels. Finally, in a serial assembly, all elements experience the same current. Therefore, in theory, the SOC is expected to evolve in a similar way everywhere in the chain (except for the imperfect balancing discussed later).

In this work, the SOC is estimated based on two approaches: the direct Coulomb Counting and the corrected Coulomb Counting. It will be compared to the SOC provided by the manufacturer’s BMS to fuel the discussions. The formula for the Corrected Coulomb Counting (CCC) is reminded below (Equation 31). The equation for the direct Coulomb Counting (CC) is identical except for the absence of the corrective coefficient $\eta_c$.

$$SOC (t) = SOC_{t=0} + \frac{1}{Q_{max}} \int_0^t I(\tau) \eta_c(I) d\tau$$

In this cumulative calculation, three important terms can be identified: the adjusted capacity $Q_{max} = SOH \times Q_{nominal}$, the coulombic efficiency $\eta_c$ and the initial value $SOC_{t=0}$. The SOH and the coulombic efficiencies will be discussed in their individual section and are supposed to be known for this calculation.

When it comes to the initial value of the SOC, it can be set in different ways. The most robust one is to identify a state of full discharge (resp. full charge) to set its value to 0% (resp. 100%). If such reference charge levels are not reached, a period of rest gives access to the Open Circuit Voltage that can be linked to the SOC via a characteristic curve. If the system is never at rest, then live estimates of the SOC using equivalent models are required.

The objective of this section is to study the accumulation of error with time, responsible for the SOC drift. For this reason, the SOC is initiated at the same value as the provided SOC to ensure an easy comparison. In the general case, it should simply be kept in mind that a different initial SOC leads to an offset in the value that remains until a reset of the cumulative calculation is performed.

Figure 26 illustrate the result obtained for the SOC estimate at rack level over a period of 5 hours. This result was obtained with an integration based on the bar approximation and with a time step of one second.
The influence of the integration method and of the time step will be addressed in the sensitivity analysis. Figure 26 also includes the normalized current, defined as positive during the discharge.

From a general perspective, the two estimates follow the provided SOC very closely. Over this 5 hours window, the absolute deviation from the provided value rarely exceed ± 1%. It should be stressed that it is not possible to determine which of the provided SOC or the proposed estimate is the most accurate. Indeed, both are estimates and the only way to get an exact measurement of the SOC would be to stop the system and perform a residual discharge. This would give an exact but only temporary value of the SOC. The comparison between the provided SOC and the proposed calculation can only be made in terms of difference between the techniques, not in terms of absolute error.

This narrow window of operation is not sufficient to clearly notice the SOC drift discussed in introduction, but it permits an analysis of the SOC provided by the manufacturer’s BMS. Indeed, the study of the fluctuations of the difference shows a very close correlation with the variations of the current. For example, at hours 2 and 4, the rapid rise of the current resulted in a corresponding variation of the difference. This means that the provided SOC uses the direct measure of the voltage and current to build an estimate of the SOC at every time step. This dynamic response of the SOC to the rapid transients is typical of the model-based estimation techniques (ECM or adaptive algorithms). Indeed, the transient regimes are hard to capture for model-based approaches and the SOC estimate ends up deviating temporarily. From this analysis, it can be concluded that the manufacturer’s SOC relies on an instantaneous calculation rather than on a cumulative one like the Coulomb Counting. The difference in the type of technique implemented (instantaneous vs. cumulative) explains the noise visible in the plot of the absolute difference.

When it comes to the long-term comparison of the three estimates, one needs to extend the temporal window. Figure 27 displays the evolution of the error over a 5 days period. In order to smoothen out the noise due to the fluctuations of the provided SOC, a 24 hours rolling window is implemented. The rolling average, maximum and minimum are proposed for more clarity.
This graph perfectly illustrates the notion of SOC drift. In the absence of correction, the elementary overestimations are accumulating and the uncorrected Coulomb Counting deviates from the provided SOC value. The elementary errors appear when the deficit of the discharge compared to the charge is not compensated in the uncorrected Coulomb Counting.

The corrected CC on the other hand follows closely the value provided by the BMS. Once again, it does not mean that the CCC is exact because it matches the indicator proposed by the manufacturer but since these two estimates are built in different ways and lead to very similar estimates one can reasonably consider that they validate each other. The difference between the BMS estimate and the CCC remains in the ±2.5% band which is satisfactory.

The results above were obtained for an integration based on the bar approximation and with a time step of 1 second. The influence of these numerical parameters can be investigated. This comparison is proposed in Annex A and concludes that the numerical integration is satisfactory, regardless of the selected approach, as long as the time step is of the order of 1 second.

As a conclusion, the SOC estimated through Corrected Coulomb Counting proves to yield values in agreement with the ones from the BMS, thereby validating both techniques. The analysis of the short-term variations of the estimate indicates that the BMS may compute its estimate on an instantaneous way rather than in a cumulative fashion. On the long run (several days in this study), the need for including the coulombic efficiency is highlighted. This coulombic efficiency is therefore not only useful performance indicator, but it is also a critical tuning parameter of the CCC. Its estimation will be discussed in 4.2.1.

4.1.2 Balancing

Keeping a good balance among all the elements operating together is an operational challenge. For parallel elements, this balancing is spontaneous as the current will flow between the components until they reach the same steady state voltage. However, there is no such natural physical adjustment for serial elements. In a BESS, this task is performed by the BMS that is responsible for making sure that all cells in a module and all modules in a rack are operating homogeneously. A good balance is a guarantee to use the module/rack at its full capabilities because it would not be limited by a marginally weak element. A good balancing is also crucial for safety as it reduces the risk of over- and under-voltages.
The balancing is monitored through the voltage. Indeed, the voltage is the physical “output” of an element, reflecting its charge level. Two cells having distinct charge levels would have different voltages. In this work, the balance in an assembly is quantified with the maximum relative spread. One can for instance calculate the maximum relative spread of voltage between cells constituting a module.

$$s_{module}(t)[\%] = \frac{U_{cell,max}(t) - U_{cell,min}(t)}{U_{cell,mean}(t)} \times 100$$  \hspace{1cm} (32)

Note that the voltages $U_{cell}$ can also represent two or more cells connected in parallel if the configuration is made of groups of parallel cells then mounted in series. Indeed, a module can always be brought back to a configuration with equivalent cells in series (one cell or multiple paralleled cells share the same voltage).

Equation (32) can be executed at every time step. The result of this calculation is proposed in Figure 28. The maximum relative cell voltage spread is displayed as a function of the current and of the State Of Charge. Every dot is the result of the calculation corresponding to one-time step.

It seems that there is no clear link between the current and the spread. On the other hand, a clear correlation is visible between the SOC and the spread with a thick curve appearing in this scatter plot. This result was expected because for a given charge imbalance, the voltage spread depends on the location on the voltage curve.

By comparing the average voltage imbalance to the nominal voltage range one can get an estimate of the maximum disequilibrium in terms of SOC. For example, a module exhibiting on average a 20 mV voltage difference between the extreme cells and for which the nominal voltage range spans over 1,2 V (1,2 V ≈ 100% SOC) has an average imbalance of:

$$\Delta SOC_{imbalance}[\%] = \frac{0,020 [V]}{1,2 [V]} \times 100 [-] = 1,7 \%$$  \hspace{1cm} (33)
This indicative value of the imbalance gives some perspective to the discussion about the SOC. The previous section (4.1.1) discussed the SOC estimated at rack level. In this part, the analysis of the imbalance performed at module level highlights that the disequilibrium between cells in a module can be of the order of 1%. The maximum charge imbalance at the level of the rack is thus at least equal to 1% if not more because the rack is a collection of modules in series.

As a consequence, the analysis of the balancing stresses the need to manipulate high-level estimates of the SOC with caution. Indeed, these average estimates do not give any idea of the extent to which the charge of its sub-elements is homogeneous. For example, an average rack SOC of 50% does not prevent some cells to have superior/inferior charge levels. This can be a problem because even if the average SOC at rack level remains within its nominal range, extreme cells could in reality be operating out of their voltage specifications, inducing accelerated ageing and safety issues. Balancing can thus be seen as a point of connection between operation, performance, ageing and safety. This discussion also illustrates the need to monitor the imbalance, in addition to the SOC, for serial assemblies.

To tackle this problem, the best approach is of course to require active or passive balancing features in the electrochemical storage during the design phase. However, for systems without such balancing capabilities, an adjustment of the operation can be suggested. The proposed calculation protocol can be used to set safety margins. If executed frequently it can provide an estimate of the imbalance in terms of equivalent SOC and this value can then be exploited to maintain the SOC within a range smaller than the traditional [0-100]% range to prevent any risk of under- and over-voltages.

4.2 Performance indicators

4.2.1 Coulombic efficiency

For any storage system, the energy efficiency quantifies the energy lost between the charge and the discharge. In the particular case of BESSs, the overall efficiency of an electrochemical assembly (cell, module, rack, bank …) can be further divided into the voltaic and the coulombic efficiencies. On the one hand, the voltaic efficiency mainly measures the impact of all resistive elements causing the overall ohmic losses. On the other hand, the coulombic efficiency quantifies the losses of electrical charges between the charge and the discharge of the element. The three efficiencies together give an overview of the ability of the system to restitute the energy it previously stored.

In addition to giving an input on the performance of the system, the coulombic efficiency is also a crucial tuning parameter used to compute the SOC through the method of Corrected Coulomb Counting presented in 4.1.1. The coulombic efficiency is the corrective coefficient (or function) that offsets the imbalance between the charges being stored and the ones being released. Because this efficiency is so important, it is the one investigated in this section. The main computation steps and discussions can be adapted to the other two efficiencies.

As an introduction, one can remember the definition of the coulombic efficiency. The definition chosen is in fact an average approach rather than an exact one, because this formula makes the calculation possible on field data as discussed in the presentation of the KPI (section 2.6.2.1).

\[
\eta_{\text{coulombic, average}} \% = \frac{\int_{\text{period}} f(t_{\text{dis}}) \, dt_{\text{dis}}}{\int_{\text{period}} f(t_{\text{cha}}) \, dt_{\text{cha}}} \times 100
\]  

The calculation of one single estimate of \( \eta_c \) requires two steps. First, a period should be identified. A period is here defined as a temporal window delimited by two identical electrochemical states. Intuitively, one can for instance always start and finish from the fully charged or discharged condition. However, for a freely operating BESS there is no guarantee that these convenient states would be reached at some point. It is thus necessary to use other state markers:
- One may think about the SOC since by definition the SOC quantifies the live state of the element under study. This is only possible if this indicator is provided by an external source (e.g. provided by the manufacturer’s BMS). Indeed, the SOC computed through the method of Corrected Coulomb Counting requires this coulombic efficiency as an input.
- An alternative to the SOC is the total voltage (U). This data is directly available from raw measurements.
- Finally, one can use the Open Circuit Voltage (V_{OC}). This value is not directly measured but can be approximated with the knowledge of the internal resistance R, provided in the cell datasheet, and the first order empirical relation U=V_{OC}+RI.

Once two identical states are identified, one can count the cumulative electrical charges exchanged between these two time steps. Total capacity for the charge and for the discharge are computed separately before calculating the ratio. The integration of the current to obtain total capacities exchanged is nothing more but the coulomb counting technique. Its parameters (integration step and method) have already been discussed in the section related to the SOC (see 4.1.1).

In the case of a large dataset, containing multiple possible windows, this calculation can be repeated over each of the identified periods. The final value would eventually be the average of all these individual estimates. As discussed in the Methodology section, this repeated calculation makes the estimation more robust to errors. The overall workflow is proposed in Figure 29.

![Workflow](image)

**Figure 29: Workflow for the estimation of the coulombic efficiency**

There is always an error about the reference state chosen. For instance, if one relies on a SOC with a ± 2% accuracy then the reference state is only known to the nearest 2% or so and the gap between two states that were expected to be identical can reach up to 4% in the worst-case scenario. In order to dampen this error, it is useful to have longer periods of integration. Over longer periods, more charge is included in the calculation, hence, the relative importance of the boundary states decreases.

The graphical layout can take advantage of this strategy by plotting the multiple estimates as a function of the duration of the period or directly as a function of the total charge exchanged (for example during discharge phases). A typical result is proposed in Figure 30 where the provided SOC was used to define the reference states. Since the exact value of the coulombic efficiency is a sensitive information, one can normalize the result by the average estimate to bring it back to 100%. However, since the coulombic efficiency is very high (>98%), this normalization still makes the discussion of the numerical values relevant.
Here, the charge is expressed in % of nominal capacity. 600% corresponds to 6 equivalent full discharges. This figure proves that having the total charge exchanged as x-axis is an appropriate choice. For short periods of time and thus little charge transferred, the error in the identification of the reference state causes a significant spread of the estimates due to its high relative importance. Then, higher amounts of charges make the estimates converge towards their median value. This graph also confirms the importance of having as many estimates as possible. The statistical treatment of this result through the median or the average gives access to a more robust value than a single estimate.

The same workflow can be repeated with the two other reference state indicators: the total voltage U and the estimated Open Circuit Voltage V_{OC} as proposed in Figure 31. For the sake of clarity, only a zoom over the estimates based on large amount of charges exchanged is displayed to study the convergence of these three methods (SOC, U, V_{OC}).
From Figure 31, one can notice that the choice of the reference state as a strong impact on the spread of the estimates obtained. For example, the estimates constructed based on the total voltage span over a much broader range than their counterparts stemming from the Open Circuit Voltage and the provided SOC. However, it seems that the average value they converge towards is very close. These assumptions can be confirmed with a statistical analysis of the estimates. A filtering can be performed based on the total discharge (>500 % of nominal capacity) or on the length of the periods (>n days) in order to only keep the most reliable estimates. The results are gathered in Table 6.

<table>
<thead>
<tr>
<th>SOC as reference</th>
<th>Open Circuit Voltage as reference</th>
<th>Total Voltage as reference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Absolute difference with $\eta$ [real %] (Standard deviation of the estimates [real %])</td>
<td></td>
</tr>
<tr>
<td>Filtered on high total charge exchanged [Ah]</td>
<td>$\eta$ ($\sigma=0.43%$)</td>
<td>$\eta - 0.01%$ ($\sigma=0.69%$)</td>
</tr>
<tr>
<td>Filtered on long periods [h]</td>
<td>$\eta + 0.03%$ ($\sigma=0.46%$)</td>
<td>$\eta + 0.09%$ ($\sigma=0.77%$)</td>
</tr>
</tbody>
</table>

Table 6: Statistical analysis of the coulombic efficiency estimates for three reference states

As expected, the standard deviation decreases with a higher precision for the indicator used to describe the reference states. Using the provided SOC or the Open Circuit Voltage is thus preferable. The other indicator for the comparison is the average value obtained, since this value is the one considered to be the final estimate. On this point, the table is very positive with the absolute (real) difference remaining low from one reference indicator to the other. Especially, the gap between the estimates based on the SOC and on the Voc and filtered based on the total discharge is only 0.01% in this calculation.
This very small difference allows to propose two conclusions. First, the SOC and the Voc can almost be used interchangeably. If one does not have access to an estimate of the SOC, the Voc can still be used to estimate the coulombic efficiency. Secondly, this level of accuracy is satisfactory for the estimate of the SOC based on the Corrected Coulomb Counting. Indeed, if the error on this efficiency is of the order of a couple of $10^{-2}$ % then the SOC drift after 100 cycles would be of the order of a few percent. In the context of SOC estimate, this rate of drift is reasonable since it leaves time to regularly reset the cumulative SOC calculation and these updates in turn ensure that the accuracy of the indicator is maintained.

4.2.2 Availability

Like any other power project, the availability is a key indicator. However, unlike traditional thermal plants for instance, BESSs have a modular configuration that imposes to adapt the traditional notions employed to assess their availability. In section 2.6.2.2, the notion of Live Level Availability (LLA) was introduced. It quantifies, at any given time, the share of the elements being operable at a given level of hierarchy (containers, racks ...).

In order to obtain results enabling a fruitful discussion, the analysis should be performed over a temporal window that is sufficiently large to cover a wide variety of regimes. This could not be achieved with the data available. For this reason, a simulation was constructed to illustrate the discussion.

The simulation setup is the following. A given level of hierarchy, the architecture is composed of 7 elements in parallel with each of them being made of 15 elements in series. In addition, the 7x15 elements configuration is supposed to operate around the clock except when a failure occurs. In the event of such failure, the time to repair is constant and set to one entire day. Preventive maintenance is omitted. The reliability of each of these 105 components is expressed in days before failure. It is simulated with a normal distribution defined with a mean $\mu$ and a standard deviation $\sigma$ [119]. The mean, which in that specific case represents the MTTF, is a varying parameter but the standard deviation is assumed to be one fifth of this mean. The values chosen here are arbitrary and with the sole purpose of providing an illustrative example to feed the discussion.

The operation of this configuration can be simulated over several years. At every time step (one day), if at least one element fails in a serial chain then the entire chain is down for the day. At the end of that day, the failed element is replaced with a new one, having its own random life expectancy. The Live Level Availability is then computed for a given day as:

$$LLA (d) [\%] = \frac{n_{chains\_operable}(d)}{15} \times 100$$

(35)

The Average Level Availability (ALA) can be computed as the mean of the daily values of the LLA over an entire period. A result of this simulation setup is proposed in Figure 32 where the average MTTF was set to 2 years.
In this simplified parametrization, the LLA can only take 8 values: 100 % when all of the 7 parallel chains are in operation, 86 % (=6/7) when one is down, 71 % (=5/7) when two are simultaneously down and so on. As a reminder, the failure of one element in a chain is sufficient to stop this entire chain. These discrete values for the LLA are clearly identifiable on the chart. On the worst days, the LLA even reaches 57% with only 4 out of 7 chains operating.

This simulation can be brought back into the context of BESSs. One can consider a fictional large-scale BESS made of 7 containers each featuring 15 modules in series. Let’s assume that in order to provide the contracted service, the system only needs to have at least 6 out of the 7 containers operating. In that case, what truly matters to the system owner is to maintain a LLA at least equal to 86%. Indeed, this threshold is what determines whether or not it is remunerated.

Subsequently, it now appears that for a BESS, the notion of vertical availability or level availability is fundamental. Indeed, BESSs are almost systematically oversized to compensate for the progressive decline of their performances caused by ageing. This oversizing can make a BESS much more resilient to failure because its design may allow it to continue to provide the service despite the loss of one of its subsections.

This reasoning come along with the notion of LLA thresholds. Indeed, even if a system has achieved a very high Average Level Availability (98.1% in Figure 32), it does not mean that the remuneration based on the day by day availability will be equivalent. This discussion on the notion of thresholds on the LLA can be further illustrated with Figure 33. To build this chart, multiple 20 years simulations similar to the one discussed above were launched. The varying parameter from one simulation to the other is the average value of the life expectancy (MTTF) of the components to illustrate the impact of the reliability. For each simulation, the ALA is computed as the average of the daily level availabilities and the percent of time meeting two service thresholds is calculated. The highest threshold is the necessity to have all chains operating to be remunerated and the second one is to have at least 6 out of 7 chains to provide the service.
Figure 33 illustrates the importance of including the notion of thresholds in the discussions related to availability. Indeed, for a given reliability (MTTF), there can be a significant gap between the two service thresholds proposed here. If one does not take into account the oversizing of the BESS which make it capable of performing its duty with only 6 elements, one may underestimate the remuneration as illustrated by the difference between the green and orange lines. For example, for a MTTF of 10 years, a BESS able to deliver its service with only 6 out of its 7 containers can capture 2% more remuneration. As expected, this gap diminishes a higher reliability as the failures are less frequent.

Of course, this discussion is based on a simplified model distant from the constraints of actual projects, but the following conclusions remain true. The hierarchical organization of BESS imposes an adaptation of the usual definitions related to availability. For example, the traditional binary definition can be replaced by a more gradual quantification. This more flexible description of the availability can be used to discuss the ability of a BESS to provide a service even if it is not entirely operational. This characteristic feature is only made possible by the necessary oversizing of BESSs. Even if this gain of serviceability decreases with a higher reliability, this nuance should be kept in mind during both the design phase and the assessment of the operational performance of a BESS.

### 4.3 Ageing indicators

#### 4.3.1 Cycles

The number of equivalent cycles performed by the system is a very convenient indicator to quantify the ageing of a BESS. Indeed, as discussed in the section related to ageing (2.4.2), the total charge throughput is the prime driver of the cyclic ageing. The number of cycles is a cumulative indicator that can be studied with a specific temporality such as the number of cycles per day or in an open loop with the total number of cycles performed by the system.

\[
N_{cycles} = \frac{Q_{dis,total}}{Q_{dis,nominal}} = \frac{\int I_{dis}(t) \, dt}{Q_{dis,nominal}} \tag{36}
\]
Its calculation relies on the notion of Coulomb Counting as the discharge current is integrated over time. This technique and its principal parameters have already been presented in the section concerning the State Of Charge. As a reminder, the conclusion was that the type of integration method does not have a perceptible impact on the estimate as long as the time step remains small compared to the typical time of variation of the system.

Just like for the SOC, the number of cycles is a dimensionless indicator. However, since their objective are distinct, their denominators are also slightly different. On the one hand, the SOC is a live indicator so it is normalized by the available capacity at the moment of calculation (including the SOH). On the other hand, the number of cycles is a cumulative indicator that can be computed over arbitrary periods. Hence, a convention is required, and the nominal capacity is usually privileged in this work since it is a constant value and a permit to translate the total throughput into equivalent cycles.

The number of cycles defined as such is a very convenient metric for multiple analyses.

- It can be used to compare two BESSs with the same battery type but performing very different duties (e.g. frequency regulation vs. arbitrage). Indeed, the number of cycles they have performed gives an indication of the degradation they have suffered.
- The number of cycles (or total throughput) can also serve as an input to ageing models to quantify the ageing due to ageing.
- This KPI also make the comparison between the expected and the actual solicitation of the BESS easier.
- The number of cycles is also as an absolute value to comply with contractual obligations. For example, cell manufacturers often guarantee the lifetime of their products in terms of number of cycles completed. This warranty is typically quantified in terms of cycles completed before reaching a certain SOH, under a specific profile, temperature and C-rate.

Because this KPI is essential to so many analyses, it is important to calculate it correctly both from a methodological and algorithmic point of view. Since the implementation of Coulomb Counting has already been discussed through the SOC, the following paragraphs intends to discuss the methodology about this KPI. More precisely, the objective is to stress the importance of building the notion of cycles on the charge exchanged rather than on the energy, an error frequently made.

To illustrate the difference, a simplified simulation was established. A cell is modeled as a simplified Thevenin Model featuring a constant voltage source (4.0 V) combined with an internal resistance (0.05 Ω). Its nominal capacity is set to 10 Ah. It is stressed with a sinusoidal current described by a 24h period and 1A peak value.
This simple model is sufficient to illustrate the difference of result obtained depending on the variable used. Due to the internal resistance, the voltage during the charge is higher than during the discharge (hysteresis). This is visible in Figure 34 with the peak charging power (<4W) being greater than the peak discharging power (<4W) in absolute terms. Over a cycle this imbalance results in a total charged energy being greater than the discharged one. Over multiple cycles, it translates into a progressive divergence of the number of cycles calculated based on these two different quantities. As a conclusion, the notion “number of cycles” is very sensitive to the definition selected.

But still, one may think that since this KPI is only a matter of convention, the discharged energy could be used as well. This proposal is acceptable, but it is much weaker than relying on the discharged capacity. This comes from the fact that, for 1 Ah released by a battery, its corresponding energy is influenced by the C-rate at which it is discharged. A higher C-rate means a lower energy output for the same capacity released because of the voltage drop induced by ohmic effects.

One can exemplify this point with two identical batteries A and B. If battery A discharges at 1A during 1 hour and battery B operates at 2A during 30 minutes and then is at rest for another 30 minutes, their total charge throughput after one hour are equal (1Ah) but the energy output from A is greater than the one from B due to lower ohmic losses. As a result, an “energetic” definition of the number of cycles would conclude that B has performed less cycles than A. This is problematic for two reasons:

- First, it proves that the “energetic” number of cycles is a function of external parameters, in this example it is the C-rate. The same conclusion can be reached about the temperature as the internal resistance varies with it and about the SOH since the ohmic losses are higher for aged cells. An exact definition thus requires controlling all these parameters.
- Second, the conclusion that B performed less “energy” cycle can even be misleading. Indeed, if the number of cycles is used as an indicator to evaluate the comparative degradation of the two batteries then this energetic definition would suggest that B has been less deteriorated than A. Actually, the opposite turns out to be true since higher C-rates cause more damages.
As a conclusion, counting the cycles performed by the system as a function of its energy output is dangerous and misleading. From a methodological point of view, it is strongly advised to monitor the cycling based on the current throughput or a normalized variant of it like the number of equivalent cycles quantified in terms of capacity.

### 4.3.2 State Of Health

While the number of cycles is interesting to evaluate the main driver of the cycling ageing, the State Of Health directly quantifies the overall consequence of these ageing mechanisms through the loss of capacity. Just like for the SOC, the SOH can theoretically be assessed for each and every element of a system, from the cell to the container. However, the loss of capacity takes places at cell level and the SOH of an assembly is only an average of the state of the cells it is made of.

The estimation technique selected in this work is based on the comparison of the capacity discharged over a portion of the voltage curve for an aged cell compared the capacity corresponding to the same portion when it was new. In other words, this technique links the SOH to the slope of the voltage curve. Indeed, as a cell ages, its capacity decreases but its voltage window remains unchanged. The result of this deformation is an increase of the slope “on average”. First, the results obtained during the study are proposed. Then a more critical review of the technique is proposed.

The workflow is similar to the one implemented for the coulombic efficiency as it relies on the definition of two reference states between which the current is integrated. The second similarity is the possibility to repeat the estimation to obtain a more robust average value. This time however, only the Open Circuit Voltage can be considered as reference state since the SOC is unknown and the total voltage is less accurate. In addition, unlike for the coulombic efficiency where the states needed to be identical, this calculation requires to have distinct state.

The first task is thus to identify rest periods where the measured voltage is physically equal to the OCV. One could name them Voc 1 and Voc 2. The second step is to count the charge exchanged between these two reference instants \(Q_{\text{max, Voc 1; Voc 2}}\). Finally, the charge corresponding to this voltage band \([\text{Voc 1; Voc 2}]\) for the nominal cell is computed. The SOH is obtained by comparing the two quantities.

\[
SOH = \frac{Q_{\text{max}}}{Q_{\text{nominal}}} \approx \frac{Q_{\text{max, Voc 1; Voc 2}}}{Q_{\text{nominal, Voc 1; Voc 2}}} \tag{37}
\]

A preferred axis can once again be selected for the plot. In this extrapolation of the SOH from the analysis of portions of the voltage curve, the broader the voltage portion the better. The length of the voltage band could be an option. An alternative is to use the total capacity exchanged as once again, more exchanged capacity is synonymous for a reduced weight of the boundaries error stemming from an inexact definition of the reference states. Figure 35 displays the estimates obtained for a 90Ah cell in operation.
First of all, a significant spread of the values can be noted. Some estimates with very small cumulative charges are found far from their expected values. Fortunately, higher exchanged charges lead to more robust estimates. The points with an exchanged charge at least equal to one third of the nominal capacity are spread within a ±5% band. This accuracy is limited compared to more complex methods where the usual uncertainty is about half of it. However, this interval is sufficient to get an idea of the health of an element without changing its operation or building empirical comparisons.

This estimation technique has its accuracy inherently limited by two aspects. The first aspect is related to the computational errors due to the definition of the reference states. The inaccuracy of the boundaries in the counting of the charge and during the comparison with the reference state is a first source of error. These inaccuracies are hardly avoidable and correspond to errors in the implementation. The second aspect limiting the accuracy is the underlying assumption of a homogeneous change of the voltage slope. This weak but necessary hypothesis adds methodological error to the method. In the literature review section, this assumption was introduced and can be further discussed here.

As the cell ages, its capacity fades but its voltage range remains unchanged. The overall voltage slope thus increases. This average voltage slope is in fact what is compared in this technique \((\equiv_1)\). But this average slope can also be seen as the sum of the elementary charges per voltage segment as proposed by \(\equiv_2\).

\[
SOH \equiv \frac{Q_{max, [V_{oc1}; V_{oc2}]} \cdot V_{oc2} - V_{oc1}}{Q_{nominal, [V_{oc1}; V_{oc2}]} \cdot V_{oc2} - V_{oc1}} = 1 - \frac{Q_{max,2} - Q_{max,1}}{V_{oc2} - V_{oc1}} \approx \frac{\int_{V_{oc1}}^{V_{oc2}} dQ_{max} \cdot dV}{\int_{V_{oc1}}^{V_{oc2}} dQ_{nominal} \cdot dV} \quad (38)
\]

In turns out that the analysis of the distribution of the elementary charge per voltage section is exactly the purpose of the Incremental Capacity Analysis (ICA). This laboratory technique is widely used to study the ageing mechanisms driving the degradation of a cell. It displays the local charge gradient \(dQ/dV\) as a function of the Voltage as proposed in Figure 36.
Figure 36: ICA of a 10Ah NMC cell at different ageing conditions. Image from [120]

The ICA can thus be considered as the laboratory version of the slope analysis performed in the SOH estimation technique. Even if an ICA is cell specific (each cell type as a different voltage curve and thus a different derivative), the analysis of Figure 36 is very representative. One can notice that as the cell ages, the shape of the ICA and thus the local gradient dQ/dV evolves greatly. The total area under the line that equals the total capacity diminishes but this process is not a homogeneous downwards shift as assumed in the SOH estimation technique. In other words, the local dQ/dV does not decreases homogeneously over the voltage range so the voltage slope dV/dQ does not evolve evenly either. As a consequence, the core hypothesis of the SOH technique that states that the voltage curve changes uniformly as the cell ages is not very robust and this can partly explain the disparity of the SOH estimates.

4.4 Safety indicator: Thermal analysis

Achieving an effective thermal management is essential to ensure a smooth operation of a BESS. Indeed, an inadequate control of the temperature environment is responsible for an accelerated ageing of the cells and can lead to severe accidents if the temperature is high enough to trigger a thermal runaway. The monitoring of the temperature in terms of temporal and physical distribution are the two angles of analysis proposed in this work.

4.4.1 Temporal distribution

One way to monitor the temperature of a BESS is to follow the extreme temperatures experienced by its elements. For instance, at each time step, the minimum and maximum temperatures recorded over all the modules constituting a rack can be checked. This gives the live temperature boundaries of the system. These extreme values can also be regarded through their temporal distributions. By doing so, one can quantify “how often” some parts of the system operate with an inappropriate temperature. Figure 37 illustrates this type of approach.
If the data covers a long period of operation, it can also be interesting to investigate how the distribution of the extreme temperatures evolve over time. As the cells age, their internal resistance grows which induces an increase of the heat generation rate. The task of maintaining the temperature within its nominal range becomes harder and excessive temperature events are expected to be more intense and more frequent.

The analysis of the abnormal temperature behaviors can also guide the maintenance. A module that is repeatedly operating at too high temperature is an indication of a possible failure of the embedded cooling system (fan or other technology) or a symptom of an advanced state of ageing that request a further investigation.

### 4.4.2 Physical distribution

The analysis of the temperature measurements can also give an idea of the homogeneity of the cooling process. To meet this objective, one can rely on boxplot charts. Such a chart is extensively used for the statistical comparison of several data series. For example, Figure 38 provides a visual description of the 5th, 25th, 50th, 75th and 95th percentiles of the temperature measured for 15 modules constituting a rack in operation. Simply put, a boxplot is nothing more than a statistical summary of a histogram.
In this chart, one can notice a slight increase of the overall temperature distribution of about 1°C from module 9 to 15. This trend is to put into perspective with the physical layout of the rack where the modules are stacked on top of each other from module 1 to 15. The temperature rise from module 9 to 15 is thus a direct image of the natural temperature gradient within the container. A similar analysis could be conducted over elements spread all over the container. By doing so, a grid of measurements permits to identify the areas hotter than the average and that deserve a special monitoring.

Note that ideally, the temperature should be monitored at cell level since this is where the heat is generated. Module and container temperatures are only by-products of the thermal behavior of the cell and of the technique implemented for the cooling. In addition, the risk of thermal failure is exacerbated by very local hot spots that may not be detected if the measurement is not sufficiently local. There is thus a clear tradeoff between the costs of the measurement apparatus and the locality of the observation.
5 Conclusions

5.1 Key learnings

Large-scale Battery Energy Storage Systems are expected to play a major in tomorrow’s energy landscape. To make sure that these complex systems are operated efficiently, safely and on the long-term, owners and operators can rely on data analytics to access synthetic and interpretable information about their assets.

Throughout this work, the emphasis was placed on the description of the links existing between the different aspects of the operation of a utility scale BESS. Unlike small scale experiments where one indicator or phenomenon is studied in depth, industrial battery storage projects should be analyzed as a whole to ensure a good overall assessment. For example, the ageing of the cells is influenced by the operation history but it also what determines the future capabilities of the system. Another illustrative example is the thermal and electrical balancing of the elements. Its realization is an operational challenge, but it can also be seen as a relevant ageing and safety parameter. As a consequence, this work stressed the need to study BESSs with a system perspective rather than at component scale, in order to capture the interactions existing between these aspects.

This work also provided a critical discussion on the notions to select when talking about battery storage systems. In particular, one can recall the choice of indicators defined in terms of capacity over their energy equivalents (SOC, number of cycles in terms of discharged capacity vs. energy). A new concept of vertical availability named the Live Level Availability has also been proposed. This instantaneous description of the availability proved to be relevant to take into account the hierarchical and highly parallel structure of the BESS, especially when it comes to the notion of minimum service requirement.

Finally, this work proposed some pragmatic guidelines for a satisfactory implementation of the KPIs. By taking advantage of the statistics applied to a large amount of data, even the simple calculations can yield results with a satisfactory robustness. In addition, the meaning of high-level indicators and their limitation was discussed. One can remind the fact that the average SOC of an assembly does not reflect the unbalance of its constituting elements and that a coarse mesh of the temperature sensors may not be able to identify the very local hot spots.

5.2 Next steps

The objective of this work was to propose a first series of KPIs mainly describing the electrochemical part of storage systems. Therefore, a continuation of the project could be to complete this list with other technical indicators covering the Power Conversion Systems and the auxiliary equipment. In the same perspective, economic (live earnings, cost of maintenance) and environmental indicators (average CO2 content of the electricity exchanged, RE curtailment avoided) could be added to complete the overview of the system.

This work also serves as an additional input for the systematic and automated monitoring of the BESS projects. Indeed, once the KPIs are tested and validated, they can be implemented by default in the monitoring process. This automatic treatment step can provide an evaluation that would be both continuous and easy to interpret for the system operator and owner.

Eventually, such a systematic monitoring could help gaining a better understanding on how to design and operate BESSs. In this work, the analysis of the data permitted to move from raw physical measurements to synthetic indicators. However, the values exhibited by an indicator for a specific project are inherently influenced by the characteristics of that specific project (cell type, control strategy, type of application and so on). By comparing the findings obtained by the KPIs over multiple separate projects, questions such as which chemistry is best suited for a particular type of application or to what extent a specific maintenance strategy can help to keep a system in service for a longer period of time could be answered. This knowledge can also be exploited to build and validate system scale numerical models used in simulations.
From a broader perspective, the Li-ion battery technology is experiencing a fast transformation, in line with the expectations placed on it. Since this storage solution is predicted to play a major role in the transformation of the transport and energy sectors, it is essential to use it in the most sustainable way possible. This goal will only be achieved by a very good level of understanding of these complex systems, an understanding in which KPIs participate in the same way as laboratory experiments. It is only with a good knowledge of the capacities and limits of these storage systems that the best decisions can be made from an economic point of view but also from an environmental and societal perspective.
6 Bibliography


7 Annex A

This annex examines the impact of a larger time step and a different integration method on the SOC estimate obtained by Corrected Coulomb Counting.

![Influence of the time step (1s, 10s, 100s)](image)

Figure 39: Influence of the time step

In this chart, the SOC is computed via CCC for three orders of magnitude of the time step: 1s, 10s and 100s. The integration method remains the bar approximation. A 24h rolling average is implemented to smoothen out the noise and have a clearer view of the trend. Maximum and minimum boundaries are also included.

The change from 1s to 10s do not seem to have a noteworthy impact on the estimate. The difference remains limited to about 0.5% after 5 days. A 10 second step for the current seems tolerable if no better accuracy can be provided. On the other hand, the move to 100s is responsible for a significant deviation. This shift makes this time step unreliable.
Figure 40 illustrates the impact of the choice of the integration method. The switch from bar to trapezoidal integration led to imperceptible difference for a time step of 1s. For this reason, the plot was not included in the figure. In order to investigate this choice anyway, a comparison of the switch from bar to trapezoidal was proposed for the higher time steps of 10s and 100s.

For a 10s sampling, the bar and the trapezoidal approaches lead to almost identical estimates. The SOC only differs from about ±0.1% over the 5 days of simulation. At 100s, the difference is more visible and reaches about -1% on average with a ±1% for local extremes. However, this difference due to the choice of the integration method remains of second order when compared to the deterioration of the SOC caused by the increased time step itself.

As a conclusion, one can state that reliability of the integration remains primarily influenced by the time step. If the measurement in performed every second, the integration of the current can be judged trustworthy, regardless of the integration approach selected.